Department of Computer Science

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Target marketing analysis and predicting customer response

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ABSTRACT

Techniques and models that enable decision making for marketing decisions are essential to the success of retail businesses. Customer segmentation, also known as customer profiling, is widely acknowledged to be a significant topic for marketing study and practice across a variety of marketing subfields. Utilizing a variety of data mining approaches can be helpful for effectively segmenting consumer bases and executing customized marketing campaigns. The RFM approach is an example of one of these methods. The ability to categorize retail clients may be achieved via the use of three straightforward ways: recency, frequency, and monetary methods. When directed at the appropriate consumers, marketing communications are at their most productive. Therefore, one of the most crucial tasks in campaign planning is deciding which clients should be contacted. The empirical targeting models are the primary emphasis of this research. We contend that the prevalent procedures used to construct such models do not take into adequate account the objectives of the organization. As a solution to this problem, we have come up with the idea of profit-conscious ensemble selection, which is a modelling framework that combines statistical learning principles with commercial objectives in the form of optimizing a campaign's profit potential. The findings of an exhaustive empirical investigation validate the practical utility of the strategy that was provided by demonstrating that it proposes target groups that are significantly more lucrative than the various benchmarks.

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1

I certify that the work presented in the dissertation is my own unless referenced

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Table of Contents

INTRODUCTION:

As a direct outcome of big data analytics, the area of decision help is in the midst of a profound transformation. When it comes to official decision aids, many managers in the past had a fair bit of mistrust, which is understandable. However, there is a degree of interest in quantitative decision support models that has never been seen before in the current day. This level of attention has never been seen before. The availability of huge amounts of data, powerful pattern extraction algorithms, and user-friendly software systems, all of which promise to boost managerial support, is driving this advancement. This progress is being driven by the availability of these factors. For instance, one piece of research estimates that increasing the deployment of marketing analytics is associated with an eight percent increase in average return on assets. This is based on an average. Their results come from a poll that was given to executives who work for a variety of different firms. In a way that is comparable, (Singoei, *et al.,* 2013) determines that the use of big data technologies is associated with an average increase in corporate productivity ranging from one to three percent. This improvement was shown to be related with the usage of big data technologies.

Methods of prediction are created with the purpose of broad application, and they are used to handle modelling issues in a range of different domains. Because it does not incorporate contextual information that is linked to the actual decision job into the building of the model, using a method that is already available off the shelf to target customers is, in our opinion, restrictive. This is because it does not allow for the model to be customized. The constraints on available finances, the lifetime value of consumers, and concurrent campaigns are all pieces of information that are essential to the design of a campaign, but they have very little of an influence on the estimation of the targeting model (Moro *et al.,* 2012). As a consequence of this, the objective of this article is to construct and validate a modelling framework with the idea of taking into account the business goals throughout the whole process of creating a targeting model. The current trends in marketing, which are only beginning to emerge, will help achieve this objective. In particular, marketing communication is getting more individualized and is increasingly being broadcast via digital media. In spite of the fact that personalization might assist in broadening the scope of options that can be targeted, digitalization often requires decisions to be made in real time. Both of these developments highlight the significance of using software to automate the process of identifying consumers as potential customers (Parlar *et al.,* 2017). It is of the utmost importance to have a clear understanding of the company's goals at all stages of the model-building process, but this is especially true when the goal is to create models that operate in a manner that is self-governed.

Background:

Companies participate in marketing efforts, which are actually simply another kind of outsourcing, with the goal of improving the financial health of their businesses and getting a competitive advantage over their "peers" (Elsalamony, H. A. 2014). Direct marketing is a method that is used by businesses when they are attempting to attract a certain demographic of clients in order to achieve a particular objective. By reaching out to clients via distant connection centers, it is possible to make the operational administration of campaigns simpler to facilitate. These types of call centers make it possible to communicate with customers via a variety of channels, including telephones (fixed-line or mobile). The selling of a product that is done over the phone or via the use of a contact center is referred to as telemarketing (Chu *et al.,* 2016). This is due to the fact that telemarketing is a somewhat solitary endeavor. Businesses often sell their products by using one of two primary methods: mass crusades, which are aimed at the whole public, or focused campaigns, which are aimed at a particular group of individuals. The results of the official inquiry indicate that the efficacy of the extensive campaign is not very high. In the majority of instances, a reaction from less than one percent of the total population will be beneficial to the wider campaign (Cortez *et al.,* 2015). It is noteworthy to note that direct marketing targets only a limited group of individuals who are considered to have a larger possibility of being attracted to the product that is being promoted and who, as a consequence, would be much more productive to engage (Mardi *et al.,* 2014). Within the context of data mining, the identification of these prospective clients presents a considerable challenge in terms of categorization. This challenge comes as a consequence of the need of connecting client qualities (such as age, marital status, educational level, etc.) and other characteristics (such as loan request/repayment, etc.) to a range of outputs. This must be done in order to meet regulatory requirements (e.g. whether or not a customer will subscribe to a term deposit).

Rationale:

As a direct consequence of the substantial expenditures that have been made in the infrastructure sector, the organization is now better able to collect data from every facet of its operations. It is possible to collect data on nearly every aspect of the firm, including its operational and manufacturing processes, management of supply chains and workflow operations, as well as the activities of customers and the efficiency of marketing efforts. The idea that information concerning the availability of external data, such as marketing trends, industry news, and competitor activities, is also extensively shared is becoming increasingly common knowledge (Bengio *et al.,* 2013). Because of advancements in computer technology, the availability of internet networks almost everywhere, and the development of algorithms that are capable of connecting datasets, it is now possible to conduct research that is not only more comprehensive but also more comprehensive than was previously possible. The availability of these large volumes of data has led to an increase in interest in the procedures that can be utilized to generate useable information and knowledge from data. This interest has been spurred on by the availability of the data. This, in the end, leads to the use of data in order to achieve a competitive advantage (Nielsen. M, 2016).

In today's world, a number of different technologies, such as cloud computing and service-oriented architecture, are working together to alter information technology, which, in turn, makes the calculation of data more difficult. Because of this, it is essential to have the capacity to do swift and dynamic data analysis on both structured and unstructured data (Lilien *et al., 2004*). In the absence of appropriate analysis, "big data" refers to nothing more than a substantial amount of data. The goal and aim of analytics is to improve the quality of decisions made by organizations by radically altering the methods in which data is examined and put to use.

RELEVANCE OF BUSINESS MARKETING STRATEGY:

No matter how big or little an organization is, marketing has to be a top priority for them all; small companies are no exception to this rule. When it comes to marketing, small businesses, in contrast to large operations, face challenges posed by a higher number of different aspects. The fundamental obstacle that impedes the progression of these efforts is a deficiency in financial and other resources. A review of the company's present state and the environment in which it operates serves as the starting point for the iterative process that is the formulation of a marketing plan. The strategy provides an overview of the market for the target consumers, the key rivals in the industry, as well as the challenges and opportunities present in the market. (Malthouse *et al.,*2008). Marketing is an essential part of running a firm, which is why it's included in the process. This portion of the process is highly important. This is the aspect of the market that serves as the connecting link between the consumer and the item being sold. There are a lot of locally owned and run firms that have an interest in expanding their customer base via the use of straightforward marketing and branding methods. The creation of a website, participation in direct mail activities such as the distribution of postcards or brochures, and participation in email marketing campaigns, which may include the distribution of newsletters, are all examples of different marketing strategies (Manvika *et al.,*2011). These marketing activities are especially cost effective because they enable you to interact with customers at a minimal cost while also enabling you to begin the steps to develop a brand that is readily recognized. In other words, they allow you to do both at the same time.

One of the benefits that comes with operating a small business is more adaptability in a variety of situations. Even if the company does not have a limitless amount of money to spend on marketing, one of their benefits is that they are able to make decisions swiftly. This is one of their advantages. In the event that a certain marketing strategy is not effective, these businesses are able to fast alter their course and modify their products and services in order to fulfil the needs of a market that is always changing. When compared to bigger companies, smaller firms have a few advantages to their advantage. When it comes to the marketing of a small business, consistency is the most important factor, and the process should be carried out as often as is practically feasible (Martens *et al.,* 2011). You are permitted to make use of a broad number of marketing tactics, such as distributing flyers on windows and hanging them on doors, sending out daily emails to customers, operating blogs on your websites, and sending out daily emails to customers. One of the opportunities that are available to a particular firm is the possibility of expanding their marketing efforts via the formation of a partnership with another business. Find a local firm that offers you a product or service that is in some way connected to what you do, and then investigate the possibility of doing business with that company (Neslin *et al.,* 2006).

When you cooperate with another company on a project, you have the opportunity to divide costs, which gives you the flexibility to pay for things like employing graphic designers, typographers, and website designers, among other creative professionals. If you can keep time and money distinct, you will have a lot better chance of making your budget last for a much longer amount of time. It is commonly known that the marketing strategy of a business is one of the most important variables among those that play a part in determining the amount of success that a company achieves. It is feasible for a smaller company to "keep afloat" provided that a marketing plan for the goods and services being offered is developed in the appropriate manner and in the right way (Olson *et al.,* 2012). The vast majority of industry professionals are in agreement that a marketing strategy may be conceptualized as either a comprehensive action plan or a collection of activities that are aimed at achieving certain goals and boosting sales. The vast majority of the time, these operations are not planned in advance; rather, strategic decisions are made based on the situation of the economy at the moment the decision is made. Customers' needs and preferences are subject to rapid and ongoing changes in today's society due to the fluid nature of modern civilization.

The current state of the economy is getting more precarious, and leaders of small businesses need to be aware of the significance of strategic marketing and its influence on the day-to-day operations of their companies. This is especially important in light of the fact that the current state of the economy is getting more precarious. Even when the firm has other functional strategies in addition to its marketing strategy, the marketing strategy is still an important one and plays a key part in the business (Partalas *et al.,* 2010). It enables the identification of target markets and, based on this identification, the selection of appropriate marketing strategies and activities. It is doable as a direct result of it. This strategy takes into account the requirements, wants, and needs of customers and then specifies how a business might work to satisfy their demands, wants, and needs. In order to devise a strategy for their company's marketing that will be successful, the chief executive officers of small enterprises need to demonstrate and practice innovation. The researchers came up with five guiding concepts that need to be adhered to in order for a marketing strategy to be effective. These guiding principles can be found in the following sentence (Perlich *et al*., 2014):

- Don't just sell, but draw consumers.
- Strive to be different.
- Give your firm a distinct identity.
- Make it your objective to connect with people on an emotional level.
- Determine your place in the market, then dominate it.
- Don't just sell, but attract customers.

When developing a strategy for the marketing of a product or service, the first step should be to identify a niche in the market. The next stage should be to fill that niche while avoiding direct competition with firms that are already in existence. Targeted strategies allow small businesses to better grasp the benefits that are inherent to their operations, and as a result, the vast majority of small businesses wish to implement such strategies. The successful implementation of a strategic marketing strategy is going to be an essential factor in determining the level of overall success achieved by the firm (Phan *et al*., 2010). The company should be able to attain a solid position in the market as a result of its execution, as well as a decrease in the risks associated with doing business, a growth of the client sector, enhanced brand awareness, and increased competitiveness. It is vital to choose the route of company development with accuracy and knowledge in the current climate of the market because it is essential to base this choice on the problems that are discovered in the course of performing a marketing research.

