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Machine Learning in Marketing Analytics

Mickey Singh

Marketing Analytics, MS in Applied Statistics, Rochester Institute of Technology, NY, USA

ABSTRACT

In the realm of marketing analytics, machine learning has emerged as a powerful tool for automating tasks, refining strategies, and optimizing outcomes. This research article delves into the significance of machine learning techniques in marketing analytics, particularly focusing on the burgeoning domain of online advertising and sales. The article begins by elucidating the pivotal role of machine learning in discerning effective marketing strategies amidst the complexity and dynamism of modern marketing environments. It highlights the transition from traditional, indiscriminate advertising to data-driven strategies, emphasizing the importance of leveraging machine learning models to target the most promising customer segments and optimize marketing efforts. Furthermore, the article explores key applications of machine learning in marketing analytics, with a specific focus on customer segmentation, predictive modeling, and recommendation systems. Through examples and case studies, it elucidates how machine learning algorithms can automatically identify and categorize customers based on their behavior patterns, predict future outcomes, and provide personalized recommendations, thereby enhancing marketing efficacy and ROI. However, alongside the myriad benefits, the article also acknowledges the challenges inherent in the implementation of machine learning in marketing analytics. Issues such as data quality, privacy concerns, and stakeholder resistance are discussed, underscoring the need for ethical and responsible use of data-driven insights. Looking ahead, the article outlines promising future trends in machine learning for marketing, including advancements in natural language processing (NLP) for sentiment analysis and the integration of machine learning with big data technologies. These developments are poised to revolutionize marketing practices, enabling more accurate targeting, automation of marketing campaigns, and greater personalization. This research article serves as a comprehensive guide to the multifaceted role of machine learning in marketing analytics, offering insights into its current applications, challenges, and future prospects for transforming the landscape of marketing strategy and decision-making.

Keywords: Marketing analytics, Machine learning, Online advertising, Sales, Marketing strategies, Data-driven strategies, Customer segments, Predictive modeling, Recommendation systems, Customer segmentation, Behavior patterns, ROI (Return on Investment), Data quality, Privacy concerns, Stakeholder resistance, Ethical use of data, Future trends, Natural language processing (NLP), Sentiment analysis, Big data technologies

INTRODUCTION

Machine learning can be used to automate this task. What is essential here is to build a model of the strategy and use what is gleaned in the comparison to improve the strategy. The best marketing strategies are data driven. A/B comparison is a data driven strategy, but even better is learning the effectiveness of a strategy by the change in probability of a customer choosing the product. (Liu et al.2020) Models can be built to discern the best customers, and what distinguishes them from others; and pitch the product to these customers in the areas where the probability of purchase is highest. This is a vast improvement over indiscriminate advertising to the general population. In each case the effectiveness of the strategy can be gauged by the change in probability. But the best use of machine learning in marketing analytics is to simply automate the process of determining the best strategy, given that marketing environments are often complex and fast changing. (Kumar, 2020).

The area of interest in specific is the use of machine learning techniques in marketing analytics. In spite of the fact that the profits of preventive marketing are well documented and accepted, marketers frequently fall back on a strategy of wait and see. (Christiansen2024) In many cases marketing activities are basically an experiment - I will send the same advertisement to the same population, but alter the "look" of the ad, and compare the effectiveness from the first to the second in terms of sales. This is a wasteful strategy in that it doesn't make best use of the data. If the purpose of the experiment is to compare two strategies, and a marketer has no prior inkling as to which strategy is better, then the most profitable course of action is to implement the two strategies in the actual marketing environment; for the two populations are apt to be different and one can glean information as to the comparative effectiveness and use that information to decide on the best strategy. (Liu et al.2020)

Definition of Machine Learning

Machine learning is a technology field that uses statistical tools to enable computer systems to improve their performance on a specific task. Machine learning plays a vital role in marketing analytics, especially with the big boom in e-commerce and online advertising in recent years. (Kumar, 2020)Despite the availability of extensively thorough web analytics tools, there are so many variables in online marketing that skew data and cause conventional analysis to fall short. Machine learning techniques are essential in mining through large amounts of unstructured and structured data. (Tayefi et al.2021) With online advertising, it can be used to model customer response to advertising (click-through rate prediction, for instance). With online sales, it can be used to mine for patterns that classify buying customers and window shoppers. However, it is not a magic bullet. Using it requires careful planning, significant technical expertise, and a considerable understanding of the method and its results by practitioners in order to be used effectively. This paper will examine what machine learning is, its importance in marketing analytics, focusing specifically on applications in online advertising and sales, and the benefits and pitfalls by practitioners.

