Analysis of Bank Marketing Strategies and Customer Behaviour

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***Abstract*—The Bank Marketing dataset has a total of about 41000 records, this collection is from the marketing campaign data which is used by a Portuguese bank. This Bank Marketing dataset was collected by contacting the customer by cellular or telephone. The dataset also features multiple aspects of a customer, like education, job, marital status, housing, etc. The most important characteristic of this dataset is the previous outcome of the marketing campaign that helps analyzers in the current campaign. The primary objective of this dataset is to predict if a customer shows interest in the bank term deposit subscription. Here in the project, we use the dataset as a way that we can analyze how different variables impact the outcome of the campaign like job, age, and education.**

This project related to the Bank Marketing dataset primarily focuses on demographic segments like job, education, age, and marital status have been explored to identify customer behavior. Apart from these factors, contact-like means of communication and contacting times like day and month can be studied and analyzed for the campaign's success.

Overall, this dataset stays a good source in the field of marketing, as this dataset concentrates on customer behavior and demographics. After the marketing campaign, based on the customer responses, an effective predictive model can be developed. This model can be used for implementing successful marketing strategies which enhances the marketing campaigns success rate.

***Index Terms*—marketing, campaign, contact, age, investment, savings, month, day, education, customer and demographics, R, Python, SQL.**

I. Introduction

In today's scenario, with the advancements that have taken in technology, especially in the banking sector, a customer is an asset to any bank. For this to happen, marketing campaigns play a significant role in retaining and attracting new customers. With technological advancements, banks have a massive amount of customer data and based on this data the banks can understand customer behavior and plan effective strategies for targeting certain customers.

The project dataset is collected from a Portuguese banking institution through its marketing campaigns, and this data has been gathered by phone calls. This data is collected between May 2008 and November 2010. All the collected records have the customer details like their age, job details, education, marital status, and a few other demographics.

There are many factors for understanding customer behavior, one such important variable is the current and previous outcome variable of whether a customer has decided to choose the subscription of a term deposit or not. A term deposit is an investment where the customers get a high rate of interest when compared to a savings account, helping the customers to withdraw their money whenever they need it[1]. One more significant factor is age because customers from different age groups have different plans for investing and saving, in this particular dataset we have the age of the customers ranging from 18 to 95 years.

Another factor is the job, which describes the income and financial stability of the customers. One more factor is education, there are three levels of education mentioned in the dataset they are primary, secondary, and tertiary. These levels help the banks to target customers with higher levels of education as it would be easy to communicate the investment and savings policies and there would be a better understanding for the customers.

Apart from the fore-mentioned factors, there are still a few factors that the dataset focuses on like the contact mode, there are two types cellular and telephone. The mode of contact plays a significant role in marketing campaigns. Also, this dataset has been gathered by contacting customers. Other factors in the dataset day and month are critical in the marketing campaigns because in the year there might be a few days or months where the customers will be more interested in those periods.

Another essential factor in the dataset is previous outcomes from the marketing campaigns which is one of the key factors because to an analyst understanding the data is highly important. With a proper understanding of the data effective marketing strategies can be developed. Based on all the results, the marketing strategies can be effective in the current campaign.

With the proper predictive models being developed by analysts using the data, potential customers can be identified and targeted to understand which sector of customers have an interest in the campaign. Overall, we get clear assumptions about customer behavior and the success of the marketing campaigns. In the following sections, we provide an in-depth analysis of significant attributes and how they can affect the outcome variable.

II. Related Work

There have been multiple studies in banking industries that were conducted to exploit customer behavior and their requirements, the studies found the key factors which impact customer's decision-making like income, education, and occupation. The banking industry is mainly fascinated by these factors.

In the current trend with technological advancements, approaching customers for the banks has become easier and made their work even easier. Unlike the traditional ways of contacting like emails, and distributing bills has always yielded a low response as very few customers were interested in it. Because of this, banks today are using few algorithms to make predictions and analyze customer behavior and their data.

One study from the Bank in the middle east that is closely related to the current project was conducted by Alkhateeb, where machine learning algorithms were used to predict customer behavioral patterns[2] for credit card acceptance offer. The study there focussed on factors like education, age, income, and gender. Of these factors income and education were essential variables for credit card acceptance.

Another study on the Banking industry was by Krishnan and Singh, where the analysis was on how social media marketing[3] had an impact on the banking industry. From the analysis, it was found that social media marketing is cost-effective when compared to the traditional ways of contacting and it has a good reach among youngsters and also enhances brand value.

