AWS Data Science OJT Project

BANK CUSTOMER CHURN ANALYSIS

A supervised machine learning approach

A presentation by Dani S. Manabat - Junior R&D Engineer

PROJECT OVERVIEW

This portion aims to address the following questions: What is bank churning all about? Why is it important in the banking industry? What are the objectives of this project?

INTRODUCTION

ABC Multinational Bank prides itself on its global reach, innovative financial products, and exceptional customer service.

MEET MARK!

Mark, the **Chief Operations Officer** of ABC Multinational Bank, oversees various operational aspects, including **customer service, marketing, and strategic planning**, all of which directly impact **customer retention**.

To say the least, Mark is very passionate about his job. He is a people person, ensuring that every decision aligns with enhancing the customer experience.

THE PROBLEM

For the past couple of months, Mark has observed that more and more customers are leaving the bank. Reviewing the latest performance metric of the bank, the **exit rate reached the all-time highest!**

NEW EXIT RATE:

21% ↑

Out of 10 customers, 2 are leaving.

BANK CHURNING?

Exit = Churning. Bank churning simply means customers closing their accounts and switching to a different bank.

IMPORTANCE?

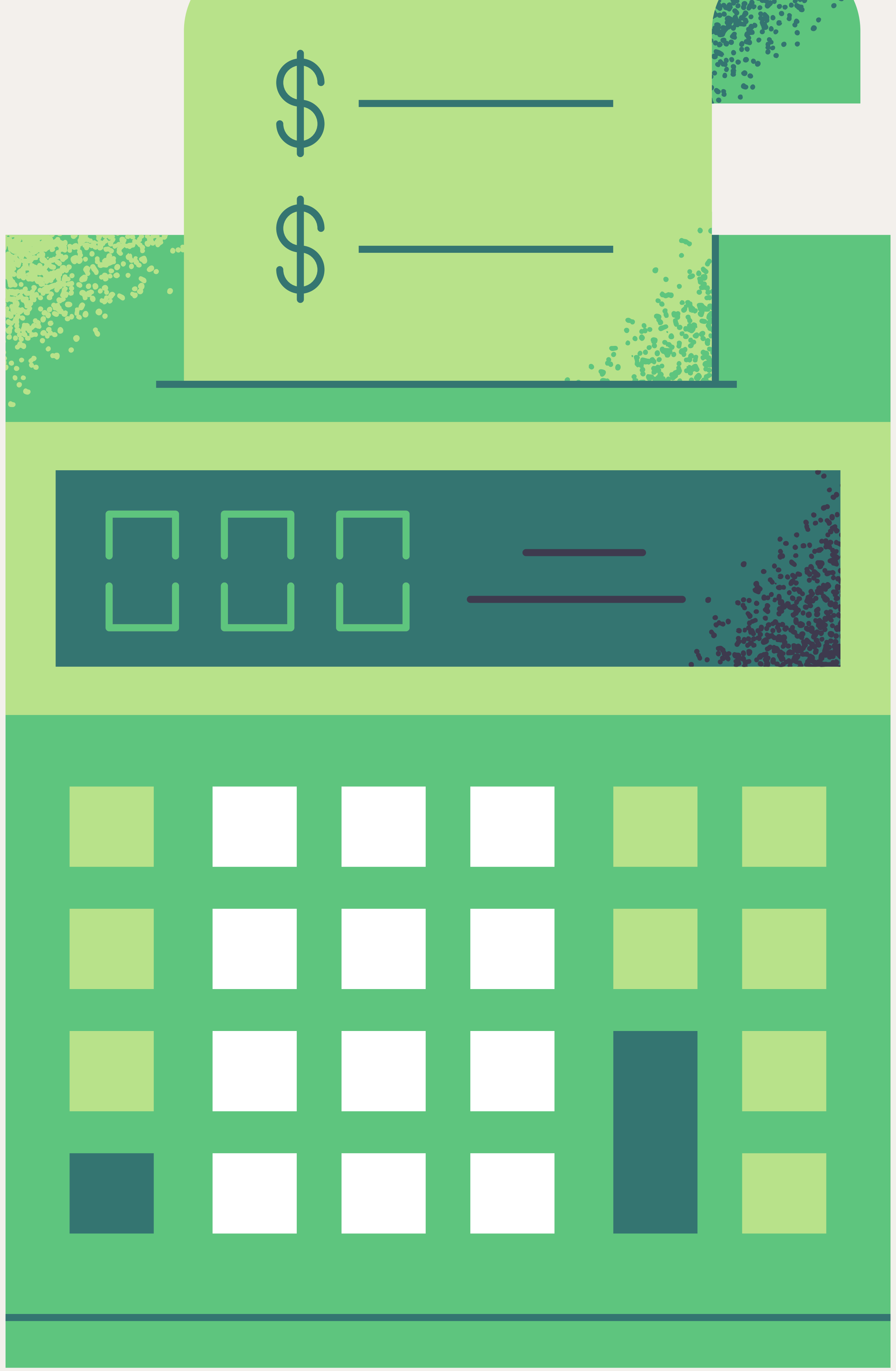
Keeping existing customers is cheaper and easier than finding new ones, so high bank churn can hurt a bank's profits and growth.