Importance of Machine Learning in Marketing Analytics

The importance of machine learning in marketing can be realized with the substantial increase in the quantum of data being generated and with the emergence of newer channels that are used by marketers. The key drivers have been the need to improve customer acquisition, retention, and loyalty. (Miklosik and Evans, 2020)Up to this point, the application of machine learning has been most widely used in the following areas. This is reflected in a number of point solutions that have been developed to address key marketing problems. An example of this would be the application of machine learning to email targeting, where the goal is to learn who should be emailed about what product. This has been provided by several vendors as a service to ESPs and marketing organizations. (Ellickson et al., 2023)Another example is in the development of recommendation systems. Many retailers have seen value in applying machine learning to learn to provide better product recommendations to customers. This can be seen with companies such as Gilt Groupe, who use machine learning to tailor their daily sales to individual shoppers, and Ditto, a new eyewear e-tailer that uses machine learning to provide virtual try-on for eyeglasses. (Yi and Liu, 2020)(Feldman et al.2022). In industries with a longer sales cycle, like automotive or financial services, many marketers have only just begun to experiment with machine learning. This is often due to both the complexity of the sales funnel and the corresponding data integration problems. (Ma and Sun, 2020)

Applications of Machine Learning in Marketing Analytics

This section requires substantial leverage of ML for analytic purpose that it tries to identify specific customers in its database and predict their behavior. Customer segmentation is an analytic process to differentiate the customers into different groups of individuals that share similar behavior or characteristics. (Wu et al.2020) For example, in a mobile service provider company, customers can be segmented into different groups regarding their usage patterns, such as occasional users, frequent users, or heavy users. The company cannot differentiate the customers only by looking at their usage because it is too dynamic and there are too many factors that can affect their decisions in using the mobile services. The best way to differentiate them is by looking at their calling records and the duration between one call to another (call gap). The customers in this case can be grouped by the amount of calls they made in a specific period of time. Occasional users may only make 5-10 calls a week, frequent users may make 15-25 calls a week, and heavy users may make as many as 30 calls a week. So, by using machine learning methods, we can cluster the customers into different groups based on their call records and duration of calls. (Alkhayrat et al., 2020)After the clustering is done, the company can give specific treatment based on each group of customers. They can give bonuses or free vouchers to the top-up card for the heavy users and give special tariffs for the frequent users. This method will be more effective rather than giving the same treatment to all customers, and the result of this treatment can be monitored by doing a further analysis to see whether the changes in customer behavior are in line with the initial clustering. (Christy et al.2021)The second step is predictive modeling. The main focus of predictive modeling is to create a model that can predict a favorable result with a specific condition. There are many methods that can be categorized as predictive modeling, such as regression, naive-bayes, decision trees, etc. The output of predictive modeling is generally more accurate when compared to the result of data mining because it uses specific variables to predict the specific outcome, unlike in data mining, which only looks at the data and tries to find a pattern. The disadvantage of predictive modeling is that the model built is too specific and sometimes cannot be used for a different problem with similar conditions. (Chekroud et al.2021)

Customer Segmentation

The key benefit of using machine learning for customer segmentation is the ability to automatically build a robust and precise classification model used to understand individual customer attributes and subsequently group them into defined segments. Classification is a supervised learning technique that will build the model using data where the outcomes, i.e., the segments, are known. (Wang, 2022)The model is built by finding the relationship between a set of input variables that will be used to predict the segment the sample belongs to. This model is then used to classify new customers into the most appropriate segment. This differs from traditional segmentation as it does not form human interpretable rules to place individuals into segments. Although this was a benefit of cluster analysis, classification provides a more accurate and flexible method to segment customers. (Acuna-Agost et al.2021)