One more study by Huang, the study was about how the segmentation of customer sectors in the banking industry affects the marketing campaign. The study also found that identifying customer segments[4] who were highly interested in the marketing campaigns was effective and is done by machine learning algorithms, customer satisfaction and the rate of response can be improved by using the right marketing strategies for a particular sector of customers.

All the aforementioned studies focus on various marketing strategies and the factors in the banking industry that impact customer behavior. Currently, we are using all the analyses from the previous studies and analyzing the bank marketing dataset by researching various factors like age, job, education, contacting means, and the rate of marketing campaign success.

III. Dataset

The bank marketing dataset is derived from the Portuguese banking institution which is related to marketing campaigns. The dataset has 17 attributes (16 input attributes and an output attribute) that include demographic information like age, job, marital, education, balance, housing, loan, and a few other attributes like contact, day and month of contact, and the most significant factor is the outcome of the marketing campaign. The dataset has 45211 records, which is a good amount and can be used for analyzing customer behavior.

The data in the dataset is gathered by phone calls made to customers by the banks and it gives data about success and failure campaigns. The dataset also emphasizes factors contributing to the marketing campaign's success.

Another aspect of the dataset is that there are many records where customers didn't take the subscription to the term deposit and there have been a high number of negative results, and without proper research about why there are many negative results, there will be issues while developing predictive models. Directing these records, effective predictive models can be developed.

DATASET			
Attribute	Data Type	Attribute	Data Type
Age	Interval	Day	Interval
Job	Nominal	Month	Nominal
Marital	Nominal	Duration	Ratio
Education	Ordinal	Campaign	Interval
Default	Nominal	Pdays	Interval
Balance	Ratio	Previous	Interval
Housing	Nominal	Previous Outcome	Nominal
Loan	Nominal	Y (outcome)	Nominal
Contact	Nominal		

Fig. 1. Dataset

The Bank Marketing dataset contains useful information about consumer behavior and the efficiency of marketing campaigns overall. The effective models developed by machine learning algorithms can be influential in the success of marketing campaigns.

IV. Higher Level Framework

The research project was based mainly on programming languages like Python and R, and a relational database query language SQL, these are used for the purposes like data cleaning, analyzing, summarizing, exploring, and visualizing. The programming language Python is used for data processing. After the data processing, the data exploration was done using R Studio, Spyder for Python, and MySQL workbench. For visualizations, R and Python have been used extensively. The following figure represents the high-level framework done in the research project.

Fig. 2. High Level Framework

Data exploration, analysis, and summarization are essential in understanding the dataset. The visualizations gives a correct depiction of the dataset and drive us to the exact conclusions.

V. Marketing Strategies Analysis based on Customer Segments

A. Job

The JOB variable from the dataset gives us data about the occupation and the employment status of customers involved in the marketing campaign. The attribute also discusses various job roles among customers. The categories involved are admin, blue-collar, entrepreneur, household, management, retired, self-employed, services, student, technician, unemployed, and others. Each category helps us understand the customer's professional background.

By analyzing the categories we can develop patterns related to different jobs and the marketing strategies can be customized accordingly. For example, from the plot below we can depict that there are more blue-collar and management customers followed by technicians, admins, and others. So, these customers are more likely to show interest in the marketing campaign. Now, the marketing team has sufficient data about the customers and their team can set few groups to target this sector of customers. This data assists in personalizing advertising campaigns and offers to various job groups' needs, interests, and goals of various job categories.

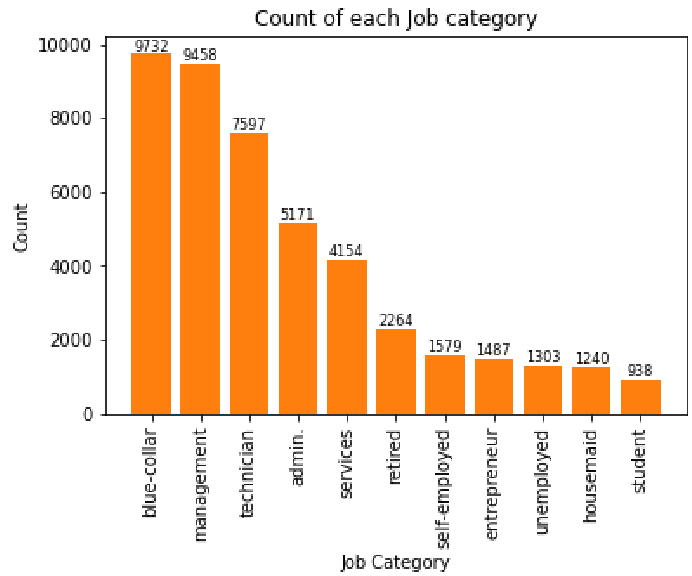


Fig. 3. Job Categories

Further, this attribute also highlights the socio-economic status of the customers, like self-employed and management customers tend to earn a high income and have great prosperity in wealth. On the other side, some customers are students, retired and unemployed suggesting the financial sustainability of these customers. The marketing team should also be interested in understanding this sector of customers and prosper marketing strategies.