FACTORS AFFECTING CHURN

Poor service

Inefficient products

Lack of competitive products



Reference: https://www.sciencedirect.com/science/article/pii/S2666764923000401

WHAT'S WRONG?

The bank's churn rate certainly poses a significant threat to its growth and profitability, particularly given that it appears to be increasing over time. Mark realized that the **bank's traditional method for customer retention is <u>no longer effective</u>**, and they need to address this problem as quickly as possible. However, Mark finds himself at a loss, unsure of where to begin!

Frustrated and desperate for solutions, Mark began exploring new avenues. It was during this time that he stumbled upon the potential of **data science.**

THE POWER OF DATA?

Mark recognized the **vast amount of customer data the bank possessed**. He believed that by analyzing this data, he could uncover the reasons behind customer churn and develop targeted strategies to prevent it.

However, Mark knows that he doesn’t have the technical expertise that will allow him to do just what he wants to do. So what will he do next?

MEET DANI!

Thankfully, ABC Multinational Bank recently hired a new data scientist, Dani. With a passion for analytical problems that challenge her keen mind, Dani leverages her expertise in machine learning to make a significant impact on the bank's operations, one data-driven solution at a time.

After hearing about her, Mark immediately asked Dani about his concerns as well as the possibility of his ideas.

A CHALLENGE!

Knowing Dani's expertise, Mark approached her about the bank's churning problem. He wanted Dani to tackle the issue and identify the key factors causing customer defection.

And without having any second thoughts, Dani accepted Mark’s challenge!

PROJECT OBJECTIVES

OBJECTIVE 1

Identify the factors that leads to customer churn.

OBJECTIVE 2

Predict potential churners and suggest strategies that may help us retain customers at risk of churning/leaving.

DATA EXPLORATION

This section delves into the challenges Dani faces in collecting data for her project. It also explores her findings, which will provide Mark with valuable insights into the demographics of churners.

ON DATA COLLECTION

Dani, with the assistance of Mark, has obtained the data that she will be working on for her bank churning project... but it is far from perfect! What will she do?