In the current climate of the market. The standard model of marketing responsibilities encompasses a wide variety of tasks and challenges, such as the growth or contraction of the assortment, the development of a pricing strategy, the production of advertising activities, the acquisition of a new market share or a section of the market, and many more. A potent competitive position and an effective operation of the company are both reliant on the marketing strategy that was chosen appropriately, as well as the action plan that was meticulously crafted and followed out. Both of these factors are essential for success (Piatetsky-Shapiro, G., & Masand, B., 1999). The relevance of the research question was determined based on these and other elements, all of which were analyzed in relation to the processes of a particular company's operations.

STEPS IN IMPLEMENTATION OF A MARKETING STRATEGY:

In order to achieve a goal and put a marketing strategy into action, it is required to take actions that not only support one another but also the success of the marketing plan itself. The following is a rundown of the seven stages of a marketing strategy: After making a decision based on the comparison of many values, the positioning of a market offering places that product in the minds of members of the target market, thereby producing value for those members of the target market. This is accomplished by dividing up the many offers that are currently available in the market in order to generate reciprocity from customers (Kotler, Philip dan Armstrong, G., 2012). Determine which clients you will serve, since the overall market is segmented into a number of smaller sections that each have their own unique characteristics. It is possible to choose to add one, two, or even more subcomponents when establishing one's objectives. It is necessary for marketers to perform the following tasks in order for target marketing to be effective: identify and profile groups of buyers who have different needs and wants; select one or more market segments; and, for each target segment, communicate and deliver the appropriate benefits to the company's market offering. Target marketing can be effective when these tasks are performed. Market segmentation refers to the act of breaking a market into smaller sections depending on a variety of different criteria. These criteria may be anything from demographics to purchasing behaviors. This strategy is carried out in order to specify the marketing actions that need to be made for each segmentation. This is necessary since the needs that are specific to the profile of each individual target market will vary (Kotler *et al.,* 2016). The following is a list of other benefits that may be derived from market segmentation:

- If the competition is unable to provide the necessary items, segmentation may be able to alleviate some of the pressure.

- If a product does not participate in the competition for a certain segment on a consistent basis, then the product's market share in that segment will fall.
- Products that are not affected by the impact of price competition and that have the capacity to retain a premium price level are able to make alterations to the industry as a whole.

There are a few distinct categories that can be broken down into when discussing segmentation. These categories include geographic, demographic, psychographic, and behavioural segmentation.

a. **The Classification of the World According to Its Location**

The market is susceptible to being segmented on the basis of criteria that are related to the consumers' geographic contexts. These factors include climate, climate zone, and country, urban, rural, and suburban settings, among others. This segmentation provides a number of advantages, one of which is the saving of resources as a result of marketing being more focused as a result of certain locations for marketing being selected. This segmentation also provides a number of other benefits. As a result of the ease with which research can be carried out in the regions in which consumers have their residences, geographical segmentation is one of the sorts of segmentation that may be considered to be among the easiest. This is as a result of the fact that it is a section of study that is conducted without bias (Kotler *et al.,* 2016).

b. **The Classification of People Based on Their Demographics**

This method of market classification divides the target audience into a number of distinct subgroups according to characteristics such as age, gender, income, employment, education level, religious affiliation, racial or ethnic background, marital status, and social class, among other characteristics. When retailers are able to comprehend the demographic subgrouping of their clientele, they will be in a position to benefit from a multitude of opportunities. For example, retailers will have an easier time understanding what it is that consumers demand and want, as well as how the demographic characteristics themselves impact the way in which customers utilize their goods. This will allow retailers to better cater to their customers' needs and desires. In addition, the data required for demographic segmentation are able to be measured with a reasonable amount of simplicity (Kotler *et al*., 2016).

c. **Division and Classification Based on Psychographic Traits**

The human psychological make-up is used as a criteria or metric in segmentation, which is used to analyze the attitudes and actions of customers. Some examples of the criteria that may be employed in psychographic segmentation include characteristics of personality and life values as well as decisions made about one's way of life. The advantage of using this type of segmentation is that it focuses on detailed consumer attributes, which are important factors in the final decision that a customer makes regarding whether or not to use a product or purchase it. Another benefit of using this type of segmentation is that it concentrates on broad consumer characteristics. On the other side, the disadvantage of psychographic segmentation is that it is difficult to quantify. This is because the factors that make up this segmentation are determined by subjective judgments, which makes the segmentation difficult to measure (Kotler *et al.,* 2016).

d. **The Classification of Behavior**

One of the objectives of the behavioral segmentation approach is to categorize clients according to the behaviour patterns, emotions, and attitudes that they exhibit, as well as the goods or services that they make use of. One of the advantages of using behavioral segmentation is that when a seller is able to learn the behaviour of the market, then the marketing will be able to be targeted more easily with varied offers for each market group. This is one of the benefits of using behavioral segmentation. This is one of the benefits that comes with using behavioral segmentation. This segmentation itself may be a problem and a detriment due to the fact that it is not always possible to precisely forecast how people will behave because human behaviour is something that is subject to continuous change and inconsistency. As for the flaw, considering that human behaviour is something that is prone to continual change and inconsistency, this segmentation itself may be a problem and a detriment. After analysing the attractiveness of each market segment as part of the process of defining a target market, a sector or sections of the market are picked for the firm to enter. When conducting an evaluation of the potential benefits offered by distinct market niches, companies should keep in mind the following three factors (Kotler *et al.,* 2016):

- The size of the market and how it has evolved over time.
- The intrinsic attractiveness that the segment has in terms of its structure.
- The goals of the firm and the resources it has available.

Marketing is one of the most essential components of operating a successful tourist site, and it plays a vital part in the tourism sector as a whole. This is due to the fact that there are a large number of other firms operating in the same sector as well as a large number of new sites where customers may go. One of the most effective strategies for drawing tourists to a location is to promote that location as a place that tourists would like visiting. A location will need a higher degree of supervision due to the increased level of activity that will be caused by having a robust strategy for marketing tourism there (Turobova *et al.,* 2016).

The phrases marketing and sales are often believed to be synonymous within many different types of businesses, notably within the food and beverage sector (Food and Beverage). This happens as a result of the fact that the sales department is the one that is physically visible to the greatest number of customers and managers in the industry. The marketing that is taking on behind closed doors and cannot be seen instantly is having an impact on increasing sales despite the fact that it cannot be seen immediately. Because they are under the impression that they are unable to significantly influence sales in any manner, a significant number of the managers and supervisors working for this organization have a negative attitude toward marketing (Oripov, M., & Davlatov, S., 2018). However, it turned out that the attitude of not caring and believing in the marketing that was implemented was caused because every advertising and promotional effort that had been marketed in the past did not go well. This was the case because it turned out that the attitude of not caring and believing in the marketing that was implemented was caused. Because of this, people developed an attitude of indifference toward the marketing strategy that was put into place and stopped trusting it. It seems like the results weren't all that significant to begin with. In point of fact, marketing accomplishes a somewhat diverse range of goals (Mukhtorovna *et al.,* 2020).

Marketing is not the only thing that is most vital; raising sales is only one of the things that is most important. Because it requires research, information systems, and planning, marketing is not the only thing that is most essential. Marketers are able to conduct research in accordance with the references and goals that are to be achieved, which may include the creation of products with specific characteristics that become advantages, the setting of prices that are in accordance with quality, and the decision-making process regarding how to distribute the products sold so that they can be sold (Narzullayeva *et al.,* 2021). The 8Ps are one of the eight different elements that are currently in existence. It is necessary to attract a huge number of potential clients, thus it is important to reach a large number of people and choose the kind of advertising that is most suited. It is possible for the marketing mix to function normally if each component of the marketing mix is sufficiently prepared and put into action in accordance with the target market that is intended.

LITERATURE REVIEW:

It has been the subject of a substantial amount of study to explore the elements that contribute to the effectiveness of model-based decision support systems (DSS), which has resulted in the accumulation of a significant body of research. Having a high degree of relevance to the choice task has been highlighted as an essential component of an effective decision assistance system in a number of recent studies. On the other hand, the impact that fit has relies on the (post)processing of DSS proposals in order to function properly. It is demonstrated how managers may learn to compensate for a lack of DSS fit in order to achieve performance levels equivalent to those of managers who have access to better technology. This was done in order to achieve comparable levels of success (i.e., higher fit). This makes sense when considering the fact that managers base their decisions on a mental model that enables them to evaluate DSS outputs in the context of a particular situation, relate this output to decision quality, and, in this way, compensate for misleading information that comes from a faulty decision support model (Urakova, M. H., 2021). According to this theory, the use of human supervision in the process of model-based decision support results in a number of major advantages. The use of such a "model-manager tandem," on the other hand, might result in high staff expenses, the likelihood of a lack of competence, especially in regard to the technology of big data, and a substantial delay in the making of decisions.

PCES works toward the goal of improving decision quality when it comes to targeting applications by combining the efficacy of completely automated, model-based decision-making with the capacity of managers to make use of information that is contextual and task-specific. This combination of capabilities allows PCES to work toward the goal of improving decision quality. Extensive use of prediction models that are driven by data in order to forecast how consumers will respond to different marketing campaigns has become more common (Umarovna, T. M., 2020). Because they need so little involvement from humans, they also seem to be ideally adapted to automate decision-making in real-time targeted applications such as online advertising or social networking. This is because of the fact that they require so little human interaction. Previous research has also looked at the question of whether or not an organization's objectives need to be taken into account throughout the process of developing predictive decision support models.

(D. Nauck, 2013) was the first researcher in the area of forecasting to write an essay that challenged the practice of employing quadratic loss functions for model estimate. This work was written in the context of the science of forecasting. He proposed loss functions that penalize positive and negative residuals in a way that is unique from one another in light of his claim that real-world applications virtually never exhibit symmetric error costs. Granger's work has been further developed on by other studies, which have also given both theoretical and empirical discoveries. These investigations have contributed both to the body of knowledge and to specific findings. In addition, PCES makes use of non-standard loss functions in the construction of predictive models and assesses the effectiveness of models based on how effectively they operate for companies. The methods that are used and the applications that are carried out are the key differentiating factors between the two. In this investigation, we focus on multivariate machine learning models as opposed to univariate time series forecasting models and investigate choice difficulties that arise during the process of designing marketing campaigns. This is in contrast to a previous study that focused on univariate time series forecasting models. As a consequence of this, it is essential that we concentrate on achieving a certain business objective (i.e., campaign profit).

Studies on asymmetric mistake costs can potentially be a part of the research being done on cost-sensitive learning. Learning that takes into account costs is its own discipline. In general, cost-sensitive learning encompasses methods that operate at the data level, such as changing the distribution between classes that have higher or lower misclassification costs and algorithmic adaptations to make standard learners cost-aware. For example, changing the distribution between classes that have higher or lower misclassification costs is an example of cost-sensitive learning. An example of cost-sensitive learning would be shifting the distribution of students across courses such that they are more heavily weighted in those with greater misclassification costs. Altering the distribution between classes that have greater misclassification costs and classes that have lower misclassification costs is one illustration of this principle in action (S. Banumathi and A. Aloysius, 2017). In the course of this investigation, the class-dependent misclassification costs have also been taken into account. To be more precise, two of the most typical sorts of errors that may be made when organizing a campaign include soliciting clients who do not react and failing to contact consumers who would otherwise answer. Both of these errors can have a negative impact on the success of the campaign (for example, buy an item). Despite this, research into cost-sensitive learning aims for generality and seeks to build modelling approaches that are successful in a broad variety of applications. This is done despite the fact that the costs of misclassification differ from one application to the next.

The pursuit of generality is something that should be encouraged, but a decision support system approach that is tailored to a specific application has the potential to more properly reflect the requirements that are peculiar to that application. Within the framework of targeted marketing, the PCES is one strategy that may be used for the purpose of making decisions. The vast majority of the time, marketing endeavours are only targeted at a small fraction of the customers who really react to them. Because of this, it is necessary to utilize a unique idea of model performance in contrast to cost-sensitive learners, the primary emphasis of which is on lowering the overall amount of error costs. In addition, there is a significant body of work devoted to the development of predictive models that may be used to the process of client targeting.