	job	count
	<chr>	<int>
1	blue-collar	9732
2	management	9458
3	technician	7597
4	admin.	5171
5	services	4154
6	retired	2264
7	self-employed	1579
8	entrepreneur	1487
9	unemployed	1303
10	housemaid	1240
11	student	938

Fig. 4. Job Count

Marketers can acquire significant knowledge about target customers by researching the distribution and characteristics of various job categories. This data can help improve decisions regarding product positioning, message, and channel selection. It enables marketers to develop campaigns that relate to their customers' professional objectives, difficulties, and motivations. In addition, analyzing the dataset's 'job' variable enables marketers to create more effective and targeted marketing strategies that optimize campaign success and increase positive interactions between customers.

B. Education

The EDUCATION variable from the dataset gives us data about the educational background of the bank customers. Education is an important aspect in defining the financial understanding of an individual and their decision-making process. Customers in this dataset are primarily categorized into 3 categories Primary, Secondary, and Tertiary. Analyzing this distribution can help the marketing department develop good marketing strategies.

Education can affect people's financial goals, risk-taking tendencies, and overall financial well-being. It is frequently used as a socioeconomic status indicator. those with higher education levels, such as tertiary education, could have different financial preferences and aspirations than those with lower education levels. By analyzing the distribution and characteristics of customers within each education category, financial institutions can identify patterns and trends in their approaches to marketing, product offers, and consumer contact techniques.

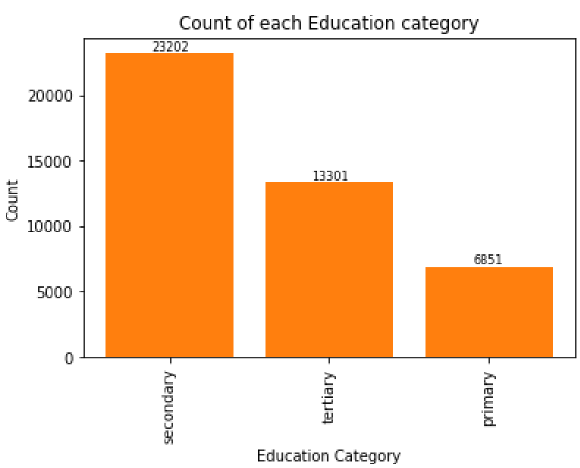
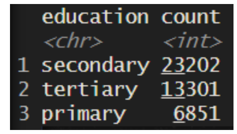


Fig. 5. Education Categories

Understanding a customer's educational background is critical for developing effective financial awareness and educational resources. Financial institutions can use the education factor to identify consumer segments who may need further support and assets to improve their financial understanding and expertise. Banks may empower consumers to make wise financial choices and improve their financial well-being by customizing educational materials and resources based on their customers' education levels.



	education	count
	<chr>	<int>
1	secondary	23202
2	tertiary	13301
3	primary	6851

Fig. 6. Education Count

Furthermore, education attribute analysis can provide insights into the relationship between education and other factors like income, job type, and customer behavior, allowing financial institutions to develop targeted strategies to meet the needs of specific customer segments.

Overall, the "education" attribute is important in analyzing customers' financial behaviors, customizing marketing techniques, and establishing educational endeavors in the banking sector.

C. Age

The AGE attribute from the dataset gives us information about different age groups. Analyzing this attribute in connection with various age groups provides significant information into the demographic composition and preferences of customers of various ages. Understanding the characteristics and behaviors of various groups of people is crucial for financial institutions to develop marketing strategies and customized offers. Customers in their 20s and 30s, for example, may have different financial goals and risk tolerance than elderly customers in their 50s and 60s who are nearing retirement. Banks may adjust their services and goods to suit the individual demands and preferences of every age group by assessing the distribution of age groups, promoting higher customer engagement and pleasure.

From the plot, we can clearly depict that more number of customers are between age 20 to 60. We can learn about generational gaps in financial habits and views by evaluating the age groups included in the dataset. Each age group has its own set of historical, social, and economic variables that influence their financial decisions.

Younger generations, such as millennials and Generation Z, have grown up in a digital age and are more likely to accept technological advances in banking and financial services. They tend to be defined by higher levels of student debt and a tendency for convenience, resulting in a greater need for mobile banking and online financial services. Understanding these generational changes allows financial institutions to modify their strategies and products to the changing demands and preferences across different age groups.

