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**UNDERSTANDING AND PREDICTING CUSTOMER DEPOSITS: A DATA-DRIVEN ANALYSIS PROPOSAL**

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BAN 586 CAPSTONE PROJECT

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# **1. Executive Summary**

The analysis uses 2022 customer data to determine which factors affect Foothill Bank's deposit growth. Foothill Bank contains vast historical customer data, yet had no established approach to determine why customers boost their deposits. The analysis of customer demographic information alongside behavioral patterns and economic environments will help establish strategies for attracting more depositors to the bank.

Among the variables targeted for evaluation were customer age and marital status, as well as income levels, along with spending habits and the local poverty rates. This research study analyzed how customers' deposit strategies changed throughout the year periods and how their choice of communication channels influenced this behavior. Subjects with higher salaries, together with people who moderately spent money, and residents from low-poverty areas, displayed increased deposit amounts according to the study findings. Statistical data revealed that married clients who used mobile [Cellular] phone communication in the month of May had the maximum probability of boosting their deposits.

Models for consumer behavior projection emerged from these variables during the project development process. The best model showed that married clients who did not have personal debts stood as the highest group likely to boost their deposit levels. The research found that specific contact in the month of May through phone calls to clients yielded better results for the bank compared to other communication channels. Also, the age above 36 years, income more than 90,000$, expenditure less than 15000$, and poverty less than 5.14$ can increase deposits. The bank will enhance its marketing targeting by utilizing this acquired knowledge. We can see that through the telephone network, we have the highest number of “No” distribution . So the foothill banks should focus on the cellular contact method.

In conclusion, this initiative gives Foothill Bank a plan for increasing deposits by concentrating on particular clients, such as married customers with better incomes and moderate expenditure, average poverty, and age. In order to encourage more customers to raise their deposits and achieve better financial success, the bank can use the insights gathered from this analysis to enhance its marketing tactics and customer engagement campaigns.

# **2. Project Statement**

# This project uses 2022 client data to identify what drives Foothill Bank's deposit growth. Foothill Bank needs to better explore the elements that influence customer deposit patterns. The bank possesses rich historical data from the year 2022 but lacks a systematic, data-driven methodology to recognize behavioral patterns or identify the customers who will increase their deposit amounts. Because analytics assists in identifying important demographic, behavioral, and economic elements that impact deposit growth, advanced analytics is the main technique used in this project. The analyzed insights will aid in developing financial and engagement strategies that focus on specific target groups and help in increasing deposits for Foothill Bank.

# **3. Data and Methods**

**3.1 Data**

Data Foothill Bank provided the primary data resources, which included comprehensive customer information about age, job description, marital status, education level, credit default record, housing loan information, contact type, interaction month and day, duration, campaign details, and previous outcome results. The analysis included macroeconomic variables, which consisted of employment variation rate, together with the consumer price index and consumer confidence index and the 3-month Euribor rate, and the number of employees. The customers who subscribe to deposit products receive the designation "y" in the target variable.

This statistical information was expanded through supplementary economic metrics that were merged into the dataset. Average poverty rate from Welfare Info.

Table 1: Average poverty rate from Welfare Info

|  |  |
| --- | --- |
| **Age group** | **Average Poverty Rate** |
| Under 18 | 5.14 |
| 18 - 34 | 13.6 |
| 35 - 64 | 10.6 |
| 65 & Above | 11.4 |

Table 2: Annual household expenditure. Data from Statista.

|  |  |
| --- | --- |
| **Age group** | **Annual Household Expenses** |
| Under 25 | $34500 |
| 25 - 34 | $54000 |
| 35 - 44 | $66500 |
| 45 - 54 | $69000 |
| 55 -64 | $64000 |
| 65 & above | $52000 |

Table 3: Annual median income. Data from Statista.

|  |  |
| --- | --- |
| **Age Group** | **Median Income** |
| 15 - 24 | $54,930 |
| 25 - 34 | $70,000 |
| 35 - 44 | $85,000 |
| 45 - 54 | $90,000 |
| 55 - 64 | $75,000 |
| 65 & above | $60,000 |

The analysis uses only 2022 data to keep all information consistent, which strengthens the results.