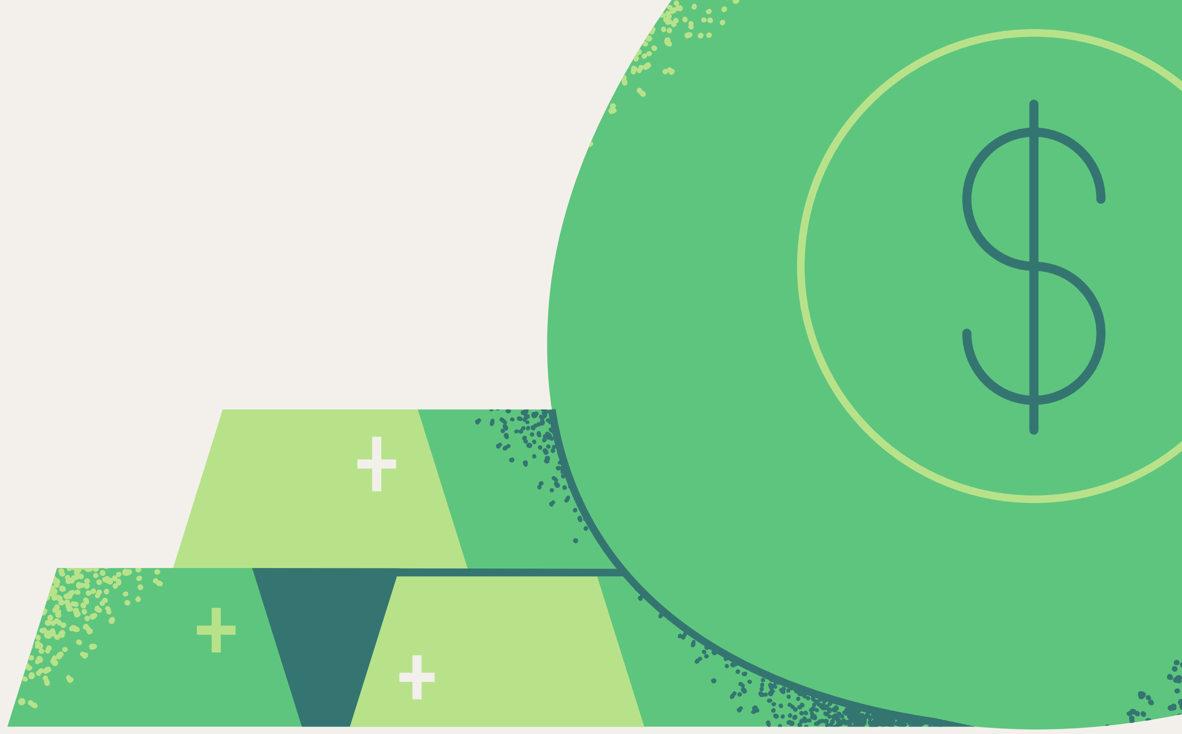
DATASET INVESTIGATION

Identify which columns are **useful**. Also, identify the column that tells us whether a record has exited or not.

LIST OF COLUMNS:

```
['id', 'CustomerId', 'Surname', 'CreditScore', 'Geography', 'Gender',
 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
 'IsActiveMember', 'EstimatedSalary', 'Exited'],
```

ON DATA COLLECTION



Dani, with the assistance of Mark, has obtained the data that she will be working on for her bank churning project... but it is far from perfect! What will she do?

DATASET CLEANING

Handle empty value transformation, remove duplicated, remove irrelevant columns, perform relevant transformations.

NEW LIST OF COLUMNS:

```
['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance',
 'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary',
 'Exited'],
```