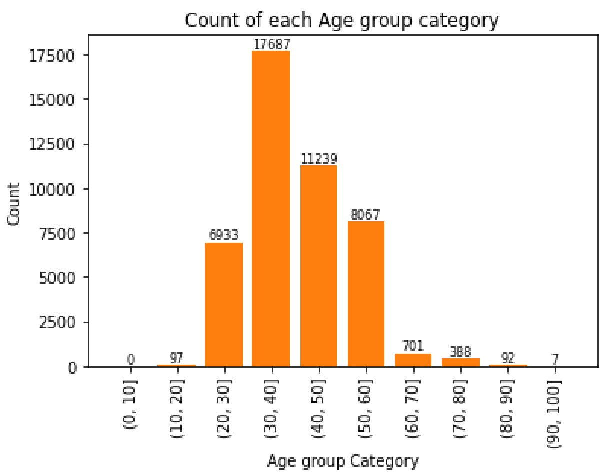


Fig. 7. Age Groups

	Average_Age	Minimum_Age	Maximum_Age
▶	40.9362	18	95

Fig. 8. Age Summary

age_group_count

(0,10]	(10,20]	(20,30]	(30,40]	(40,50]	(50,60]	(60,70]	(70,80]
0	97	6933	17687	11239	8067	701	388

(80,90]	(90,100]
92	7

Fig. 9. Age Groups Count

Overall, the ”age” attribute is important to analyze relationships with different age groups to get insights into customer demographics, financial activities, and preferences over their lifespans. Understanding the particular requirements and characteristics of every age group enables financial institutions to develop targeted strategies, products, and services that serve the specific needs of various age groups, promoting stronger customer relationships and better meeting their financial needs.

D. Marital Status

The MARITAL attribute from the dataset gives us information about the customer's marital status. The marital status attribute in the dataset gives useful information about the customers. relationship status. It shows whether the customers are single, married, or divorced. Customers' marital status segregation could be useful in understanding their socioeconomic background and lifestyle preferences. We can gain an understanding of the tastes and needs of different married status groups by analyzing the marital attribute, which is useful for creating targeted marketing strategies.

According to the data, a significant number of customers are married, indicating a potential focus on family-oriented products and services. Married customers may have different financial goals and priorities than single customers. Understanding the married customers' needs and preferences could help banks to customize their strategies to meet their long-term financial planning, such as mortgage loans, joint bank accounts, or family investing choices. Married consumers may also require specialist solutions to family planning, education savings, or retirement planning.

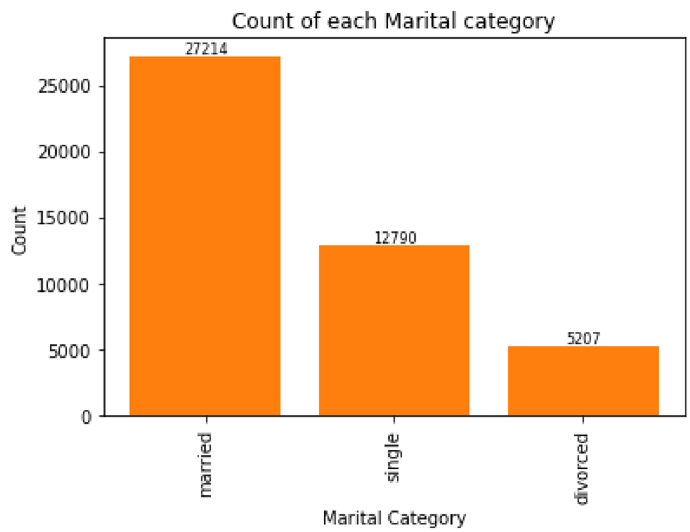


Fig. 10. Marital Categories

Customers who are single, or divorced are also included in the dataset. These customers may have different spending patterns and priorities than those who are married. Single customers, for example, may have more disposable income and place greater importance on personal financial goals such as personal savings, investments, or travel. Divorced people can look for financial guidance and assistance to help them manage their assets and responsibilities throughout this adjustment phase.

	marital	count
	<chr>	<int>
1	married	27214
2	single	12790
3	divorced	5207

Fig. 11. Marital Count

Overall, the marital attribute is important to analyze marital status as a critical component in understanding customers' financial behaviors, preferences, and demands.

VI. Mode of Contact

The contact attribute in the dataset contains useful information on the method of contact used to contact clients. Telephone, cell phone, and other communication channels are available. Analyzing the contact attribute improves identifying customers' preferred communication channels, which can be critical in developing efficient marketing campaigns and customer engagement strategies.