**3.2 Methods**

**Excel:** The first data cleaning process, together with initial exploratory analysis, occurred through Microsoft Excel usage. The tool efficiently managed our dataset to facilitate both input and output operations for economic and customer records. Using the Microsoft Excel tool helped detect initial patterns in deposit activities and research how additional information affected the results.

**Tableau:** Tableau provided capabilities to generate interactive visual depictions that pertained to our main dataset plus our secondary data sources. The visual dashboards provided an easier way to understand complex data patterns and delivered useful insights about customer deposits and their determining variables.

**Python:** Advanced data analysis, along with predictive modeling operations were conducted through the Python programming environment. We utilized libraries, namely Pandas together with Scikit-learn, to create predictive models that analyzed historical data effectively for deposit behavior forecasting and key factors determination.

**RapidMiner:** The Random Forest algorithm within RapidMiner served to create machine learning models for evaluation purposes. The model provided effective prediction capabilities for various complex data patterns, allowing us to determine important deposit decision drivers through its non-linear analysis and distribution of “y”.

# **4. Models and Analysis**

**4.1 Models**

**Logistic Regression:** The research used Logistic Regression for predicting customer subscription behavior to deposit products through analysis of categorical and continuous variables comprising marital status data and call duration records. Analysis of longer calls exceeding 17.33 minutes for single and divorced customers resulted in 99% accurate predictions of positive deposit subscription.

**Linear Regression:** The analysis of customer parameter summation to deposit amount adopted Linear Regression as its analytical approach. The analysis employed age together with annual household expenditure and annual median income, contact method, and poverty rate as predictive variables. Both accuracy and efficiency reached 89.06% as the model established positive correlations between higher income levels and moderate expenditure amounts and increased deposit amounts.

**The Random Forest** algorithm examined deposit influencers through variables while detecting non-linear relationships among them. Analysis based on the Random Forest model confirmed poverty rate, together with median income and household expenditure, as the most important proprietary factors. The model exhibited robust detection ability for advanced models present in the dataset while producing trustworthy rankings of its variables.

**RapidMiner:** A Random Forest model operated in RapidMiner to execute its tasks. The data division process allocated 70% of the data to training, along with 30% allocated to testing during distribution. The visual workflow system in this tool simplifies sophisticated model training and evaluation procedures and data processing tasks for end users. The model provided a 24.5% distribution rate of the no category within the results.

The Project started by conducting an exploratory data analysis through Excel to determine supplementary economic indicators relationship with deposit activities. Outcomes from descriptive statistics revealed major patterns within the data sample. The observations for Average Poverty Rate span from 10.6% to 13.3% with an average value of 11.69% and a standard deviation of 1.43. This indicates a higher likelihood of customers increasing their deposits. Deposits from customers tended to increase when the poverty rate fell in the vicinity of 10.6%. which we can see the Appendix A.

Annual Household Expenditure demonstrated wide variations because its mean was $61,590.86, yet its median equaled $66,500. People in the middle and upper expenditure brackets generally showed better ability to make deposits. We can see the Appendix B

The data revealed that Annual Median Income exhibited a mean value of $79,019.32 as well as a median value of $85,000. from above and at the median income level demonstrated substantial capacity to make deposits, or they can increase deposits. which we can see the Appendix C.

**4.2 Analysis:**

An additional research stage was developed to evaluate the effects that customer conduct and personal statistics had on deposit performance. Using pivot tables and visualizations, the data showed that May registered the maximum 884 deposits, whereas the minimum number of 89 deposits occurred during December, according to the data in Deposits by Month and Contact Method. The outcome rate for successful deposits exceeded telephone deposits when customers used cellular phones for the transaction. Which we can see in Appendix D. And also, here we can see about the month & contact method in the below figure 1.

Figure 1: Deposit Trends by Month & Contact Method Graph.