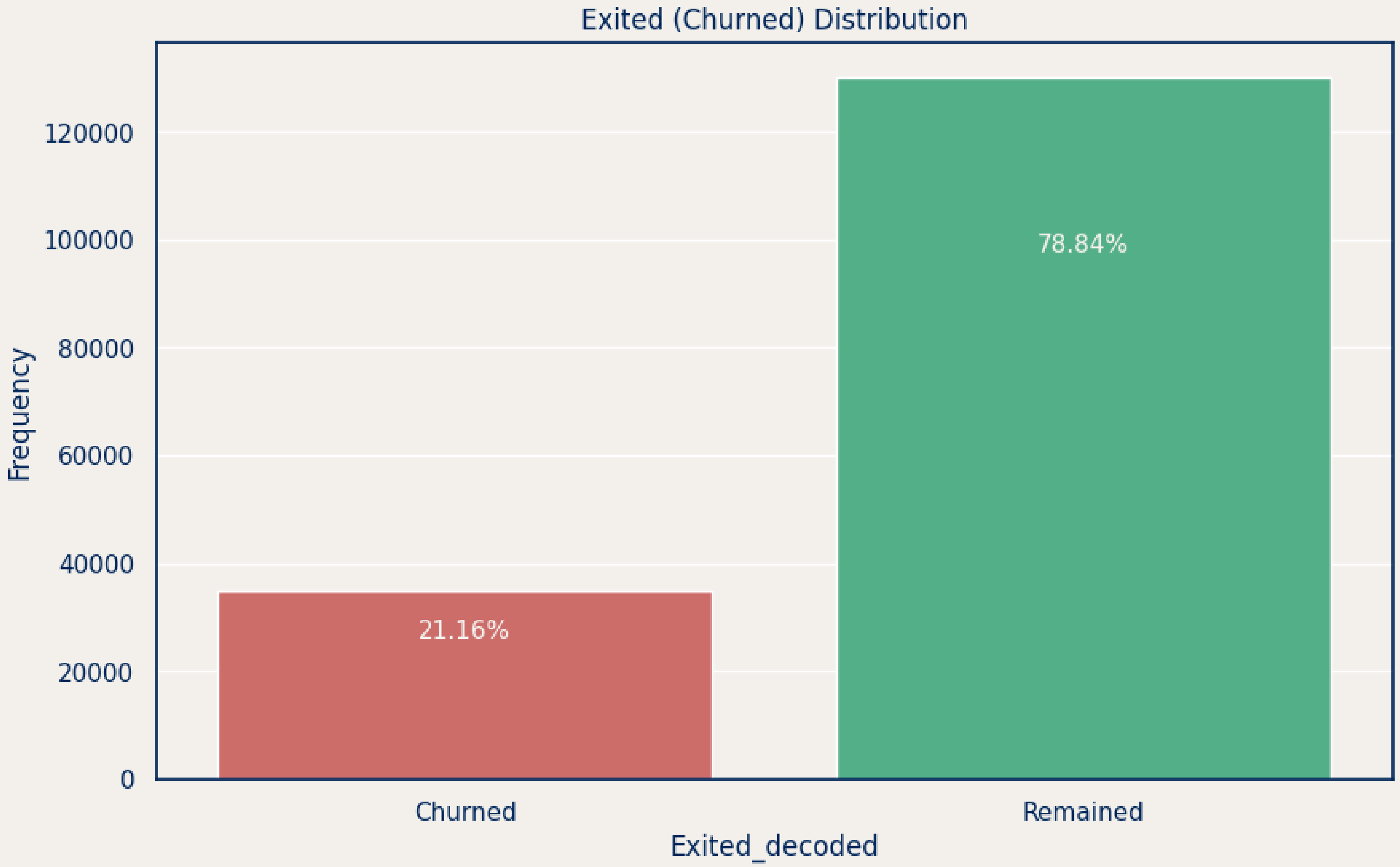
For this process, Dani did not really had a hard time because the data that Mark provided does not really have any nulls nor duplicates. Isn't that rare!

EXPLORATORY DATA ANALYSIS

This section analyzes the insights Dani uncovers from the dataset she received from Mark. This analysis will help Mark understand the factors contributing to customer churn, enabling him to formulate targeted strategies.

BASIC DEMOGRAPHICS

Firstly, Dani explored the basics of the dataset.



Exited indicates whether a customer has remained with the bank or churned (left).

Dani found that approximately 20% of the customers in the dataset churned.