Customer segmentation is the process of defining and subdividing a large homogeneous market into clearly identifiable segments having similar needs, wants, or demand characteristics. Using machine learning techniques to perform customer segmentation allows companies to sift through the data and find patterns about individual customers. Traditionally, segmentation techniques such as clustering analysis have been widely employed to analyze and interpret customer information. (Alkhayrat et al., 2020)With the ever-increasing volume of data and the growing complexity of customer relationships, traditional segmentation methods are becoming less adequate. This is because cluster analysis and other segmentation techniques are often restricted to using one or two key variables to form the clusters. This simplification does not accurately reflect the complex reality of customer behavior. Therefore, there is potential for machine learning techniques to make significant improvements to customer segmentation. (Tirkolaee et al.2021)

Customers are key revenue drivers for a company and through understanding customer behaviour, marketing performance, particularly in multi-channel industries, can be greatly improved. An important marketing step of understanding customer needs is to clearly identify different groups of customers and their characteristics. This is called market segmentation. Customer segmentation is widely used in both strategic and tactical marketing. On the strategic side, the ability to identify different groups of customers and the ability to determine which groups are most important to the company can drive customer acquisition and retention initiatives. On the tactical side, customer segmentation can be used to customize product offerings, marketing strategies, and sales messages. (Dolnicar, 2022)

Predictive Modeling

Predictive models are used to speculate the result of a specific marketing strategy or tactic with the aim to improve upon it the next time around. Imagine "model" as just a thought influenced by strategy, which you will want to test. The most common use of a predictive model is by gauging the effect of change in a tactic, before it is actualised. For example, you may be unsure about the effect of changing the copy in your AdWords on PPC. (Purba et al.2021)Create a model using your current conversion rate as a basis and compare this to predicted conversion rates using different copies of AdWords. This will give you an indication of whether the different copies will have a positive, negative or no effect. At this point, it is probably best to follow through with the most educated change. This can also be applied to testing the effect of change in price on demand for your products, i.e. increase or decrease. It is always good to nest changes like these because it gives you the most advantageous understanding of the effects and helps to articulate the best future strategy. It doesn't matter if the model "fails", going back to the previous example it would still be good to learn that decreased AdWords copy A resulted in no change of conversion rate, giving a conclusive understanding of the impact of the initial ad copy. Unfortunately, the complexity of predictive models is increasing and this is a great example of a task now best left to machines! (Ma and Sun, 2020)

Recommendation Systems

Recommendation systems are a widely used application of machine learning in marketing. They are employed in an attempt to model user preferences, and the most effective recommenders are those that provide an accurate prediction of a user's rating for an item (or preference) that the user has not yet evaluated. In this context, a "user" can be a customer or a browser and an "item" can be a product to sell, a document, a video or a piece of information. (Hamid et al.2021)There are two approaches to recommendation systems, one which is based on collaborative filtering, and the other which is based on predictive modelling. Collaborative filtering methods are based on building a model of user preferences, and recommend items to users based on their predicted preferences. These methods are widely used, but have the limitation that they cannot recommend items or products with no (or very few) ratings, and as a result the system is unable to provide recommendations for new products. Predictive modelling based recommenders attempt to find a model that can predict ratings for items, and are able to provide recommendations on the top rated (or predicted) items for a user, these type of recommenders are effective when the items are new products for which there are no (or very few) ratings. (Zhang et al., 2020)