In the model of Tableau in Appendix E, we can observe that we have the highest deposits of 2400 at 10.6% poverty, and 1917 deposits increase at 13.6%, through the exploratory analysis in Excel. We can see in Figure Appendix F that the average poverty rate of 10.6% has the highest number of 2400 deposits, as we can see in the Tableau dashboard. So that we can see that 66500$ has the highest deposits of 1165, and at 69000$, expenditures have 751 deposits, and also at the median income of 85000$, it has 12,271 deposits. Also, we can see in the Figure below by average poverty, and also we can observe it in the Tableau dashboard, which was shown in Appendix F.

Figure 2: Deposit Patterns by Average Poverty Rate Graph.

Marital Status Analysis demonstrated that married customers made the most deposits at 2,526, while single clients made 1,618, and divorced clients made 476. Targeted marketing strategies should focus on married families because they have demonstrated the greatest potential for increasing their savings. Which we can see in Figure Appendix G.

People living below poverty rates in areas with 10.6%, as 2400 people, and 13.6%, as 1917 people, poverty levels experienced higher deposit rates. Which we can see in Figure Appendix H

Telephone survey data reveals the highest number of participants (24.85%) who failed to deposit, while the analysis demonstrates linkages between population statistics and both financial condition and interview format, and the resulting choice. The figures in Appendix P,Q,R show the data presentation in the Rapid Miner.

The analysis indicated that married clients without personal loans who owned houses showed the highest level of deposit increase (2,093). The analysis of economic factors showed that married clients who were not taking personal loans demonstrated higher deposit tendencies, followed by those who took housing loans. The highest number of clients subscribed for the deposit service, with total expenses of $66,500 (1,165) users. Deposits had the strongest inclinations among individuals earning between $85,000 and $90,000 (12,271 and 7,916 subscriptions). Data-based decision making was used to identify predictive features that became the basis for utilizing regression along with classification methods.

Here we can see that we used linear regression because we got the highest accuracy of 89.06% compared to all machine learning models in figure Appendix M, By focusing on these profiles, Foothill Bank may effectively expand its deposit base through predictive analysis, which indicates that customers who fit the suggested criteria shown in Figure Appendix N are more likely to increase their deposits. On the other hand, Foothill Bank can better target its marketing efforts and narrow down its emphasis to more potential prospects if a customer exhibits the traits linked to reduced deposit likelihood, as depicted in the image. This indicates that these individuals are less likely to make deposits in Appendix O.

# **5. Validation and Testing**

**5.1 Validation**

Multiple hypothesis tests were administered to verify the importance of connections discovered within the analyzed data. Different marital status groups underwent a two-tailed t-test evaluation of their call durations. Statistical analysis of the phone call durations between married and divorced individuals, along with divorced and single individuals, as well as married and single people, yielded p-values exceeding 0.05, thus establishing no statistical significance between these groups. Statistical analysis between clients who are single versus divorced showed a p-value of 0.085, yet failed to achieve significance, thus indicating a worth exploring patterns. The correlation between lower poverty rates and higher annual incomes, and moderate household expenditures, positively influences deposit growth according to both Exploratory Data Analysis (EDA) and descriptive statistical analysis. Supplemental economic data confirmed how robust the findings proved to be about bank deposits. We can see this in figures H, I, G.

**5.2 Testing**

The analysis involved developing several models and conducting evaluations for predicting deposit growth from customer details. The best accuracy rate of 99%, Logistic Regression emerged from analyzing call length and marital status using logistic regression modeling, as we can see in Appendix K. Based on model outcomes, it was observed that, Single or divorced customers are more likely to subscribe or deposit more if the call duration exceeds 17.33 minutes we can see this in Appendix L.

A broader predictive modeling evaluation used customer attributes consisting of Age, Annual Household Expenditure, Annual Median Income, Average Poverty Rate, Contact Method, Month, Loan Status, Marital Status, and Housing Loan Status which Linear Regression analyzed with 89.06% prediction accuracy for selecting as the predictive model method used for customer deposits prediction we can observe this in figure M, N, O.