BASIC DEMOGRAPHICS

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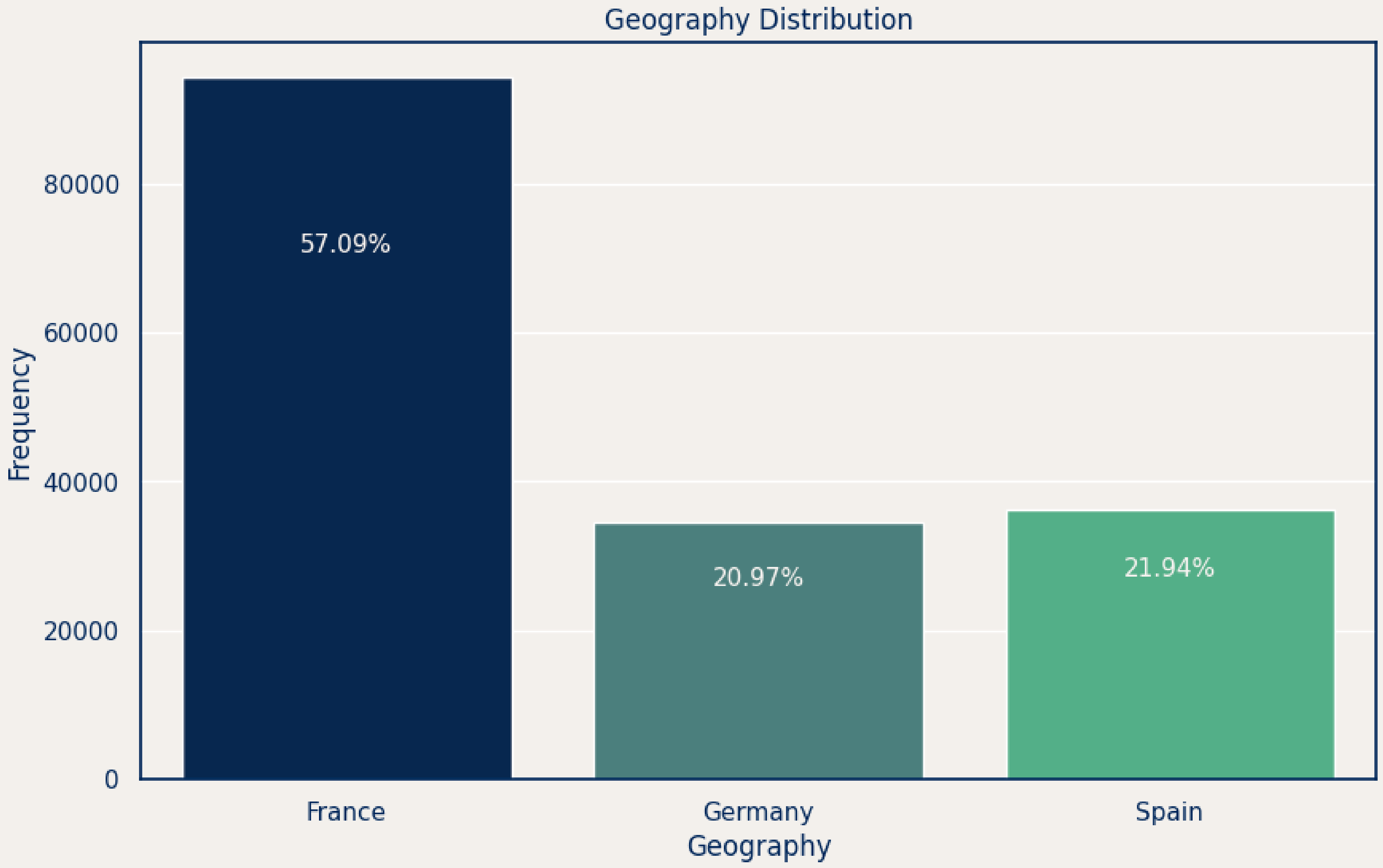

Geography refers to the place where the customer lives. The visualization shows that majority of the customers came from France, followed by Spain and Germany.