In general, previous research has investigated all stages of the process of predictive modelling, beginning with the construction of an analytical database and continuing on through the collection of data from previous campaigns and test mailings, followed by data preparation, which includes target variable definition, independent variable development, encoding, and selection. This process begins with the construction of an analytical database and continues on through the collection of data from previous campaigns and test mailings. On the other hand, the overwhelming bulk of the older research estimates the targeting model using the standard prediction methodologies. This strategy does not take into mind the actual business difficulty, which is the maximization of campaign profits; as a result, we refer to it as a profit-agnostic approach. During the process of model creation, this strategy does not take into consideration the real business issue.

Some studies highlight the inability of statistical accuracy indicators to reflect marketing objectives and propose alternatives for specific applications such as the maximum profit criterion for churn modelling. Other studies highlight the inability of statistical accuracy indicators to reflect marketing objectives. The potential of statistical accuracy measures to match marketing goals is emphasized in other research. Expanding the scope of our inquiry even further, we do so using two distinct approaches. First, we take into account a wide range of targeted applications by utilizing a profit function that is more flexible (Abbasi *et al.,* 2015). This allows us to take into account churn modelling in addition to the other options. Second, in order to concentrate on the construction of a model that is driven by profits, we provide the company's objective during an earlier stage of the modelling process. This enables the corresponding information to have a greater impact on the final model. Third, in order to focus on the construction of a model that is driven by profits, we provide the company's objective during an earlier stage of the modelling process.

Numerous researchers and data miners have invested a significant amount of time and energy into researching the phenomenon of bank direct marketing via the use of telemarketing operations, and they have discovered a number of intriguing discoveries as a result of their efforts. Both decision support systems and other data-driven strategies have attracted a significant amount of attention and research as of late. A research (L. J. Fülöp *et al*., 2012) was carried out with the primary intention of engaging customers via direct marketing (telemarketing), with the ultimate objective of outsourcing long-term deposits. We used the techniques of logistic regression, decision tree analysis, neural network analysis, and support vector machine analysis. With an area under the curve (AUC) of 0.8 and an accuracy of prediction that reached 81%, NN obtained the greatest performance out of all the models.

In a study that was relatively comparable to the one carried out by (L. Cao, 2017*)*, the methods of logistic regression and decision tree analysis were used to a dataset consisting of information about an Iranian bank. Despite the fact that several exciting discoveries were made, a comparison of the error rate using unpruned and trimmed trees in addition to bagging does not offer a strong basis for prediction. This is despite the fact that some of the results were rather intriguing.

In (Olson, D. L., & Chae, B., 2012), an investigation was carried out to determine whether or not it was possible to glean information from previous campaigns in an effort to enhance the efficiency of SVM-based long-term deposit marketing efforts. The goal of this investigation was to determine whether or not it was possible to enhance the effectiveness of these efforts. It was discovered that the last three months of each quarter are the most productive ones for initiating direct marketing efforts.

In addition to this, the findings of their study revealed that customers who had already been contacted had a larger possibility of subscribing to term deposits. This was one of the conclusions drawn from their investigation. They were able to determine the mean impact of a variable by using a tool called the Variable Effect Characteristic (VEC) curve. Using this technique, they were able to determine that the duration of a call was responsible for more than 20% of the performance of their model. In spite of the fact that these findings shed light on previously unknown information, a comprehensive validation was not performed. A random split does not reveal the temporal measurement that a genuine prediction system would have to adhere to. This is because a genuine prediction system would have to use historical patterns to fit a model in order to issue predictions for upcoming customer contacts. A random split does not reveal this information. The authors of (Partalas *et al.,* 2010) focused their attention on determining the main elements that contribute to the effectiveness of Bank Telemarketing of consumer subscription to term deposits. Both the Chi-square test and the information gain test were used within the scope of this investigation. In what seemed to be a rather swift evaluation, measures of accuracy and recall were used. They arrived at the verdict that decreasing the number of features led to improved classification performance.

It is possible that the findings of research conducted by (Perlich *et al.,* 2014) that is comparable to our own will serve as a point of comparison. They carried out the most extensive and in-depth study that has been done to this point on the topic that is now being addressed. The researchers examined and contrasted the efficacy of a variety of machine learning techniques, including neural networks, decision trees, Bayesian belief networks, and logistic regression. According to the conclusions of the study, DT had the highest value in terms of the number of samples used for training, but NN came out on top in terms of the percentage of samples used for testing. Throughout the whole of this step of the review process, several measures of classification accuracy, sensitivity, and specificity were used. In spite of the comprehensive nature of their inquiry, neither class equality nor social mobility were discussed in any manner. Due to the fact that the binary values of the class attribute are very unbalanced and the fact that the results that would be generated without balancing the class would lead to overfitting if the class were not balanced, it is imperative that the class be balanced.

METHODOLOGY:

Dataset:

The marketing campaign data has been taken from Kaggle and could be found at kaggle.com. The dataset has a total of 29 different features and 2240 observations. We have a mix of categorical and numerical variables in this case. A response model may significantly improve the effectiveness of a marketing campaign by either raising the number of replies received or reducing the amount of money spent. The goal is to determine which potential customers would react favourably to an offer of a product or service. The primary purpose here is to train a predictive model that will enable the firm to optimize the profit that can be made from the subsequent marketing campaign. Following is a one line description of each of the attribute present in the dataset

(Kaggle):

- If the consumer accepted the offer during the first campaign, the value for AcceptedCmp1 is 1, and if not, it is 0.
- AcceptedCmp2 will have a value of 1 if the consumer accepted the offer during the second campaign, and it will have a value of 0 otherwise.
- AcceptedCmp3 will have a value of 1 if the client took advantage of the offer in the third campaign; otherwise, it will have a value of 0.
- AcceptedCmp4 will have a value of 1 if the customer accepted the offer during the 4th campaign, and it will have a value of 0 otherwise.
- If the consumer accepted the offer during the fifth campaign, the value will be 1, and if not, it will be 0.
- Response (target) is a value of 1 if the client accepted the offer during the previous campaign, and a value of 0 otherwise.
- Complaint — One point if the consumer has filed a complaint during the last two years
- Customer is the date when the client started doing business with the firm.
- Education: the degree of education held by the consumer
- Marital - customer's marital status
- Kid home refers to the total number of young children living in a customer's home.
- Teen home refers to the amount of adolescents living in a customer's home.
- Income is the annual household income of the consumer.
- MntFishProducts is the total amount of money that has been spent on fish products during the last two years.
- MntMeatProducts is the total amount of money that has been spent on meat products during the last two years.
- MntFruits is the total amount of money spent on fruit and fruit items during the last two years.
- MntSweetProducts is the total amount of money that has been spent on sweet items during the last two years.
- MntWines is the total amount of money spent on wine and wine-related items during the last two years.

- MntGoldProds is the total amount of money that has been spent on gold goods during the last two years.
- NumDealsPurchases is the total number of deals that a customer has purchased.
- NumCatalogPurchases represents the total number of purchases done via the use of the catalogue.
- NumStorePurchases is the total number of purchases done at physical retail locations.
- NumWebPurchases represents the total number of sales generated by a company's online storefront.
- NumWebVisitsMonth represents the total number of users who have visited a company's website in the preceding month.
- Recency is the amount of days that have passed since the most recent purchase.

Data Preprocessing:

Data preprocessing is an important step in any data science problem. Reason behind is to have a cleaned and well formatted data to avoid biasness. In this case, almost all of the data is cleaned and only few steps are applied in this case which is checking for null values. On checking for missing values, we found out that the income column has 24 missing values, hence those values are replaced by the mean income. Another preprocessing step performed for building machine learning model includes scaling the data and for this purpose minimum and maximum scaler function is used. The third step performed is data balancing and the data is over sampled in this case to have a balance between observations from class 1 and 0 respectively. Finally, the data is divided into training and testing set with 70% for training and 30% for testing.

Machine Learning Models:

The machine learning models that are applied to predict the customer response includes logistic regression, naïve bayes, decision tree, random forest and adaboost. The evaluation metrics that have been used in this case includes precision, accuracy, F-1 score, and recall and confusion matrix.

The Random Forest method is a kind of Supervised Machine Learning that has found considerable usage in the fields of classification and regression. This type of machine learning was inspired by random forests. It first generates decision trees with the help of a range of samples, then utilizes the results of a majority vote on those samples to decide how to categorize them, and then uses an average to figure out how much they vary. The capability of the Random Forest Algorithm to handle data sets comprising continuous variables, as in the case of regression, as well as categorical variables, as in the case of classification, is one of the most essential properties of this machine learning algorithm. The Random Forest Algorithm is distinguished by a number of essential properties, one of which is this capacity (Dewi, C. and Chen, R.C., 2019). When used to categorization activities, it delivers results that are better. The direct combining of a number of different models is what's meant to be referred to as an "ensemble." As a result, rather of placing all of one's faith in a single model, it is more common practice to base forecasts on a collection of models. The method known as random forest may be broken down into the following phases (Dewi, C., and Chen, R.C., 2019):

- The first thing that is done in a random forest is to pick n records at random from a data collection that includes a total of k records.
- The second phase in a random forest involves the building of distinct decision trees for each sample.
- During the third stage of the process, an output will be generated by each decision tree.
- The final result is then reviewed in the fourth phase using either majority voting or averaging, depending on whether it is being used for classification or regression. This evaluation may take place either manually or automatically.
- Random forests make use of hyper parameters in order to either improve the performance and predictive capacity of models or make the model run more rapidly. These are two of the goals that may be achieved via the use of hyper parameters.

The prediction power may be increased by following certain hyper parameters (Dewi, C. and Chen, R.C., 2019):

- The number of trees that the algorithm constructs before averaging the predictions is referred to as the n estimators.

- Max features is the maximum amount of features that random forest will evaluate when deciding whether or not to divide a node.
- Mini sample leaf is the function that establishes the bare minimum number of leaves necessary to separate an internal node.

The following hyper parameters, when increased, will result in increased speed (Dewi, C. and Chen, R.C., 2019):

- N jobs – This parameter instructs the engine on the maximum number of processors it is permitted to employ. If the number is 1, it can only utilize a single processor, but if it is -1, there is no restriction to how many processors it may use.
- Random state is the variable that regulates how randomly the sample is chosen. If the model has been provided with the same hyper parameters and training data, as well as if it has a fixed value for the random state, it will consistently provide the same outcomes.
- Oob score — OOB is an acronym that stands for "out of the bag." This technique is known as random forest cross-validation. In this case, one-third of the sample is not used in the training of the data but is, rather, utilized to assess how well it functions. The term "out of bag samples" refers to these particular samples.

Logistic regression is a method of statistical analysis that, based on previous observations of a data set, may make a prediction about a binary conclusion, such as yes or no. The results of this kind of study are used to respond to queries such as "how probable is it that...?" A model that examines the link between one or more independent variables that already exist in order to create predictions about a dependent data variable is known as a logistic regression model. These predictions may be made by the model. For instance, one may use a logistic regression to forecast whether a certain political candidate would win or lose an election, or if a particular high school student will be admitted into a particular university. Both of these scenarios involve making predictions about the future. These two possible outcomes are presented in a binary format, which allows for a straightforward choice to be made between the two possibilities. Several different kinds of input criteria may be taken into consideration by a logistic regression model (Dinesh, P. and Kalyanasundaram, P., 2022). The logistic function may take a student's grade point average, SAT score, and the number of extracurricular activities they engage in into consideration while deciding whether or not to accept the student to college. It then gives scores to new instances based on their risk of falling into one of two result groups, taking into consideration historical data on prior outcomes using the same input criteria as the previous cases. In other words, it compares each new instance to the previous ones. In recent years, logistic regression has established itself within the realm of machine learning as a tool of critical importance. It makes it possible for the algorithms that are used in applications that use machine learning to classify incoming data based on data that has been collected in the past. As more recent and pertinent data is added to the mix, the predictive abilities of the algorithms with regard to the classes included within the data sets continue to improve (Dinesh, P. and Kalyanasundaram, P., 2022).