RapidMiner used a Random Forest algorithm on three features together with the y target variable and annual household expenditure, as well as annual median income and average poverty rate. The training data set contained 70% of the data, while 30% became the testing data. The highest percentage of customers who had not subscribed (24.85%) made their contact choices through telephone. Higher spending consumers with lower incomes tended to decrease their deposit activities. It is shown in Appendices H, I, and G.

**5.3 Cross Validation**

Model overfitting prevention and reliability testing required splitting the data into training and testing subsections. The model using Logistic Regression achieved 99% efficiency in predicting deposit transactions from call time and marital data points. Linear Regression succeeded in reaching 89.06% accuracy performance when analyzing demographic and economic variables. The Random Forest model in RapidMiner conducted multiple splits of the data, which confirmed that poverty rate, income, Duration, contact method, month, and expenditure serve as primary factors influencing deposits.

# **6. Results and Recommendations**

**6.1 Results**

Economic Indicators Influence Deposit Behavior: People living in regions with lower poverty average levels (10.6%) were likely to raise their deposits in significant numbers. People with average incomes exceeding $85,000 tended to have better economic power, which led them to support deposit growth. The household demographic with annual expenses of approximately $66,500 displayed the highest deposit activity levels compared to other economic ranges.

Demographic Trends in Deposit Patterns: The majority of clients who became subscribers or raised their deposits belonged to the married category (2,526), with single (1,618) clients following closely behind and divorced clients (476) in the third position. Clients who did not have personal loans or held housing loans showed better success rates when it came to deposit conversion.

Timing and Communication Channels Matter: During May, there were 884 cases of deposit conversion, whereas December recorded only 89 such cases. The Cellular phone method proved superior to telephone communication in driving clients to subscribe or boost their account deposits.

Predictive Model Performance: The model based on Logistic Regression reached the maximum prediction accuracy at 99% when assessing deposit behavior for customers with specific durations matched to marital status, as well as economic indicators. Statistical data showed that Linear Regression delivered an accuracy of 89.06% when making deposit outcome predictions from behavioral and economic variables. RapidMiner utilized Random Forest, which detected sophisticated patterns in deposit tendencies while recognizing poverty rate, together with expenditures and contact method as fundamental influencing elements.

**6.2 Recommendations**

Target High-Potential Segments The organization needs to concentrate its services on married clients who have higher incomes but spend moderately, because this group demonstrates maximum deposit volume potential. The financial institution should channel its services toward clients located in regions having lower poverty levels because statistical evidence shows these populations will boost their deposit amounts.

Optimize Communication Strategy Cell phone outreach programs will prove more effective because they replace established phone telephone methods during contact outreach. The period of running promotional activities in May generates the highest success rates for attracting deposit subscription customers. Contact them in the month of May or August for higher deposits.

Service package modifications for businesses need to correspond with the client's economic conditions. The marketing efforts for deposit products should concentrate on these consumers because they present the best opportunity to use deposit services. The company must establish adaptable saving opportunities designed to attract clients who hold personal or housing loans.

Predictive Models need to be deployed by the organization within their proactive engagement approach. Using Logistic Regression, the banking organization should forecast potential depositors based on behavioral patterns through single and divorced clients with above 17.33-minute phone contacts. The linear regression model needs to use demographic and economic data to forecast customer behavior and maximize marketing segmentation results. The model requires constant observation together with model updates. New datasets incorporated during model maintenance periods allow predictive models to achieve better accuracy levels. For the business to quickly adjust its strategy in response to changes in both factors, it needs systems for tracking customers and monitoring economic data.

# **7. Conclusion**

# An analysis at Foothills Bank sought to determine the main elements that affected customer deposit actions by incorporating 2022 banking records in addition to average poverty statistics and annual income profiles, and annual family spending levels. The program achieved strategic value through its combination of visualization tools and exploratory research with predictive modeling to generate decisions about raising consumer engagement rates.

# The initial EDA performed using Microsoft Excel showed distinct patterns and trends in demographic and economic data points. The analysis revealed that clients located in poverty zones of less than 10.6% demonstrated increased willingness to increase their deposit amounts. The dependent ability to make deposits was demonstrated by consumers with average household spending and median income surpassing $85,000 per year. The economic data confirms that financial stability occurs when people increase their savings activities and investments.