Challenges and Limitations of Machine Learning in Marketing Analytics

In the field of marketing, data often has not been maintained with future research uses, resulting in data files that are difficult to use. This is particularly true in secondary data analysis, the use of existing data previously collected for other purposes. Even when the data has been well maintained, it may be difficult to acquire the needed permissions from gatekeepers due to the sensitive nature of the research models. Step 3.1.2 is challenge 3.3. These marketing and research stakeholders may have requirements concerning the ethical use of data, which could not be possible to fulfill. For example, protecting the confidentiality of the data might be impossible if the analysis requires testing machine-learning methods that have been known to work improperly. (Liu et al.2021) Data cleaning and specification to improve accuracy of predictive models may be anathema to the stakeholders who have existing beliefs about the right way to approach marketing problems. Finally, the most general challenge is in giving and implementing research findings decision making, covered by step 3.3.2. This often involves the necessity of convincing practitioners to change, something that is difficult when it implies improving decision making with data that has already been shown to be suboptimal. (Sundarakani et al., 2021).

Successful implementation of machine learning in marketing analytics poses a great number of potential benefits, but it does not come without challenges. Challenges mentioned in this application are more or less common to machine learning in other fields, but they are particularly acute in this field due to the current state of marketing science. (Shrestha et al., 2021)Three related to the research using existing data to improve marketing decision making. Data quality and availability is challenge 3.1, 2. This is commonly a problem for research in using data to make decisions. In the case of marketing data often has not been maintained with future research uses with the result that they are data files that are difficult to use. This is particularly true in secondary data analysis, the use of existing data previously collected for other purposes. Even when the data has been well maintained, it may be difficult to acquire the needed permissions from gatekeepers due to the sensitive nature of the research models. Step 3.1.2 is challenge 3.3. These marketing and research stakeholders may have requirements concerning the ethical use of data, which could not be possible to fulfill. For example, protecting the confidentiality of the data might be impossible if the analysis requires testing machine-learning methods that have been known to work improperly. Data cleaning and specification to improve accuracy of predictive models may be anathema to the stakeholders who have existing beliefs about the right way to approach marketing problems. Finally, the most general challenge is in giving and implementing research findings decision making, covered by step 3.3.2. This often involves the necessity of convincing practitioners to change, something that is difficult when it implies improving decision making with data that has already been shown to be suboptimal. (McGilvray, 2021)

Data Quality and Availability

The data used for marketing analytics come in various forms. There are customer databases, purchase orders, and point of sales data. However, there are also datasets that are purchased or rented for marketing campaign optimization and customer acquisition or for segmentation and customer profiling (Srivastava et al., 1999), such as data from Acxiom, Experian, and Polk. In some cases, this data may contain too few cases or too many variables. Sometimes it's in the wrong format, or it has been obtained at too great a cost. At worst, it may be the wrong data, as it is often said that today's data is about yesterday's customers. In this rapidly evolving world of digital marketing, it is expected that data provided by SEO, SEM, and online display advertising will be some of the most useful data available, but its quality and format will vary. This wide array of marketing data is a result of the growth of technology and complex systems. (Kundu, 2021)Unfortunately, this often means that marketing data is also dirty data, as it may contain inconsistencies, errors, outliers, and is often incomplete. All of these forms of data are subject to change, given that the environment is always evolving and new technology is always emerging. (Singh and Dwivedi, 2020)

Interpretability of Machine Learning Models

The increasing volume of marketing data and the complexity of applied models can make interpretation difficult. While the application of machine learning models can significantly improve our understanding of customer preferences and choices, marketing analysts are often more comfortable with traditional regression-based models because they can be interpreted. There is an inherent trade-off between accuracy and interpretability. (Ray et al.2022)Some of the most accurate prediction methods, such as the support vector machine, are not easily interpretable. Decision tree models provide a rules-based predictive structure which can be very useful and easy to interpret, however, the trade-off here is often one of predictive accuracy. In some cases, for example when a marketing mix variable has a non-linear and complex association with sales, the more accurate but less interpretable model can be an acceptable compromise. However, there are other cases when the need for model accuracy must be balanced against the necessity for a clear understanding of customer responses and marketing implications. An example here is the use of customer segmentation methods. (Lee et al.2022) Cluster analysis is a descriptive tool used to identify groups of customers who have similar characteristics. Marketers are often more comfortable with an interpretable method such as multivariate regression analysis, however, this may not provide as accurate prediction of segment membership or the association of segment defining variables. This is an instance where the trade-off between model accuracy and interpretability is a critical consideration. The availability of really good data that's relevant to your marketing issue can also influence the nature of the model. More accurate models are obviously more useful, however, they require good data to inform the complex relationships and interactions between marketing variables and customer behavior. If the data is not so strong, there's a danger that a more accurate model will over-fit the data and provide misleading results. In this scenario, a simpler model may be more robust and the higher accuracy model should be revisited when there is sufficient data to fully inform the complex relationships. (Satre-Meloy et al., 2020)