One common use of the probabilistic method known as Naive Bayes is in the solving of classification issues. The Naive Bayes method is not only easy to understand but also unexpectedly effective in many different scenarios. It is a method of categorization that is predicated on Bayes' theorem and operates on the premise that predictors are independent from one another. A Naive Bayes classifier, to put it in more layman's words, works on the assumption that the existence of one specific characteristic in a class is independent to the presence of any other feature. The following instructions are used to carry it out (Dinesh, P. and Kalyanasundaram, P., 2022).

- Converting the data set into a frequency table is the first step.
- Construct a likelihood table by determining the various probabilities, such as the possibility of an overcast day being 0.29, and the probability of actually playing being 0.64.
- At this point, you will compute the posterior probability for each class by making use of a Naive Bayesian equation. The result of making a forecast is going to be the category that has the greatest posterior probability.

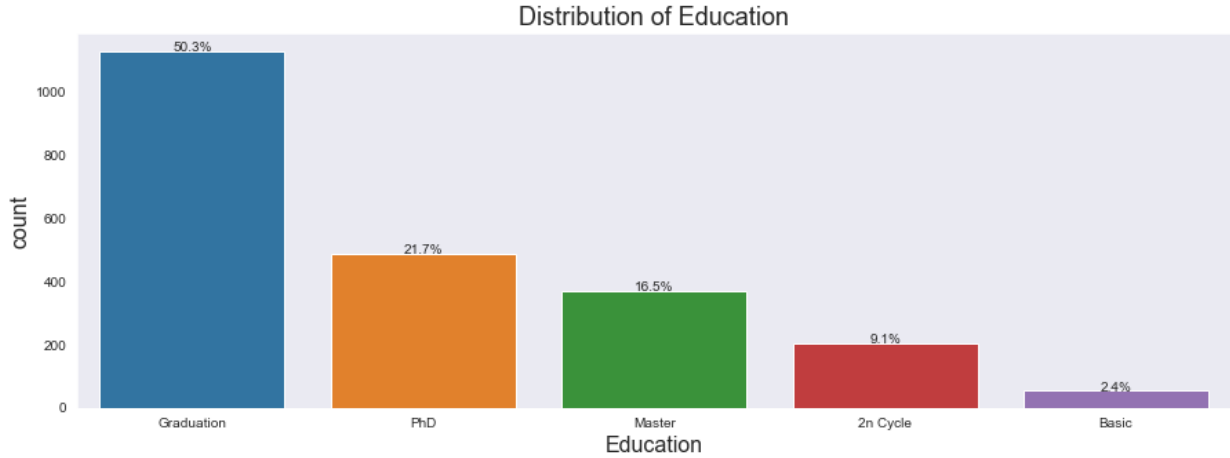
The first step of the classification process in machine learning is known as the learning stage, and the second stage is known as the prediction stage. During the learning phase, the model is formed by making use of the data that was supplied for training purposes. During the stage of prediction, the model is used to make projections about the reaction based on the information that is made available. Because it is straightforward, easy to understand, and straightforward to interpret, the Decision Tree approach is one of the most common categorization systems employed. The Decision Tree technique is an example of supervised learning, which is a family of learning algorithms that includes many other well-known methods. In contrast to other supervised learning algorithms, the decision tree technique may also be used for the purpose of addressing problems involving classification and regression. (Ray, S., 2019). Utilizing a Choice Tree for the purpose of creating a training model that can be used to the task of predicting the class or value of the target variable by learning fundamental decision rules derived from previous data is the goal of this technique. You may use this model to teach other models how to behave. When making predictions using Decision Trees in order to determine the class label that should be assigned to a record, we start at the tree's root in order to do so. We check to see whether the values of the root attribute and the attribute of the record are the same. As a result of the comparison, we go down the route that is associated with that value, and after that, we move on to the next node (Ray, S., 2019).

An example of an ensemble learning strategy, or what is more often known as "meta-learning," is the algorithm known as AdaBoost. When it was initially created, the major objective behind it was to enhance the overall performance of binary classifiers. AdaBoost is an iterative technique for improving the performance of weak classifiers by first gaining an understanding of their flaws and then changing them into robust classifiers.

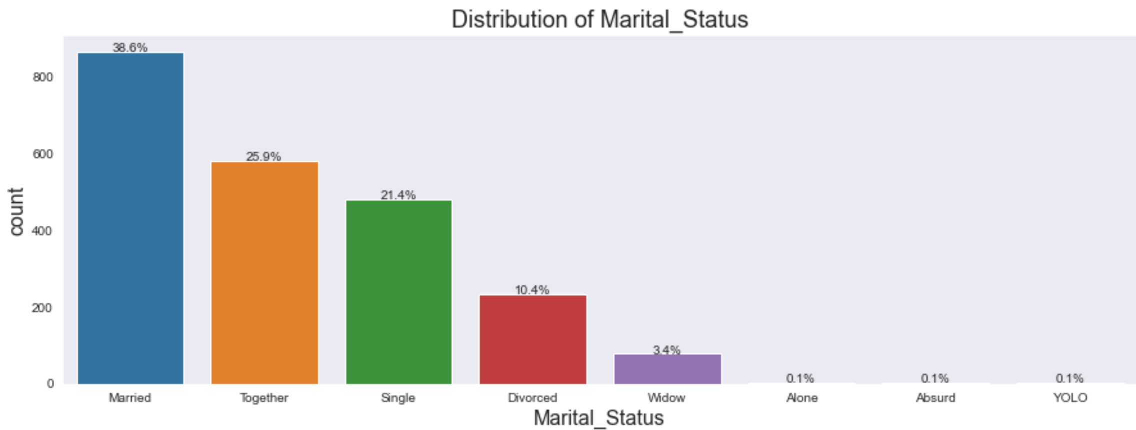
EXPLORATORY DATA ANALYSIS:

Univariate Analysis:

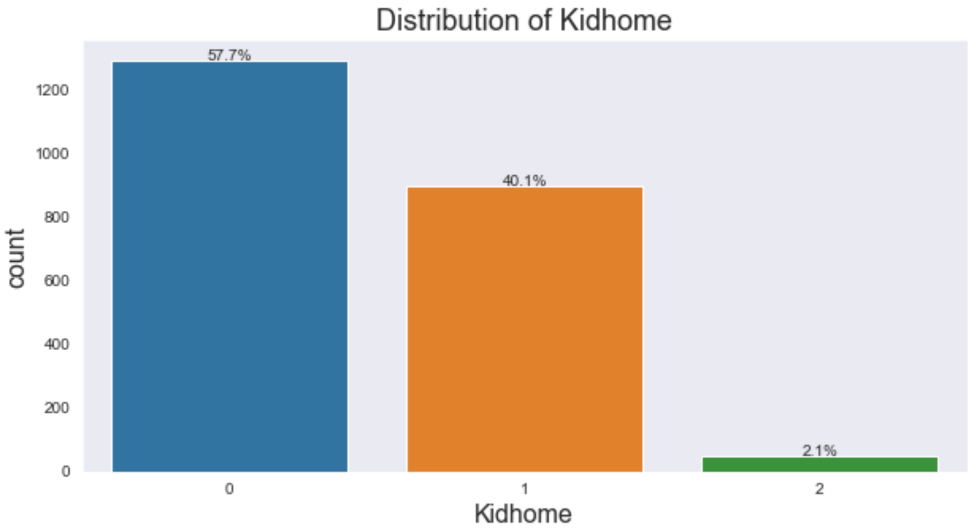
Below, beginning with a univariate analysis, you'll see a bar chart depicting the distribution of education among the various types of clients. It is clear that nearly half of the patrons have completed their education and received their diplomas. Overall, we can see that 50 plus 21 plus 16 equals around 87% of clients are highly educated and have at least a master's degree, a doctorate, or a bachelor's degree. On the other side, around 12% of the clients do not have a high school diploma or equivalent. This demonstrates that the majority of our clientele have a high level of education and is literate.



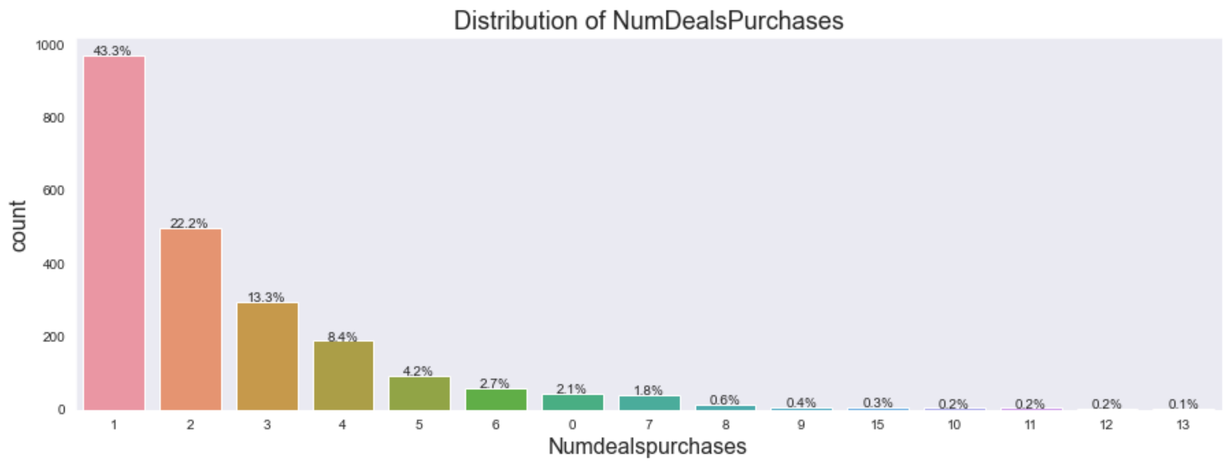
Towards the equal dissemination of information about marital status the accompanying bar chart for this issue may be seen down below. It is plain to observe that 39% of the patrons are married in some capacity. Roughly 26% of the candidates are married, approximately 21% of the candidates are single, and approximately 10% of the candidates are divorced. This informs us that the majority of our clients are either married, in a committed relationship, never married, or divorced. We have a relatively small percentage of single consumers, which also includes widows, YOLO, and other such phrases.