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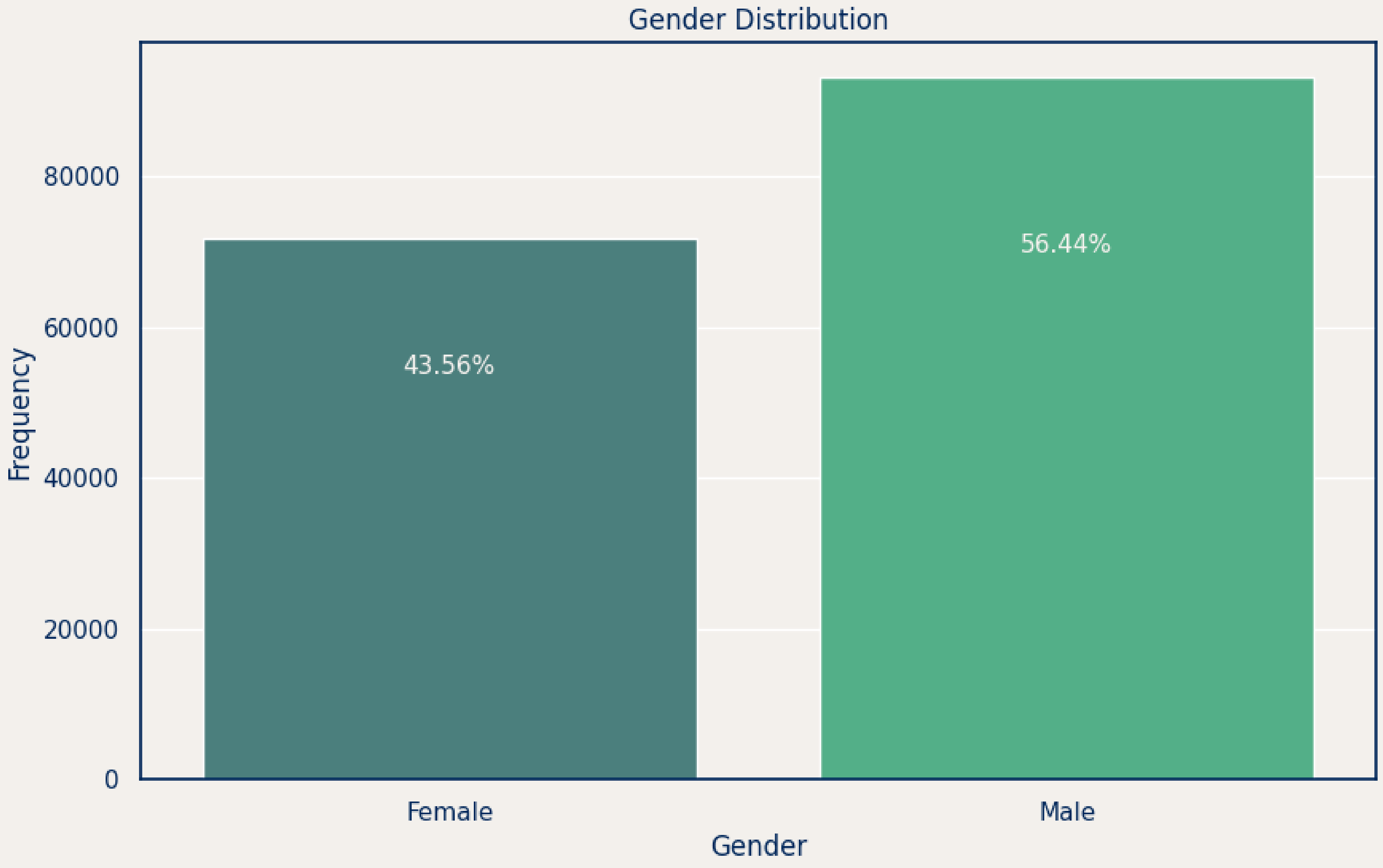

Gender-wise, it appears that 44% of the customers are female, while 56% of the customers are male.