According to the research, a large number of customers prefer to be contacted via cellular devices. This trend emphasizes the increasing dependence on mobile technology, as well as the need for organizations, especially banks, to adjust their ways of communicating accordingly. Banks can use this knowledge to design mobile-friendly platforms, mobile-optimized websites, and mobile applications that offer convenient and smooth banking experiences.

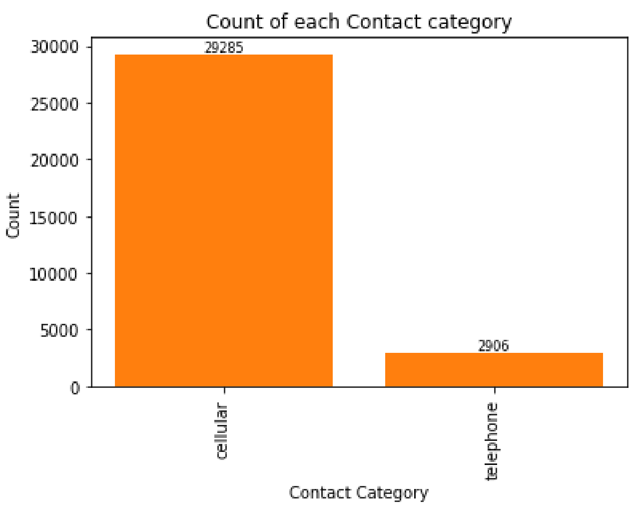


Fig. 12. Cellular Categories

Another common means of communication noticed in the research study is telephone communication. While its use has declined in recent years due to the rise of cellular connectivity, it remains important for specific consumer categories that can't be ignored. Banks may alter their approach to customer service to offer efficient and customized support over the phone by analyzing the preferences of customers who prefer telephone communication.

The dataset contains alternative communication methods that customers may select in addition to cellular and telephone contact. Email, mail, and in-person interactions are examples of this category. Understanding how customers are distributed throughout all of these ways benefits banks in determining the most successful channels for particular customer groups. For example, some consumers may prefer to get important paperwork via traditional mail, while others may choose emails for simpler and quicker contact.

Specific methods of interaction may be chosen based on characteristics such as age, technological advances usage, and personal preferences. Younger, technologically proficient customers may choose cell phones or online

	contact	Other_Means
▶	unknown	13020

Fig. 13. Unknown Means Count

communication channels, whereas elderly customers may still prefer traditional methods such as telephone or in-person contacts. Banks can alter their marketing strategy and maintain successful interaction across different age groups by segmenting customers depending on their contact preferences.

The contact attribute is essential not just for initial customer outreach, but also for continuous client engagement and relationship management. Banks can customize their communication and marketing efforts by identifying their customer preferred contact channels. Sending customized promotional offers, for example, over the customer's preferred communication channel may improve the success of marketing campaigns and enhance customer satisfaction.

	contact	count
	<chr>	<int>
1	cellular	29285
2	telephone	2906

Fig. 14. Cellular Means Count

Overall, the contact attribute has importance in understanding consumer communication preferences and building effective engagement strategies

VII. Periods

A. Day

The "day" attribute indicates the month's last encounter with the marketing campaign. The numbers displayed vary from 1 to 31, signifying the month's specific day. Analyzing this, the distribution may offer insights into customer spending trends throughout the month. It can assist marketers to recognize specific days with higher response rates or rates of conversion, enabling them to optimize campaign timing and use resources more effectively.

We recognize interesting trends in responses from customers based on the days of the month. For example, due to salary or payment cycles, there may be a higher reaction rate toward the start or end of the month. Understanding such patterns might help alter marketing strategies and dedicate resources during different periods of the year to maximize campaign performance. Identifying any discrepancies or abnormalities in the distribution can also provide major insights into customer behavior and help with a campaign targeting improvement.

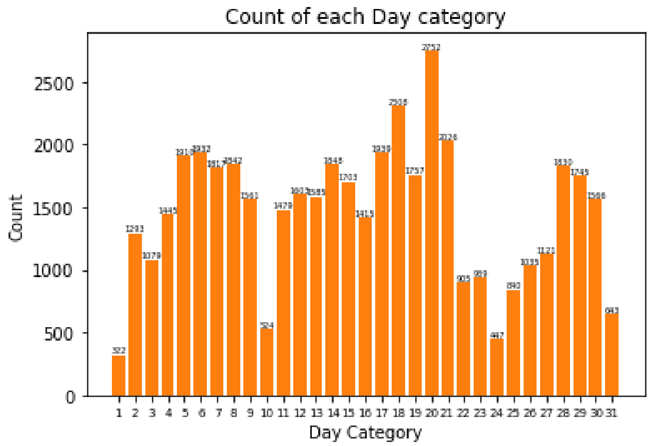
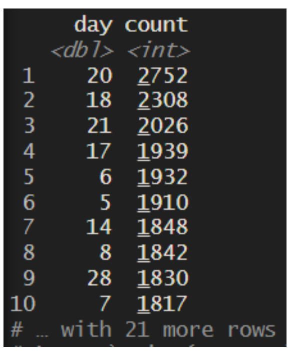