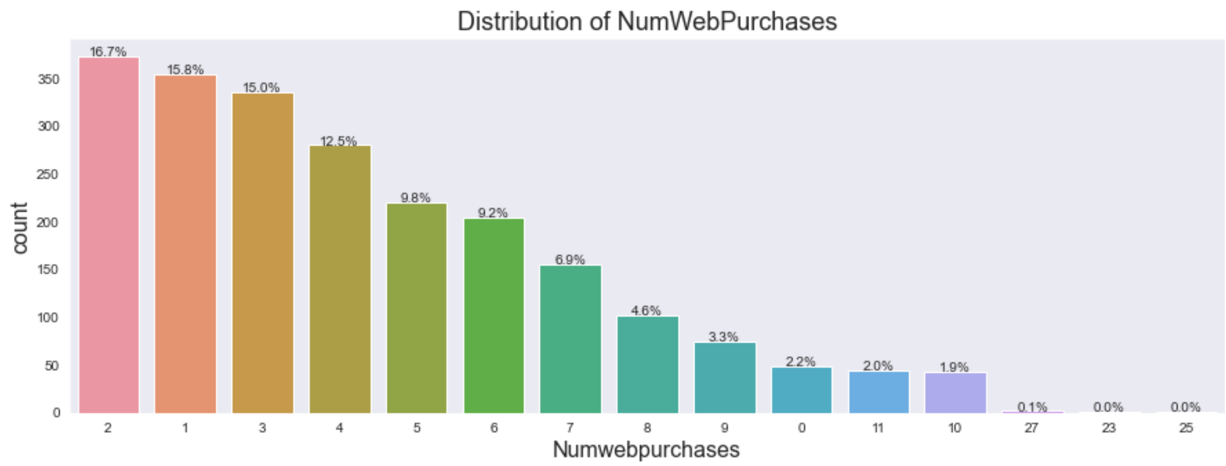
Investigating the number of children living in the household. Another bar chart is made, and this time it shows that the majority of customers do not have any children living in their homes; the proportion of customers who fall into this category is roughly 57%. The chart is attached. On the other hand, only around forty percent of the customers have at least one child living in their homes. Last but not least, the percentage of consumers who have a household consisting of two children is quite low and is roughly 2%. This provides us with information on the children of our clients. It might have an impact on their choice as to whether to go with a yes or a no answer to the customer's question.



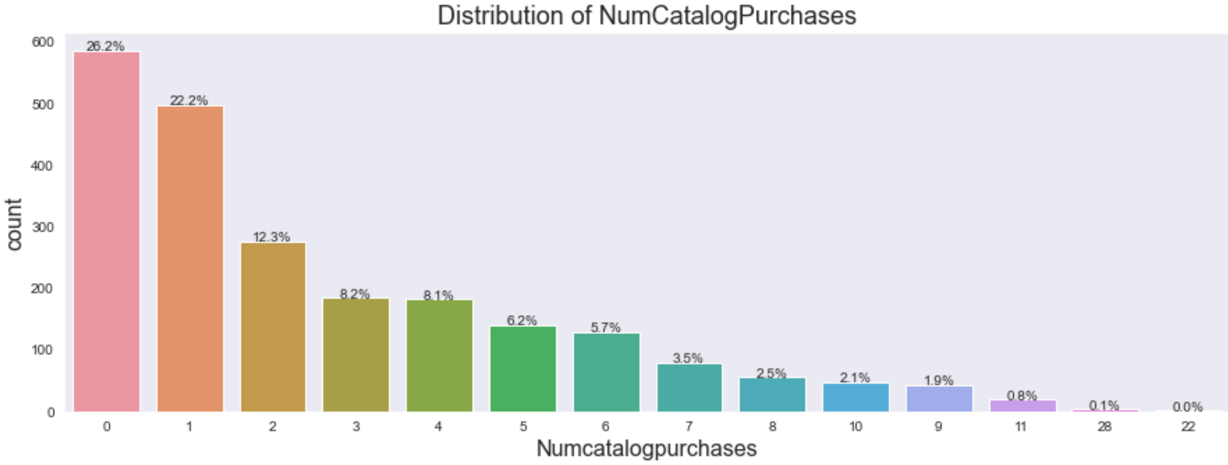
Moving on to the number of bundles that were bought by a single consumer, another bar plot was generated and can be seen attached further down. It is clear that around 43% of consumers have only bought one of the available deals, which accounts for the biggest percentage of customers. There are 22% of customers who have bought two offers, and there are 13% of consumers who have purchased three deals. This informs us that 43 plus 22 plus 13 plus 8 equals 86% of the consumers have bought between one and four offers, while the customers who have purchased more than four deals account for around 14% of the whole customer base. As a result, we can claim that the likelihood of a buyer purchasing one to four different promotions is high. There is a strong possibility that the number will be between 1 and 4. Only around two percent of the clients have never made a single transaction at all.



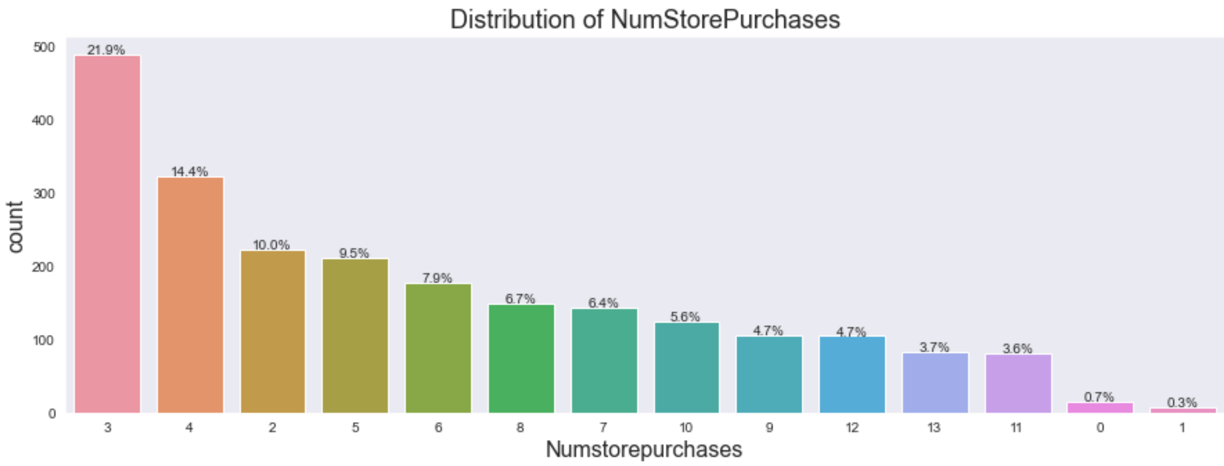
Moving on to the topic of the quantity of online purchases that a client has made, another bar plot was generated and can be seen attached below. It is clear that around 16% of consumers have only made two transactions, which is the biggest percentage of customers who have done so. There are around 15% of consumers who have made between one and three transactions online, and there are approximately 13% of customers who have made four purchases online. This informs us that 16 plus 15 plus 15 plus 12 equals 58% of the consumers have made one to four purchases through the website, while the customers who have made more than four transactions via the website account for around 42% of the total customers. As a result, we can estimate that a buyer is likely to make anything from one to four purchases when shopping online. There is a strong possibility that the number will be between 1 and 4. Only around two percent of the clients have never made a single transaction at all.



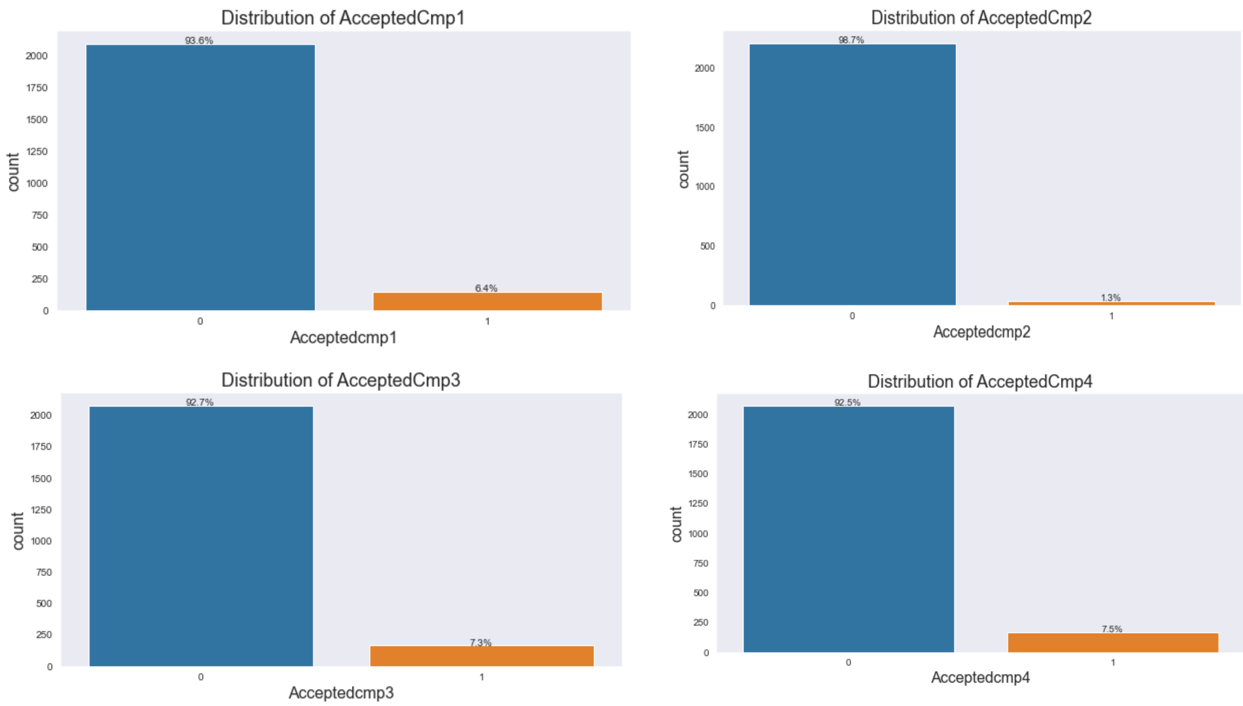
Again, a bar plot is constructed, and this time it is attached below. This time, the focus is on the amount of catalogue purchases that a client has made. It is clear that around 26% of consumers have never made a purchase from a catalog, which is the biggest percentage of customers that fall into this category. There are around 22% of customers who have only made a single purchase from the catalog, and there are approximately 12% of consumers who have made two transactions from the catalog. This informs us that 26 plus 22 plus 12 plus 8 equals 68% of the consumers have made 0 to 3 purchases from the catalog, while the customers who have made more than 3 transactions from the catalogue account for around 32% of the total client base. Because of this, we are able to claim that it is probable that a consumer will not make any catalogue purchases, given that the proportion of customers who do not make any purchases is the largest. On the other hand, there is a very good likelihood that the number will be between 0 and 3.



Moving on to the number of times each individual shopped at a certain establishment, another bar chart was generated and can be seen linked below. It is clear that the majority of consumers who have made three separate purchases from the shop account for around 22% of all customers. It is estimated that around 14% of consumers have made four purchases at the business, while 10% of customers have made two transactions at the store. This informs us that 22 plus 10 plus 14 plus 9 equals 55% of the clients have made between 2 and 5 shop transactions, whilst the customers who have made more than 5 store purchases account for around 43% of the total customer base. As a result, we are able to claim that it is probable for a consumer to make three purchases inside a shop given that the proportion of customers that make three purchases is the largest. On the other hand, there is a good likelihood that the number will be between 3 and 5. Customers that make either one purchase or none at all make up 1% of the total population.