Ethical Considerations

Machine-learning models are increasingly used to assist in business decision making, to help consumers and businesses navigate complex environments, or to provide richer or more convenient personalized services. As machine learning is integrated into a growing number of consumer and business services, there are opportunities to use it to tackle a range of societal challenges. At the same time, the use of machine learning raises several ethical considerations, and in some instances use of machine learning may affect individuals or groups in discriminatory or other harmful ways. The sections that follow outline some of the potential benefits from machine learning and some issues of concern. We identify eight broad areas of opportunity and risk. In later sections of the paper, we elaborate on the issues introduced here, providing case studies and further analysis. (Char et al.2020)(Mühlhoff, 2021)

Future Trends in Machine Learning for Marketing Analytics

]Automation and personalization in marketing campaigns is another trend we will see due to the cost-effectiveness and accuracy of predictive models. As machine learning continues to automate data analysis and pattern recognition, it will quickly be applied to automate the control of marketing campaigns. This includes things like programmatic ad buys which are already becoming quite common. But machine learning will take this to the next level using predictive models to make real-time decisions (bid more, bid less, change message, etc) in an adaptive manner. This automation will free up marketers to focus more on strategy and less on execution. Personalization is a common theme in marketing and is facilitated by machine learning. But we are still only scratching the surface because personalization requires sifting through a great deal of data to make inferences about what each individual's wants and needs are. As machine learning accurately identifies patterns and makes decisions, automated marketing campaigns will become more and more personalized. (Kotras, 2020)(Haleem et al.2022)

Machine learning is becoming more and more integrated with big data. As cloud and distributed computing becomes more efficient and affordable, storing and processing large data sets will become less of a burden. Machine learning algorithms are very scalable and are a natural fit with big data technologies. A greater number of marketers will begin to harness the power of machine learning to gain insight from data. This is still a maturing trend, but big data technologies are quickly evolving and making machine learning in marketing a reality. (El and de2020)

The future trends in machine learning for marketing are promising. Natural Language Processing (NLP) has come a long way and will continue to do so. According to a survey reported by Twist Market Research, "most business leaders believe NLP will have a significant impact on their marketing and sales effectiveness." Companies are developing better ways to decipher language and more correctly judge the sentiment of statements and phrases. This will become increasingly important as the vast amount of unstructured text data available continues to grow. (Hartmann and Netzer, 2023)

Advancements in Natural Language Processing

On the topic of understanding written natural language speech (voice such as people use in queries and voice responses to users), this is a particularly exciting area for application of NLP. However, it is a more futuristic feature of NLP capabilities that might see more action in the next section. Currently, there have been huge advancements in scientific understanding of NLP spoken language, particularly in the field of neurolinguistics. This has spurred a growth in understanding of the psychology of language and how it is represented and processed in the human brain. This knowledge is now being used in various industries for the advancement of NLP technology. Notably for a plethora of learning applications (of which only a select few are web-based language learning tools).