BASIC DEMOGRAPHICS

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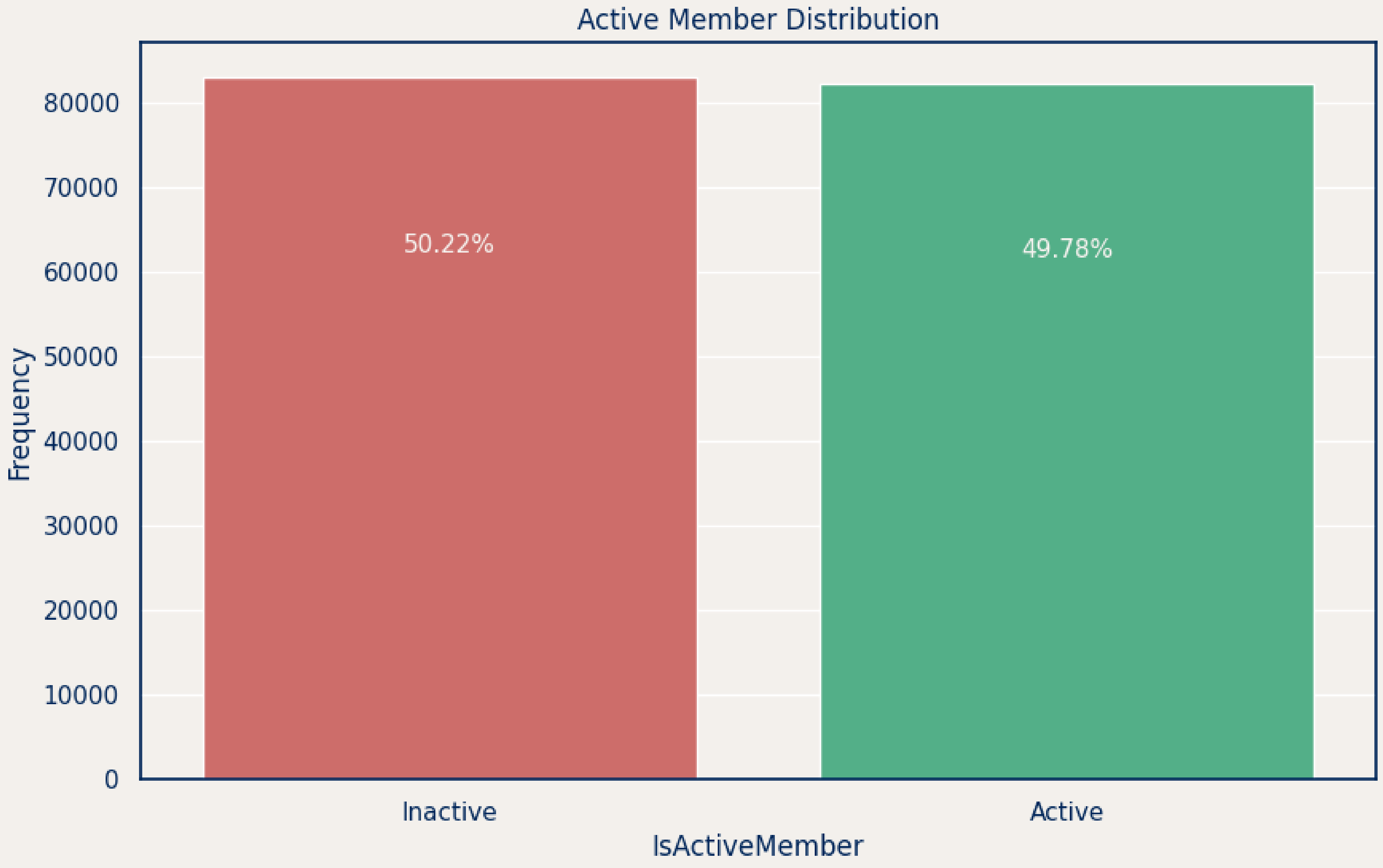


Upon checking how many customers were **Active**, Dani saw that 50% were inactive.

Inactivity could be attributed to the reasoning that customers may not find the bank's services/products particularly useful.