Fig. 15. Day Trend

It could, for example, suggest whether certain days of the week or month are more effective for engaging customers and achieving desired results. This data can help marketing teams develop successful outreach strategies, such as focusing resources on days with historically better response or conversion rates



	day	count
	<dbl>	<int>
1	20	2752
2	18	2308
3	21	2026
4	17	1939
5	6	1932
6	5	1910
7	14	1848
8	8	1842
9	28	1830
10	7	1817

… with 21 more rows

Fig. 16. Day count

This information can be used to make judgments about the frequency and timing of future marketing functions, ensuring that they align with customer preferences and increase the possibility of successful results. Overall, the day attribute has importance in analyzing the ”day” attribute in the dataset and how it could help understand customer behavior and improve marketing campaigns.

B. Month

In the dataset, the month attribute indicates the month in which customers were contacted for the marketing campaign. By analyzing this we can provide important information about customer involvement trends and patterns throughout the year.

The distribution of contact with customers over the months indicates distinctive seasonal variations. According to the data, the months of May, June, and July have the highest number of interactions with customers, showing that the summer months are the most active for marketing campaigns. In contrast, the months of December, January, and February show considerably smaller interactions with customers, indicating a quieter period during the winter season. Based on customer engagement data, these seasonal patterns can help marketing teams better allocate resources and design campaigns.

Analyzing response and conversion rates by month can provide insight into the marketing campaign's success. We can select months that have higher conversion rates by comparing the number of successful conversions to the total number of contacts in each month. For instance, if the conversion rate is higher in particular months, it could indicate that the campaign strategies were more successful during those months, and further analysis can be done to figure out how.

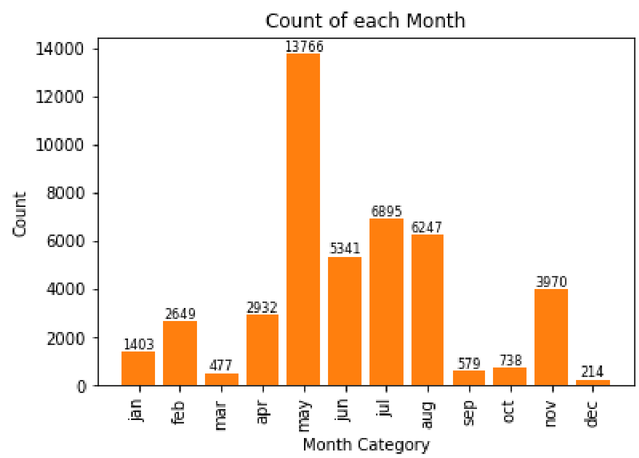


Fig. 17. Monthly Trend

Examining the differences in customer contacts from month to month may reveal fascinating trends and patterns. It is crucial for deciding whether the marketing strategy achieved a steady number of customers each month or if there were major changes. For example, if there are significant increases or decreases in customer contacts in specific months, it could show the impact of external variables such as holidays, promotional events, or market conditions, which might have affected customer engagement.

The month attribute analysis may assist marketing teams plan strategies for the future. Marketers should carefully regulate their campaigns to capitalize on moments of greater interest by recognizing the months with higher interaction with consumers. To maximize campaign efficiency, for example, commit additional funds, produce specific messaging, or provide special promotions during peak months. Quieter months, on the other hand, can be used for preparing and organizing, exploring new marketing channels, or carrying

	month	count
	<chr>	<int>
1	feb	2649
2	mar	477
3	sep	579
4	aug	6247
5	apr	2932
6	jun	5341
7	jul	6895
8	dec	214
9	jan	1403
10	oct	738
11	nov	3970
12	may	13766

Fig. 18. Month count

out market research to improve future campaign outcomes.

Analyzing the month attribute over some time could reveal long-term trends and patterns in customer behavior. Marketers can spot repeating patterns, seasonality, or altering customer preferences by aggregating and visualizing data over time. This data may be utilized to improve forecasting techniques, find growth opportunities, and make data-driven decisions for subsequent advertising campaigns.