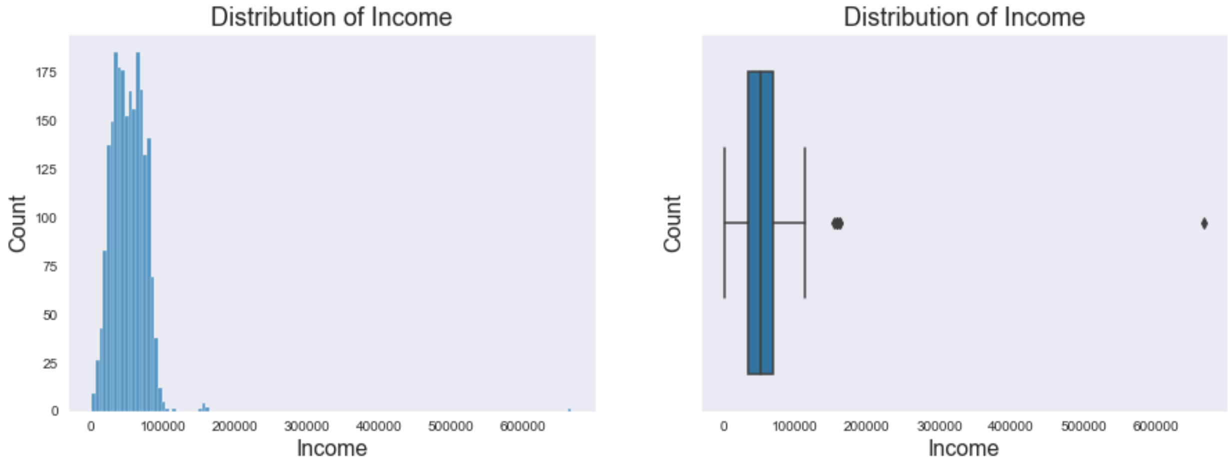


In conclusion, four bar charts depicting the distribution of acceptance and non-acceptance responses across four distinct campaigns have been constructed. The proportion of people who accepted the first campaign was only 6.4%, and the percentage of people who accepted the second campaign was just 1.3%. This can be seen in the graphs that are linked below. This informs us that we need to take a deeper look at the second campaign to see why the second campaign has the lowest acceptance rate. The proportion of clients accepting has improved to 7.3% and 7.5% respectively in the third and fourth campaign.

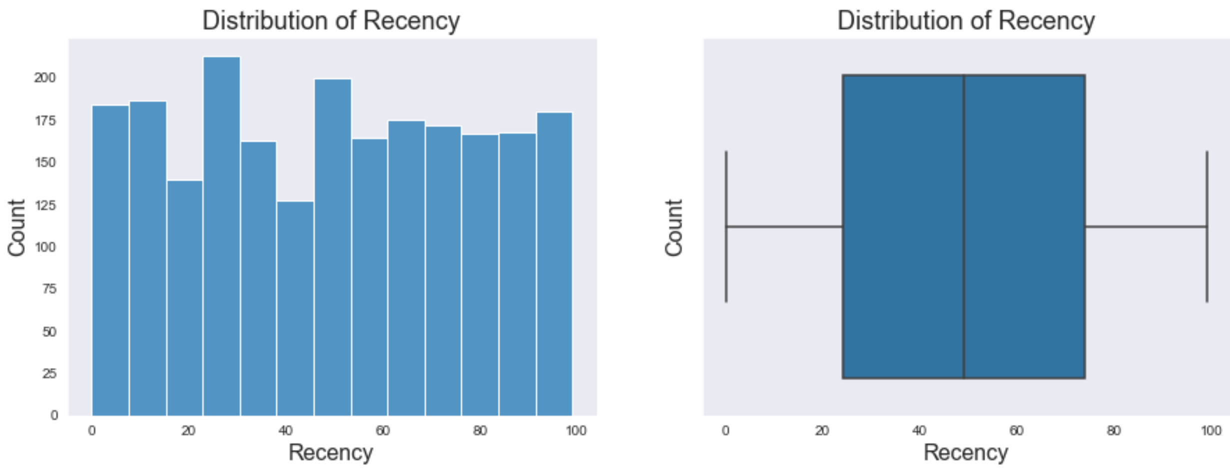


The following chart illustrates how the revenue was divided up. It is clear that the majority of clients have incomes ranging from zero to one hundred thousand dollars.

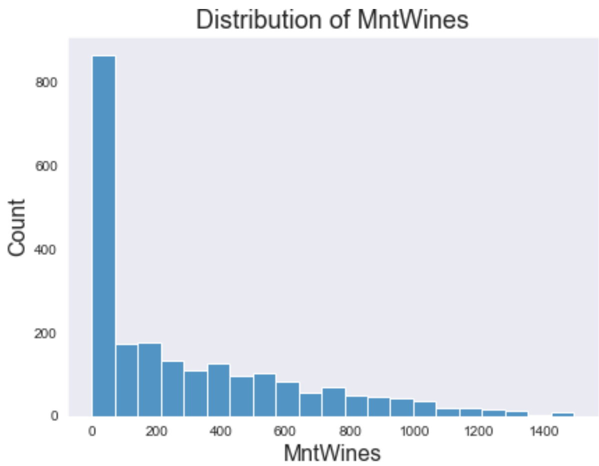
The typical annual income of a client is between $70,000 and $80,000.

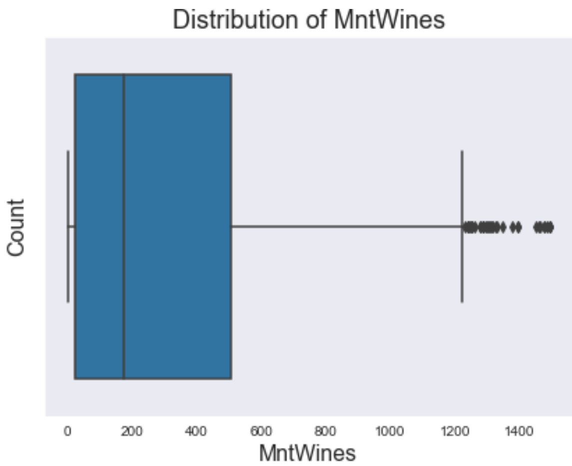


The following chart illustrates the distribution of recent events. It is clear that the biggest number of occurrences of regency occurs between the ages of 20 and 30. In this particular instance, the typical recency rating for the consumer base is somewhere around 50. When we examine the box plot for this instance, we do not find any instances of outliers.

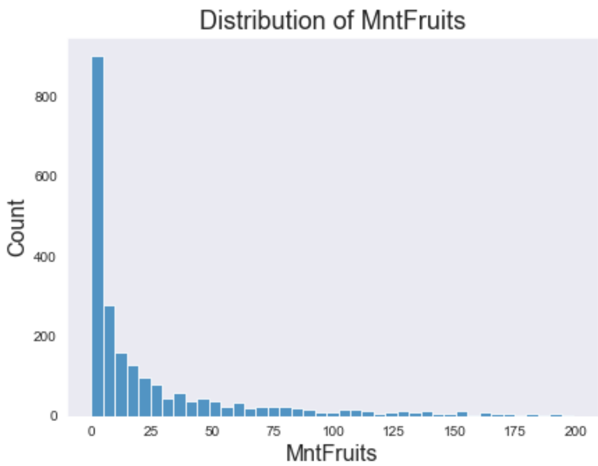


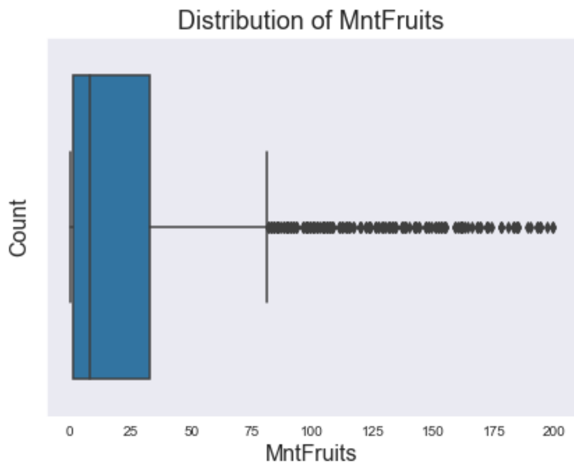
The breakdown of the total amount spent on wines is shown in the table below. It is clear that the majority of individuals spend a relatively little amount of money on wine and goods linked to wine. It is shown in the histogram that is linked to this post. We may deduce from the boxplot that the typical amount spent on wines and products linked to wine is somewhere around 200 dollars, and there are some extreme values included in the data.



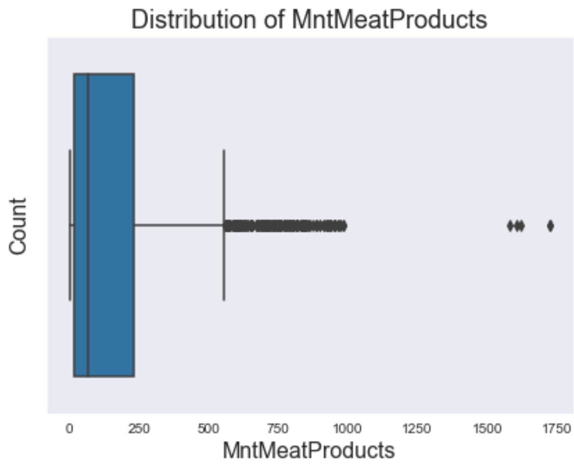


The breakdown of the total amount spent on fruits is shown in the table below. It is clear that the majority of individuals place a relatively low value on fruits in their budgets. It is shown in the histogram that is linked to this post. We can deduce from the boxplot that the average amount of money spent on fruits is somewhere between 10 and 15, and the data also includes a few instances of outliers.



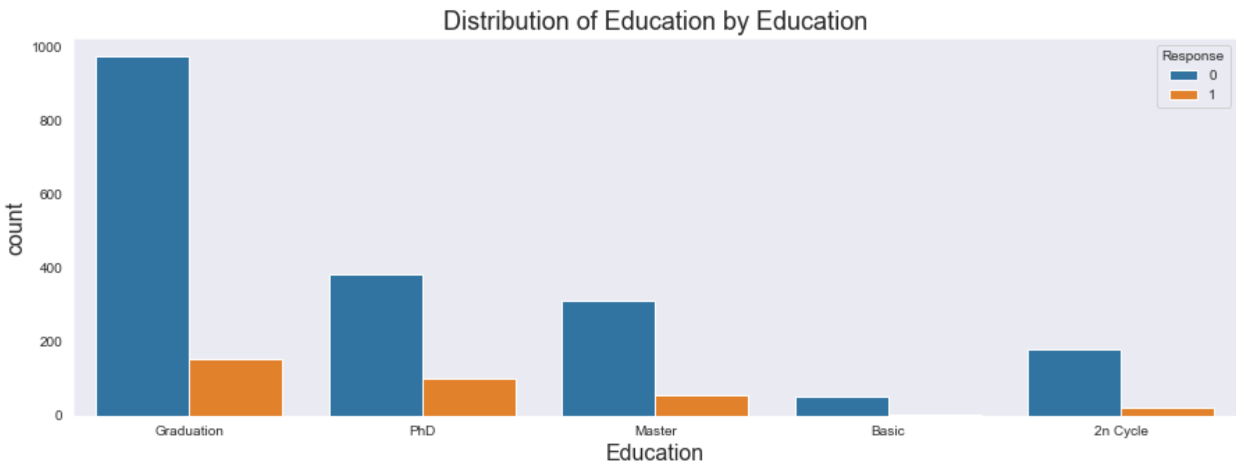


The breakdown of the total amount spent on meat items may be seen in the attached spreadsheet. It is clear that the majority of people place a very low priority on purchasing meat and animal products. It is shown in the histogram that is linked to this post. We can deduce from the boxplot that the typical amount of money spent on meat items is somewhere between 120 and 150 dollars, and the data also includes a few instances of outliers.