A historical analysis shows that deposit success directly depends on the combination of contact channels alongside their scheduling methods. The chosen approach of using cellular communication proved superior to traditional phone calls in May period since it achieved the highest successful deposit conversions. The likelihood of clients to increase their deposits was most prominent among married clients, followed by single and divorced clients, according to data on marital status demographics. The data obtained reveals the necessity for customized marketing methods among advertisers. contact methods and understanding of clients according to their relationship condition and financial abilities. Tableau visualization enabled a better understanding of data relationships, which proved that deposit-making clients displayed typical characteristics of permanent housing residents, alongside no existing personal loans and positive financial traits. The predictive modeling processes using logistic regression, linear regression, decision trees, and random forest algorithms reached remarkable model accuracy results, where logistic regression reached 99% success in particular cases. The modeling approaches validated initial analysis findings while providing dependable methods to predict new and existing customer deposit actions in the future.

Furthermore, hypothesis testing and regression analysis validated significant monitoring variables that the bank should focus on for actionable results. The research indicates that clients who spend more than 17.33 minutes on calls have greater odds of subscribing to deposit services when they are unmarried or divorced. The supplementary data analyses through regression models confirmed that customers between 36 years of age and older, along with those generating median incomes over $90,000 and located in areas with poverty rates under 5.14%, and May contact months demonstrated the strongest likelihood to deposit funds.

Based on integrated insights, Foothills Bank formulates data-driven approaches that focus on serving its customers. Deposits at Foothills Bank have increased significantly as a consequence of stable married customers with personalized financial solutions and extremely successful marketing techniques based on client data. By regularly reviewing and monitoring its prediction models for precise modifications, the bank maintains efficient market adaptation.

The project created an entire framework to help Foothills Bank increase deposit subscriptions while satisfying customers and improving sustainable financial success by using exact data-driven choices.

# **8.** **Acknowledgements**

# My deepest recognition goes to Kristin Marie Greenwalt, who maintained unending support throughout my capstone work period. The successful completion of this project required essential guidance from her as well as her meaningful feedback and inspiring support.

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I would like to thank BCC; they provided essential backing for the development of my presentation, together with poster delivery and report completion, and they helped me find and fix any mistakes.

# **9. References**

Bank Data: Foothills Bank 2022.

Supplementary Data:

Average Poverty Data: <https://www.welfareinfo.org/poverty-rate/arizona/>

Median Income, Annual Household expenses:https://www.statista.com/statistics/233184/median-household-income-in-the-united-states-by-age/

**10. Appendices**

**Appendix A**

|  |  |
| --- | --- |
| *Descriptive Statistics for Avg Poverty Rate* | |
|  |  |
| Mean | 11.7 |
| Standard Error | 0.0 |
| Median | 10.6 |
| Mode | 10.6 |
| Standard Deviation | 1.4 |
| Sample Variance | 2.1 |
| Kurtosis | -1.6 |
| Skewness | 0.6 |
| Range | 8.5 |
| Minimum | 5.1 |
| Maximum | 13.6 |
| Sum | 479364.5 |
| Count | 41017.0 |

**Appendix B**

|  |  |
| --- | --- |
| *Descriptive Statistics for Annual Household Expenditures* | |
|  |  |
| Mean | 61590.86 |
| Standard Error | 38.16 |
| Median | 66500.00 |
| Mode | 54000.00 |
| Standard Deviation | 7728.19 |
| Sample Variance | 59724859.74 |
| Kurtosis | 1.51 |
| Skewness | -1.19 |
| Range | 34500.00 |
| Minimum | 34500.00 |
| Maximum | 69000.00 |
| Sum | 2526272500.00 |
| Count | 41017.00 |