Lastly, analyzing the month attribute in the dataset provides helpful information on seasonal patterns, campaign efficiency, month-to-month disparities, campaign planning, and long-term trends. This data can help marketing teams enhance their strategies, distribute resources more effectively, and increase overall campaign performance.

VIII. Multiple Linear Regression

By performing multiple linear regression analysis on age and job, we want to know how these variables influence the dependent variable. This approach helps clarify the link between age, job, and outcome variables while taking other variables into consideration for any confounding effects. The outcomes of the regression analysis provide a quantitative explanation of the relationship, allowing us to base our conclusions and predictions on the model.

A. Residual Plot

The residual plot gives us the ability to assess our view of homogeneity and investigate the residual distribution. The residual plot in our analysis shows the residuals on the y-axis and the predicted values (age) on the x-axis. The graph illustrates whether the residuals have constant variance and whether the age-job relationship is linear. The residual plot

demonstrates that the residuals have a random distribution around the horizontal line, implying that the assumption of homogeneity is correct. This suggests that the linear regression model is reasonably well-fitted.

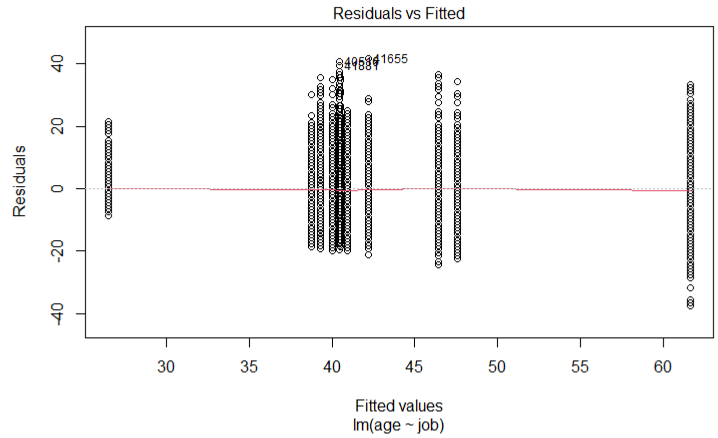


Fig. 19. Residual Plot

B. Normal Q-Q

The normal plot, commonly known as a Q-Q plot, is used to evaluate the residuals' normality assumption. It analyzes the observed residual quantiles to the expected normal distribution quantiles. The normality plot in our analysis shows the quantiles of the residuals on the y-axis and the predicted quantiles of a normal distribution on the x-axis.

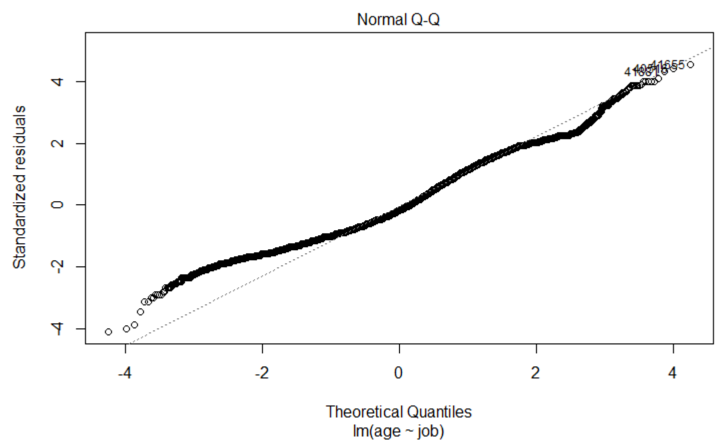


Fig. 20. Normal Q-Q Plot

If the points are almost parallel, it indicates the residuals have a normal distribution. The points on the normality plot roughly follow a straight line, showing that the residuals tend to be normally distributed.

C. Scale-Location

The scale-location plot supports us when assessing the residuals' assumption of constant variance. The scale-location plot in our analysis shows the square root of the absolute standardized residuals on the y-axis and the predicted values (age) on the x-axis.

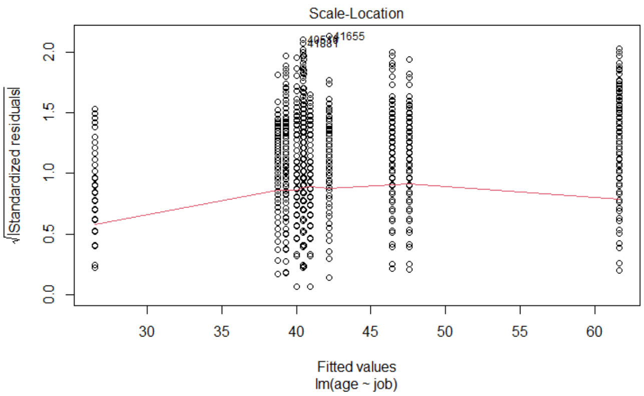


Fig. 21. Scale Location Plot

The plot helps us to look for patterns or trends in the residual spread. We can see from the scale-location plot that the spread of the residuals is fairly uniform across different levels of predicted values. This implies that the presumption of homogeneity is correct.