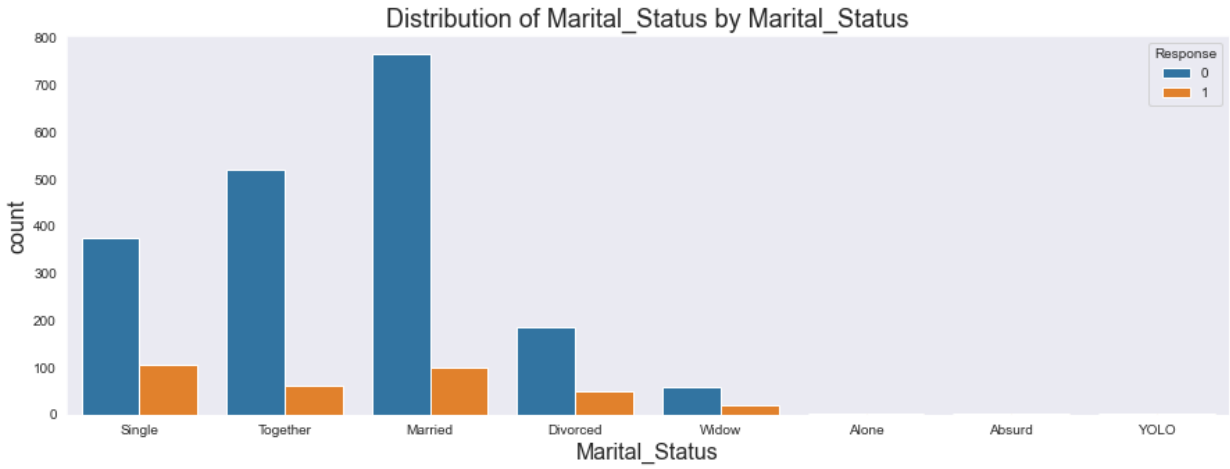


Multivariate Analysis:

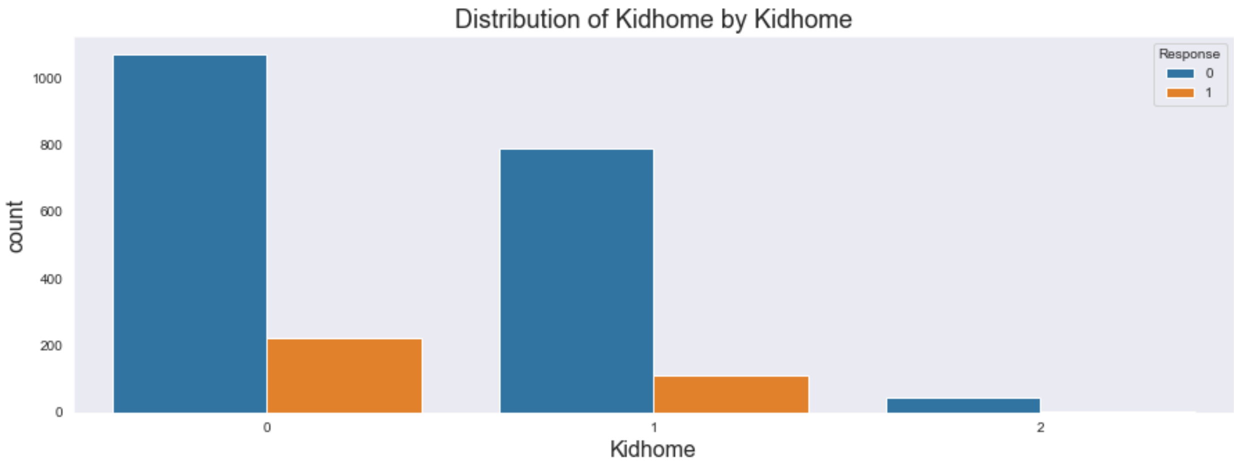
Beginning with the multivariate analysis, the attached graph can be seen below and shows whether or not a customer is accepted or rejected dependent on their level of education. It is clear that the clients who have higher levels of education are more likely to take advantage of the offer, whilst the clients who have lower levels of education are more likely to decline the opportunity. It is clear that the greatest level of acceptability is reserved for those consumers who have obtained a bachelor's degree, a doctorate, or a master's degree, in that order.



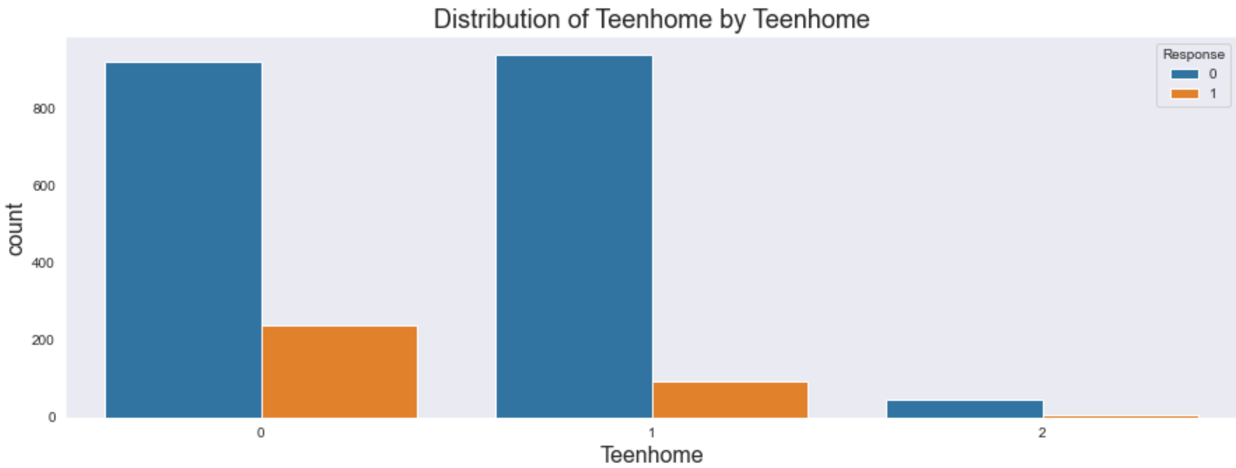
If we are talking about people's marital status, then the individuals who are married or single have the greatest level of acceptability depending on their marital status. The proportion of customers who are together and divorced also has a fair acceptance rate, while the percentage of customers who are alone, ridiculous, YOLO, or widowed has a very poor acceptance rate.



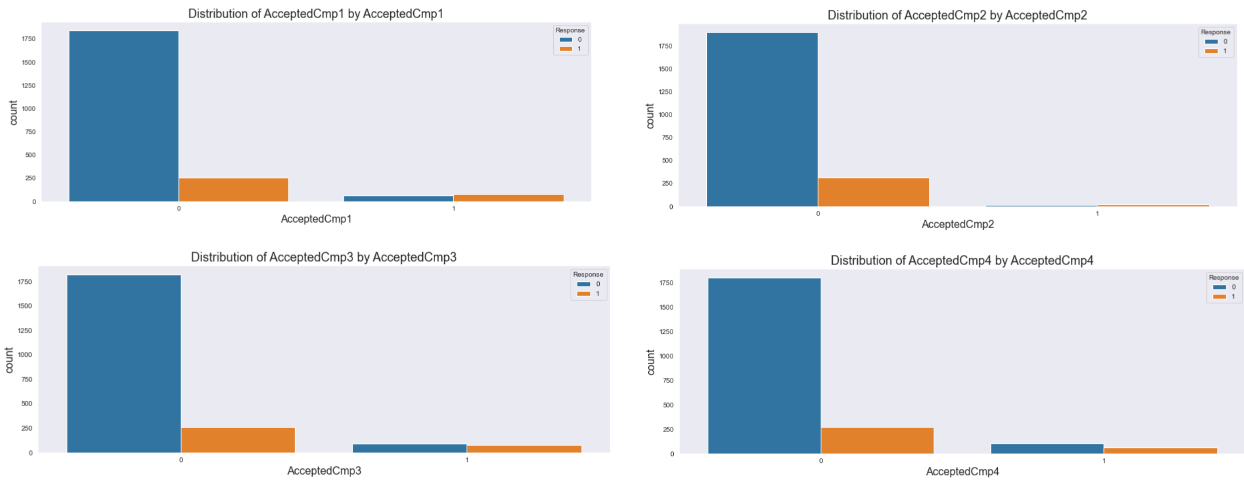
Those who do not have any children or who only have one child at home are more likely to accept the offer, but those who already have several children do not seem to be interested in the position at all.



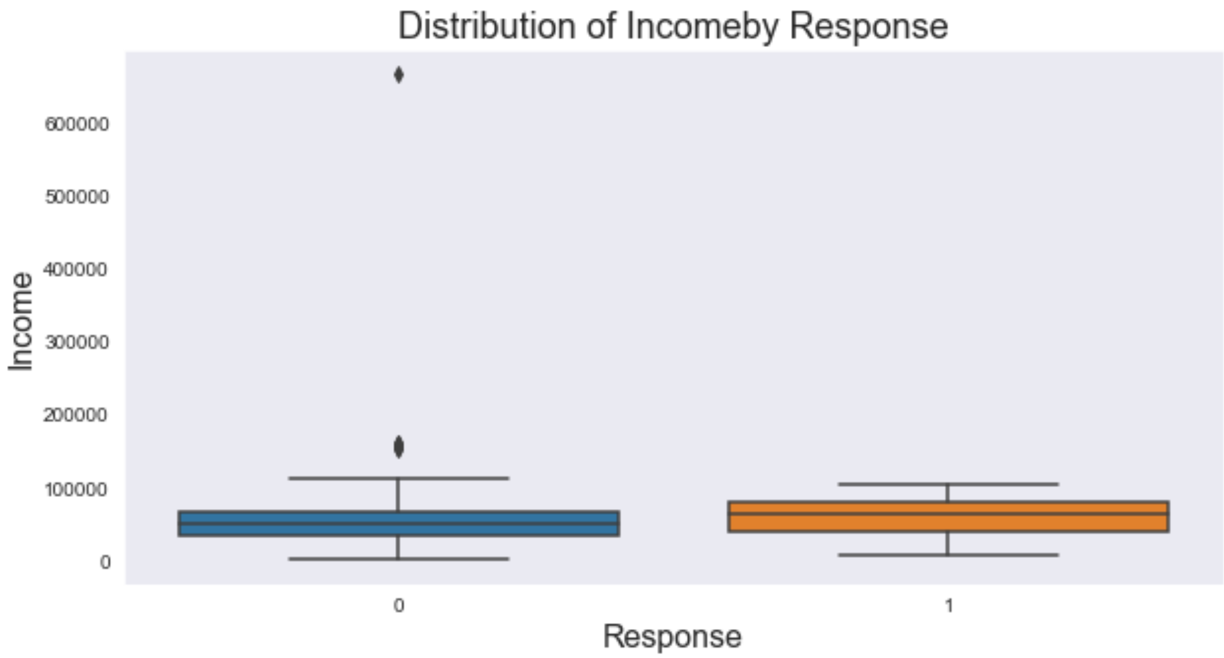
The same holds true for the adolescent at home. Those who do not have any teenagers living at their residence or who have just one teenager are more likely to accept the offer, but those who have more than one teenager seem to have absolutely no interest in participating.



Based on a couple of charts that are attached below, we can draw the conclusion that customers who have not accepted the offer in the first, second, third, or fourth campaign have a greater chance of accepting the offer in comparison to customers who have already accepted the offer in the first, second, third, or fourth campaign. This demonstrates that advertisements are having a beneficial influence on the choice that consumers make about whether or not to accept the offer that is being presented to them. On the other side, it seems that those who have previously accepted the offer in the 1st, 2nd, 3rd, or 4th campaign are less interested in taking the offer once again.