**Appendix C**

|  |  |
| --- | --- |
| *Descriptive Statistics for Annual Median Income* | |
|  |  |
| Mean | 79019.32 |
| Standard Error | 45.94 |
| Median | 85000.00 |
| Mode | 70000.00 |
| Standard Deviation | 9304.09 |
| Sample Variance | 86566024.08 |
| Kurtosis | -0.79 |
| Skewness | -0.46 |
| Range | 35070.00 |
| Minimum | 54930.00 |
| Maximum | 90000.00 |
| Sum | 3241135310.00 |
| Count | 41017.00 |

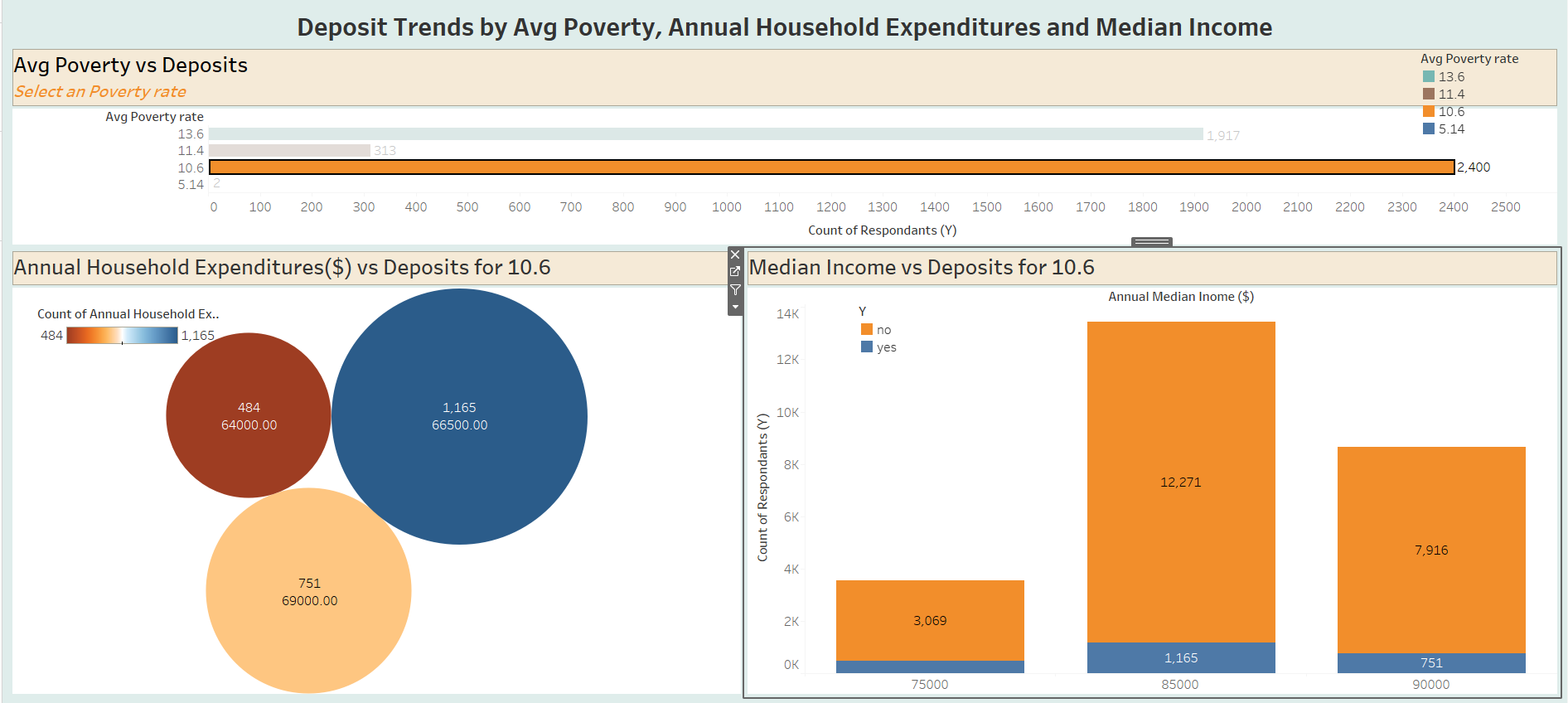