D. Cooks Distance

Cook's distance estimates the impact of each data point on the regression model. The Cook's distance plot helps us to recognize influential data that may have a large impact on the model's parameters. The Cook's distance plot in our analysis depicts the Cook's distances on the y-axis and the observation indices on the x-axis.

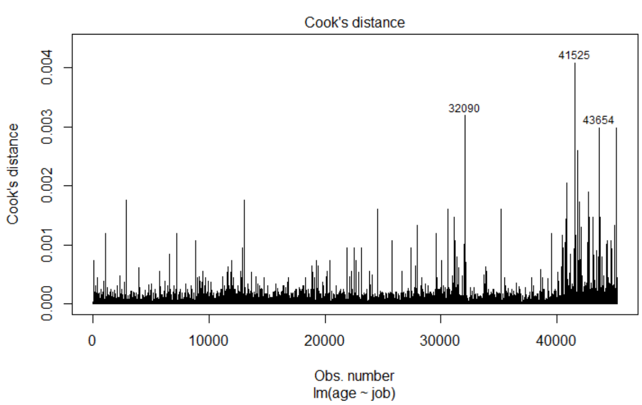


Fig. 22. Cooks Distance Plot

The distances for each observation are determined using Cook's distance plot. Higher Cook's distances indicate that the model's results are influenced by more data points. Any places with high Cook distances should be examined for potential outliers or significant results.

IX. Discussion

The plots provide useful information on the distribution and interactions of different attributes in the dataset. They provide a visual depiction of the counts and proportions of various categories within each attribute, offering information on the dataset's composition and features.

The visualizations illustrate the dataset's diversity across several attributes. They show the frequency of each category and enable comparisons. These visualizations can be used to identify any data imbalances or biases. For instance, if one category outnumbers the others in terms of count, the interpretation and analysis of the dataset may be impacted. Such patterns can assist researchers in making well-informed choices about gathering information or sampling methods.

Furthermore, the plots serve as a basis for examining potential correlations between attributes. Researchers can visually evaluate the distribution of different categories across characteristics by analyzing the bar plots side by side. This can lead to the identification of interesting trends or associations that can be used to drive subsequent research or modeling.

The visual representation of the dataset using bar graphs additionally assists in understanding the overall composition and attributes of the data. It gives an overview of the dataset's framework, such as the prevalence of various categories and the likelihood of outliers or imbalances. This understanding is vital for later data processing, feature selection, or modeling procedures.

Furthermore, bar graphs provide for effective communication and presentation of the dataset's attributes. They provide a short and visually appealing overview that is easily comprehended by people of all backgrounds. Researchers may utilize these plots to convey essential findings and conclusions in a clear and accessible way, promoting conversations and collaborations among researchers.

Overall, bar charts are essential in the exploratory data analysis process. They let researchers analyze the attributes, distributions, and possible relationships of the dataset, providing the groundwork for subsequent analysis and interpretation. These plots enhance understanding, increase communication, and contribute to the overall quality of study findings by illustrating the properties of the data.

X. Future Work

Based on the dataset analysis, there are several possibilities for growth in the future. To begin, more research on the relationships among characteristics and results can be conducted. It might involve examining additional variables that were not included in the current research but may have an impact on the results that are wanted. Researchers may develop a greater understanding of the elements affecting the observed patterns by extending the scope of the analysis.

The dataset can be used for forecasting and predictive modeling. Establishing models of prediction based on available variables can aid in the identification of trends and patterns that can be utilized for predicting future outcomes. This is particularly helpful in deciding and organizing processes because it allows researchers to anticipate possible consequences and take preventative measures and remedies.

The dataset can also be built with outside sources of information in order to gain more information and improve the study. Integration with demographic, economic, or social media data, for For instance, can provide additional information into the relationships between qualities and outcomes. Researchers can get a greater understanding of the subject under investigation through the combination of varied datasets.

In summary, future research could include exploring more factors, constructing prediction models, and integrating external data sources to improve the dataset's analysis. These efforts may contribute to furthering our understanding of the references between qualities and outcomes, providing useful insights for a wide range of applications and decision-making processes.

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