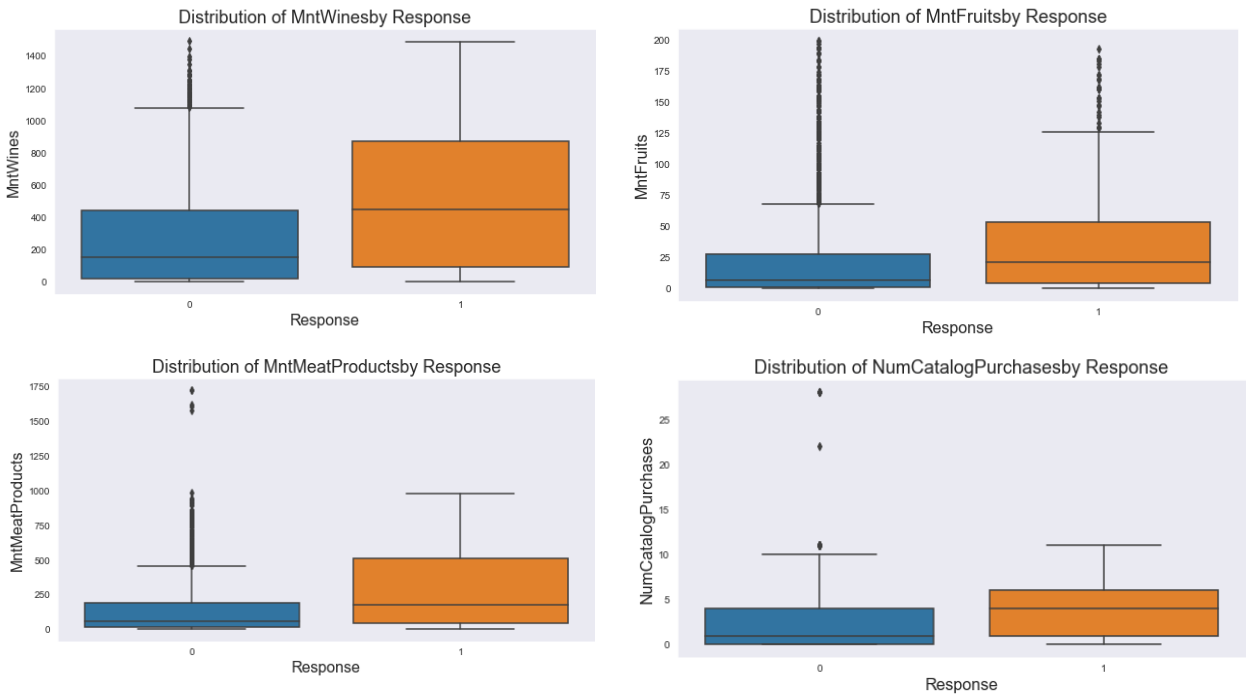


Consumers who have a higher average income are more likely to accept the provided answer, as opposed to customers who have a lower average income. This indicates that the choice of a consumer to accept or decline an offer is influenced by their income to some degree.

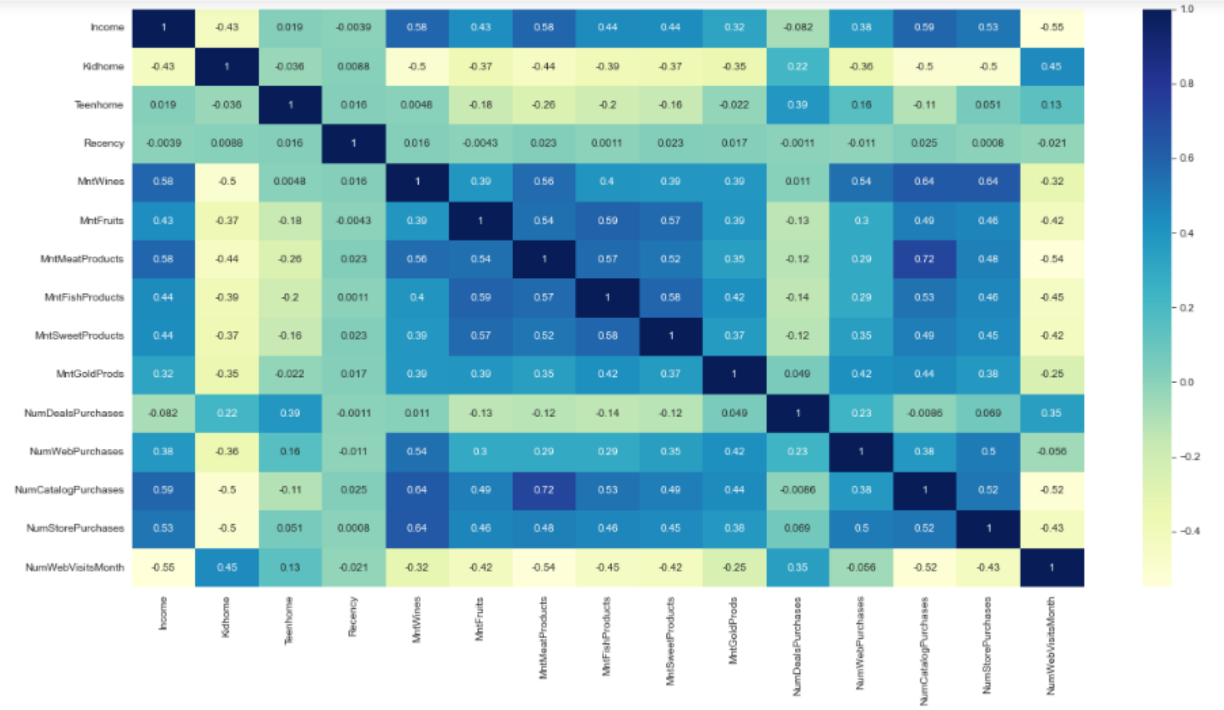


Finally, from below couple of boxplots attached we can deduce that:

- Those who accept the offers, have higher average spending on wines and wines related products.
- Those who have accepted offer have higher average spending on fruits.
- Those who have accepted the offer have higher average spending on meat products.
- Those who have accepted the offer has higher average catalog purchases.



Finally, the correlation plot is created and is attached below.



DATA MODELLING RESULTS:

In this step, 4 different machine learning models have been trained and tested on the test set. The results thus obtained from each of the model thus trained are attached below. It can be seen from the results attached below that the accuracy for logistic regression is 79%, for naïve bayes its 67%, for decision tree model its 93%, for random forest model its 96% and for Ada boost its 79%. Hence comparing based on the accuracies, we can see that the random forest classifier has the best performance on the test set with the highest accuracy of 96% and the second highest accuracy is for decision tree model with prediction of 93% observations correctly. The model having lowest accuracy in this case is the naïve bayes model. Moreover, the F-1 Score too is highest for the random forest model compared to all other models. Hence we can say that the random forest model outclassed all other models in terms of accurately predicting the observations with an accuracy of 96%.

Logistic Regression	Naïve Bayes

```
Accuracy:         0.79
******************************
Precision:        0.79
******************************
Recall:   1
******************************
F1-score:         0.79
******************************
Roc-AUC Score:    1
******************************
```

```
Accuracy:         0.67
******************************
Precision:        0.81
******************************
Recall:   0
******************************
F1-score:         0.67
******************************
Roc-AUC Score:    1
******************************
```

Decision Tree Model

```
Accuracy:         0.93
******************************
Precision:        0.88
******************************
Recall:   1
******************************
F1-score:         0.93
******************************
Roc-AUC Score:    1
******************************
```

Random Forest

```
Accuracy:         0.96
******************************
Precision:        0.93
******************************
Recall:   1
******************************
F1-score:         0.96
******************************
Roc-AUC Score:    1
******************************
```

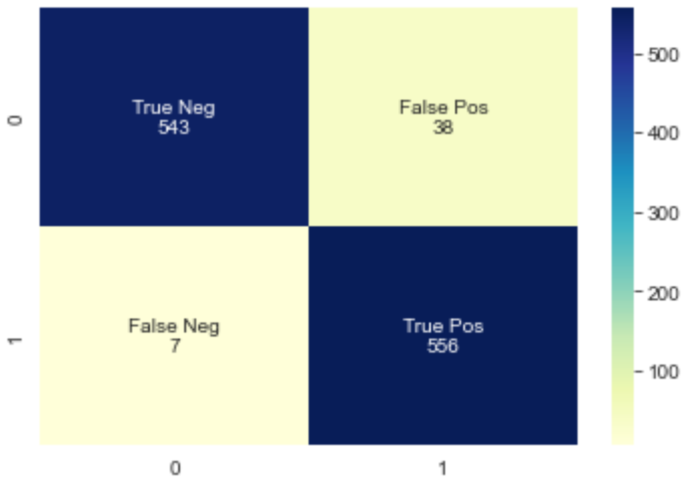
AdaBoost

```
Accuracy:         0.79
******************************
Precision:        0.79
******************************
Recall:   1
******************************
F1-score:         0.79
******************************
Roc-AUC Score:    1
******************************
```

Finally, the random forest tuned model is created. The testing results are attached below. It can be seen that the accuracy is 96%, the precision for class 1 is 93.6% and for class 0 its 98% approximately. The weighted average for both the classes is 96% approximately.

```
ACCURACY SCORE:
0.9607
CLASSIFICATION REPORT:
                   0           1  accuracy    macro avg  weighted avg
precision   0.987273    0.936027  0.960664     0.961650      0.962053
recall      0.934596    0.987567  0.960664     0.961081      0.960664
f1-score    0.960212    0.961106  0.960664     0.960659      0.960652
support   581.000000  563.000000  0.960664  1144.000000   1144.000000
```

The confusion matrix showing true positive, true negative, false positive and false negative is attached below. It can be seen that only 45 observations are misclassified in total.



CONCLUSION:

The purpose of using predictive analytics is to enable improvements in data-driven decision making by predicting future trends, events, and behavior based on the data that is now available. The use of predictive analytics in marketing is on the rise, particularly for the aim of predicting the behaviors of customers when businesses start keeping track of their replies and transactions and then using that information to better focus their marketing efforts. The activity of customers might shift suddenly in reaction to shifting requirements and alterations in their lives. As a result, data on past behaviors might sometimes be more predictive than data on past demographics. With the behavior informatics and analytics approach, it is anticipated that a deeper understanding of customer behavior will be gained to support more accurate prediction analysis and to increase business decision making. This will be accomplished through the construction of behavioral data, which maps transaction data into behavioral data, and through behavioral analysis, which identifies behavioral patterns.

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APPENDIX A:

College of Engineering, Design and Physical Sciences Research Ethics Committee
Brunel University London
Kingston Lane
Uxbridge
UB8 3PH
United Kingdom

www.brunel.ac.uk

23 August 2022

LETTER OF CONFIRMATION

Applicant: mr Lakshmi nivas talluri

Project Title: target marketing analysis and predicting customer response

Reference: 39604-NER-Aug/2022- 41356-1

Dear mr Lakshmi nivas talluri

The Research Ethics Committee has considered the above application recently submitted by you.

The Chair, acting under delegated authority has confirmed that, according to the information provided in your application, your project does not require ethical review.

Please note that:

- **You are not permitted to conduct research involving human participants, their tissue and/or their data. If you wish to conduct such research, you must contact the Research Ethics Committee to seek approval prior to engaging with any participants or working with data for which you do not have approval.**
- The Research Ethics Committee reserves the right to sample and review documentation relevant to the study.
- If during the course of the study, you would like to carry out research activities that concern a human participant, their tissue and/or their data, you must inform the Committee by submitting an appropriate Research Ethics Application. Research activity includes the recruitment of participants, undertaking consent procedures and collection of data. Breach of this requirement constitutes research misconduct and is a disciplinary offence.

Good luck with your research!

Kind regards,

Simon Taylor

Professor Simon Taylor

Chair of the College of Engineering, Design and Physical Sciences Research Ethics Committee

Brunel University London