**Appendix D**

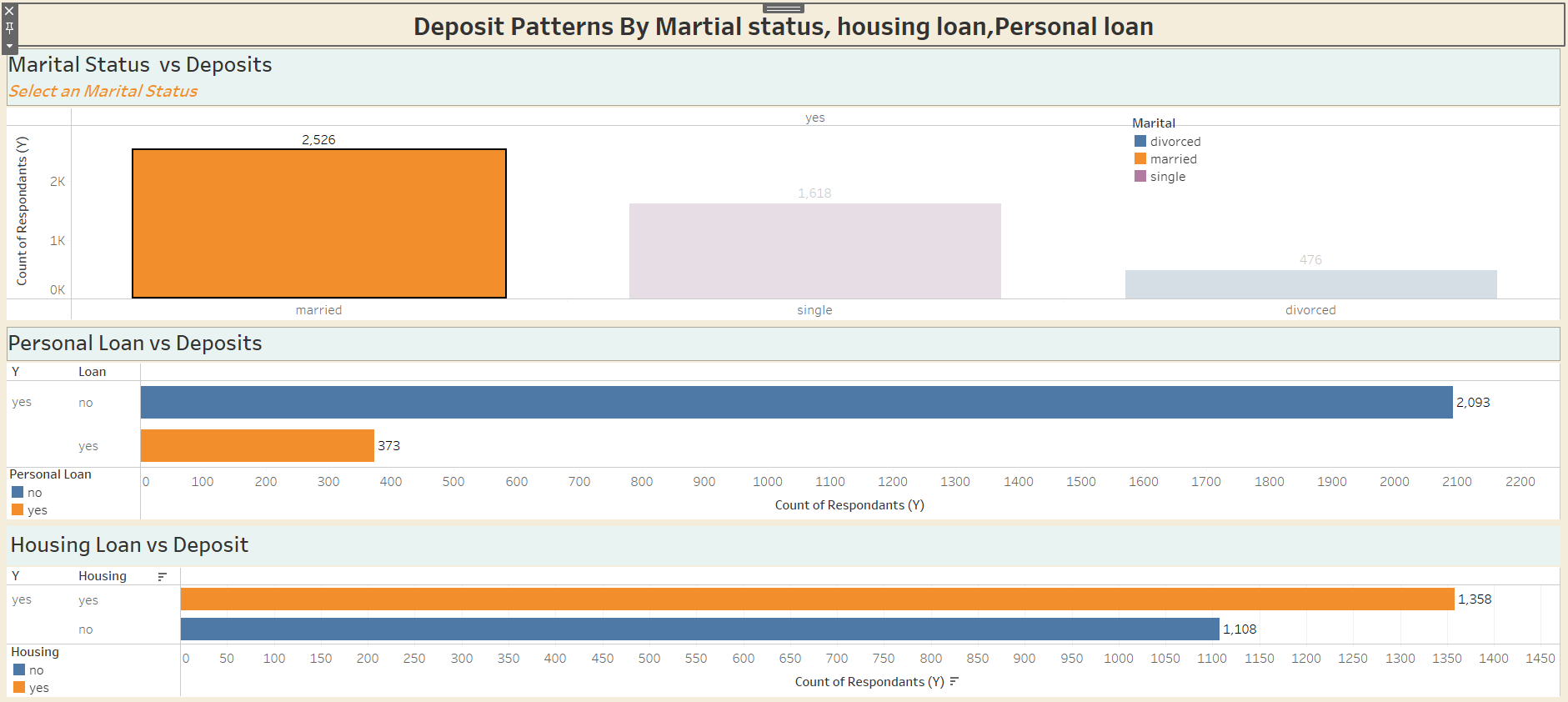
|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Count of y** | **y** | **month** |  |  |  |  |
|  | **yes** |  |  |  | **yes Total** | **Grand Total** |
| **contact** | **may** | **jun** | **aug** | **dec** |  |  |
| cellular | **612** | 349 | 614 | **78** | 1653 | 1653 |
| telephone | 272 | 210 | 36 | 11 | 529 | 529 |
| **Grand Total** | **884** | **559** | **650** | **89** | **2182** | **2182** |
|  |  |  |  |  |  |  |