For example, given the current information that we have about the brain and language, how can we produce feasible exercises to strengthen language processing and production in the brain for a stroke victim? Currently, we know that Broca's area in the left hemisphere of the brain is heavily involved in language processing and production (instead of speech occurring solely in the left hemisphere). This might lead to experimentation with fMRI and NLP technology to produce an accurate 3D model of language areas in the brain, the results of which might provide therapies to production-impaired aphasics. (Torfi et al.2020)Advances in machine learning have also led to the extraction of large quantities of spoken language data used to produce computational models of human language processing. Although too detailed to explain here, these models are usually processed in logical functional programming frameworks (an alternative to the well-known object-oriented framework that you found in Java, Python, or C++). This type of work has been used in fields ranging from psycholinguistics to computational paralinguistics (machine analysis of emotion in speech). (Sharmin et al., 2020)

Integration of Machine Learning with Big Data Analytics

The potential for machine learning to advance marketing analytics and marketing practice in general is clear. This can be evidenced by machine learning's association with big data and analytics, which could be used to build a model of customers' propensity to purchase, modeling dynamic pricing strategies, and the prediction of customer churn. (Chaudhuri et al., 2021) Machine learning integrated with big data analytics has huge potential for marketing. There are far too many potential research topics to list in a single article; however, the trend is clear that machine learning will play a larger role in future marketing practice. This ranges from using machine learning to improve customer segmentation, product and service decision making, pricing, and sales promotion strategies. In the future, we may see marketing departments with a Chief Data Scientist and marketers with core competencies in machine learning. (Ma and Sun, 2020)Much has been written on big data and analytics in recent years; however, the best is yet to come. For the astute marketing researchers or practitioners, it is clear that machine learning represents a clear evolution in the process of data-driven decision making. In large, machine learning is still in its infancy in regards to supervised techniques, which build predictive models from historical data, to optimize decisions. At present, many decision makers still rely on decision rules developed from experience and intuition. It is simply a matter of exposing these decision-makers to the potential of machine learning – a task easier said than done. (Sarker, 2021).

Automation and Personalization in Marketing Campaigns

The formal definition of a marketing campaign could be a significant launch program or a more targeted and strategic initiative. It is customary to consider an advertising campaign in response to a specific consumer group or product. In its entirety, the marketing mix (i.e., the price, product, promotion, and distribution of the product) will be customized to influence consumer purchasing behavior. The marketing campaign should be developed with careful logistical planning, which is where the upcoming learning methods become relevant. As mentioned earlier, conventional approaches often rely on standard machine learning algorithms that do not take into account human relationships, making them somewhat irrelevant. In this context, we will discuss the applications of directed relationships and reinforcement learning methods to the task of scheduling a sales boost through promotional advertisements. Given that advertising frequently has an immediate impact on product sales, we believe that a passive approach, based solely on periodic intervals of advertising budget and a response variable y representing the effect on sales due to increased advertising spending, falls short. The data at hand is dynamic. Therefore, a comprehensive analysis of the market is necessary to successfully implement a supervised learning model of regression for y, utilizing relevant sales data. By viewing advertisements as interventions that can impact the level of the response variable, we can establish a sequence of actions and decisions on how to optimize budget allocation for achieving desirable sales outcomes.

CONCLUSION

This research article underscores the pivotal role of machine learning in revolutionizing marketing analytics. By leveraging advanced statistical tools and algorithms, machine learning enables marketers to automate and optimize various aspects of their strategies, leading to more efficient and effective outcomes. The significance of machine learning in marketing analytics is underscored by its ability to handle vast amounts of data, particularly in the context of e-commerce and online advertising, where conventional analysis falls short.

Through applications such as customer segmentation, predictive modeling, and recommendation systems, machine learning empowers marketers to gain deeper insights into customer behavior, personalize marketing efforts, and make data-driven decisions. Moreover, the integration of machine learning with big data technologies promises further advancements in marketing analytics, facilitating scalable and efficient data processing and analysis.

Despite the immense potential of machine learning in marketing, there are challenges that need to be addressed, including data quality and availability, ethical considerations, and the implementation of research findings into decision-making processes. However, as technology continues to evolve and marketers become more adept at harnessing the power of machine learning, the future holds promising opportunities for automation, personalization, and enhanced marketing effectiveness. In essence, this research highlights the transformative impact of machine learning on marketing analytics and emphasizes the need for marketers to embrace and leverage these technologies to stay ahead in today's dynamic and competitive landscape.

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