**Appendix E**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Count of y** | **Avg Poverty rate** |  |  |  |  |
| **y** | **5.14** | **10.6** | **11.4** | **13.6** | **Grand Total** |
| no | 3 | 23256 | 349 | 12777 | 36385 |
| yes | 2 | 2400 | 313 | 1917 | 4632 |
| **Grand Total** | **5** | **25656** | **662** | **14694** | **41017** |

**Appendix F**



**Appendix** **G** :

**Appendix H:**

|  |  |  |
| --- | --- | --- |
|  | *Divorced* | *married* |
| Mean | 254.31 | 257.84 |
| Variance | 62140.15 | 67064.19 |
| Observations | 4595.00 | 24813.00 |
| Hypothesized Mean Difference | 0.00 |  |
| df | 6565.00 |  |
| t Stat | -0.88 |  |
| P(T<=t) one-tail | 0.19 |  |
| t Critical one-tail | 1.65 |  |
| P(T<=t) two-tail | 0.38 |  |
| t Critical two-tail | 1.96 |  |

**Appendix I:**

|  |  |  |
| --- | --- | --- |
|  | *Single* | *Divorced* |
| Mean | 261.92 | 254.30 |
| Variance | 69793.54 | 62140.15 |
| Observations | 11529 | 4595 |
| Hypothesized Mean Difference | 0 |  |
| df | 8916 |  |
| t Stat | 1.72 |  |
| P(T<=t) one-tail | 0.04 |  |
| t Critical one-tail | 1.64 |  |
| P(T<=t) two-tail | 0.08 |  |
| t Critical two-tail | 1.96 |  |

**Appendix J:**

|  |  |  |
| --- | --- | --- |
|  | *married* | *Single* |
| Mean | 257.84 | 261.926 |
| Variance | 67064.19 | 69793.55 |
| Observations | 24813.00 | 11529 |
| Hypothesized Mean Difference | 0.00 |  |
| df | 22075.00 |  |
| t Stat | -1.38 |  |
| P(T<=t) one-tail | 0.08 |  |
| t Critical one-tail | 1.64 |  |
| P(T<=t) two-tail | 0.17 |  |
| t Critical two-tail | 1.96 |  |

**Appendix K:**

|  |  |
| --- | --- |
| Model | Accuracy |
| Linear Regression | 88% |
| Logistic Regression | **99%** |
| Decision Tree | 91% |

**Appendix L :**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Duration (Seconds) | Duration (Min) | Single | Divorced | Deposit |
| 824<= | 17.33<= | Yes | Yes | No |
| 824> | 17.33> | Yes | Yes | Yes |

**Appendix M :**

|  |  |
| --- | --- |
| Model | Accuracy |
| **Linear Regression** | 89.06% |
| Logistic Regression | 89% |
| Decision Tree | 88.05% |
| Random Forest | 87.96% |

|  |  |
| --- | --- |
| Metrics | Value |
| Age | >=36 |
| Annual Household Expenditures | <=15000$ |
| Annual Median Income | >90000$ |
| Avg Poverty Rate | <=5.14 |
| Contact | Cellular |
| Month | May |
| Loan | No |
| Marital | Yes |
| Housing | No |

**Appendix N:**

**Appendix O:**

|  |  |
| --- | --- |
| Metrics | Value |
| Age | <=35 |
| Annual Household Expenditures | >15000$ |
| Annual Median Income | <90000$ |
| Avg Poverty Rate | >5.14 |
| Contact | Telephone |
| Month | May |
| Loan | No |
| Marital | Yes |
| Housing | Yes |

**Appendix** **P**:

A diagram of a computer

AI-generated content may be incorrect.

**Appendix** **Q**

A screenshot of a computer

AI-generated content may be incorrect.

**Appendix** **R** A screenshot of a computer

AI-generated content may be incorrect.