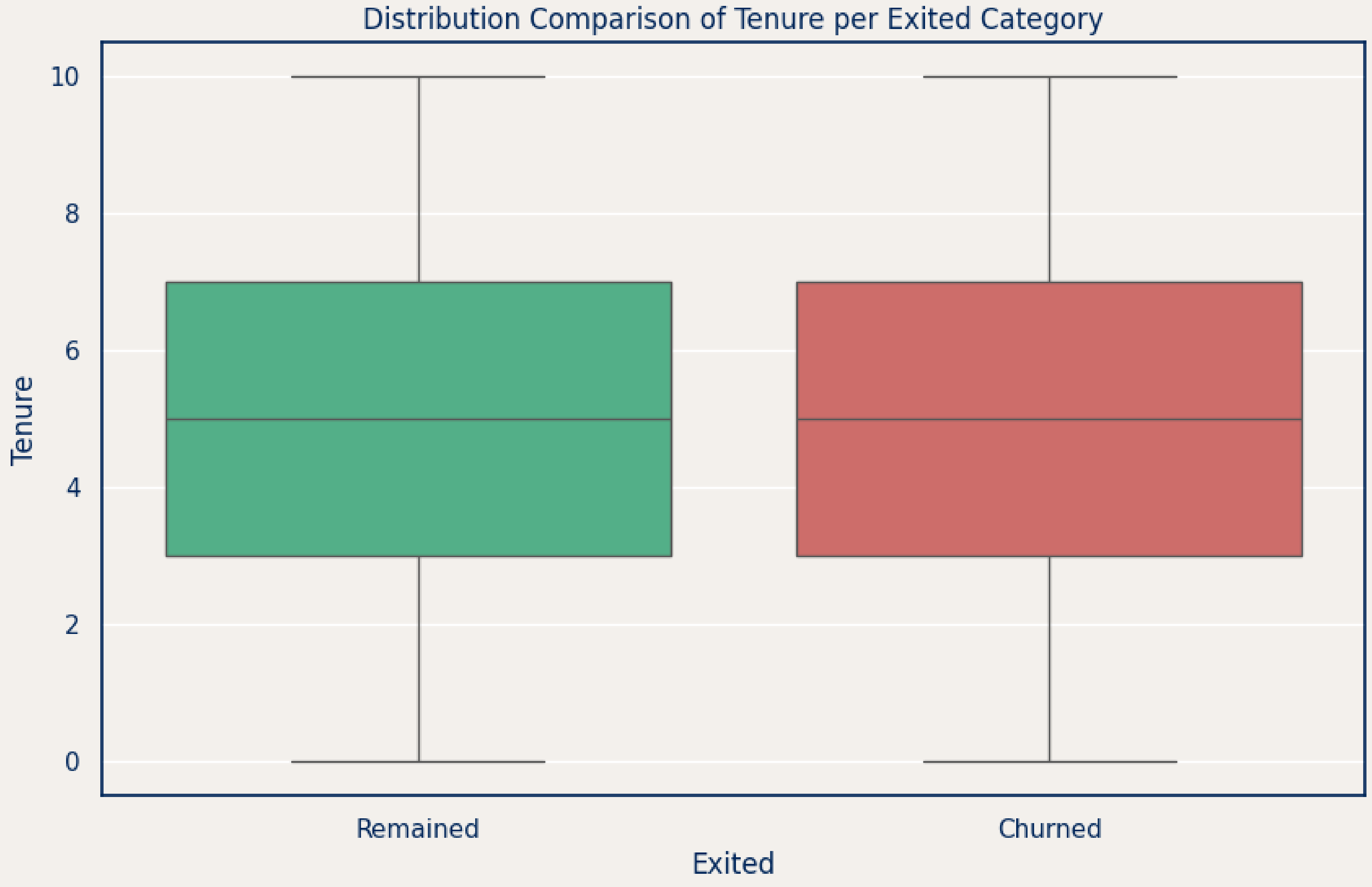
MARK'S HYPOTHESES

Before proceeding with the EDA, Dani asked Mark about his guesses regarding the factors that affect customer churn. For Mark, the factors he thinks influence their decision to exit are **tenure, credit score, balance,** and **number of products**.

With that, Dani ensured to check those factors and their association with customer churn.

ON TENURE

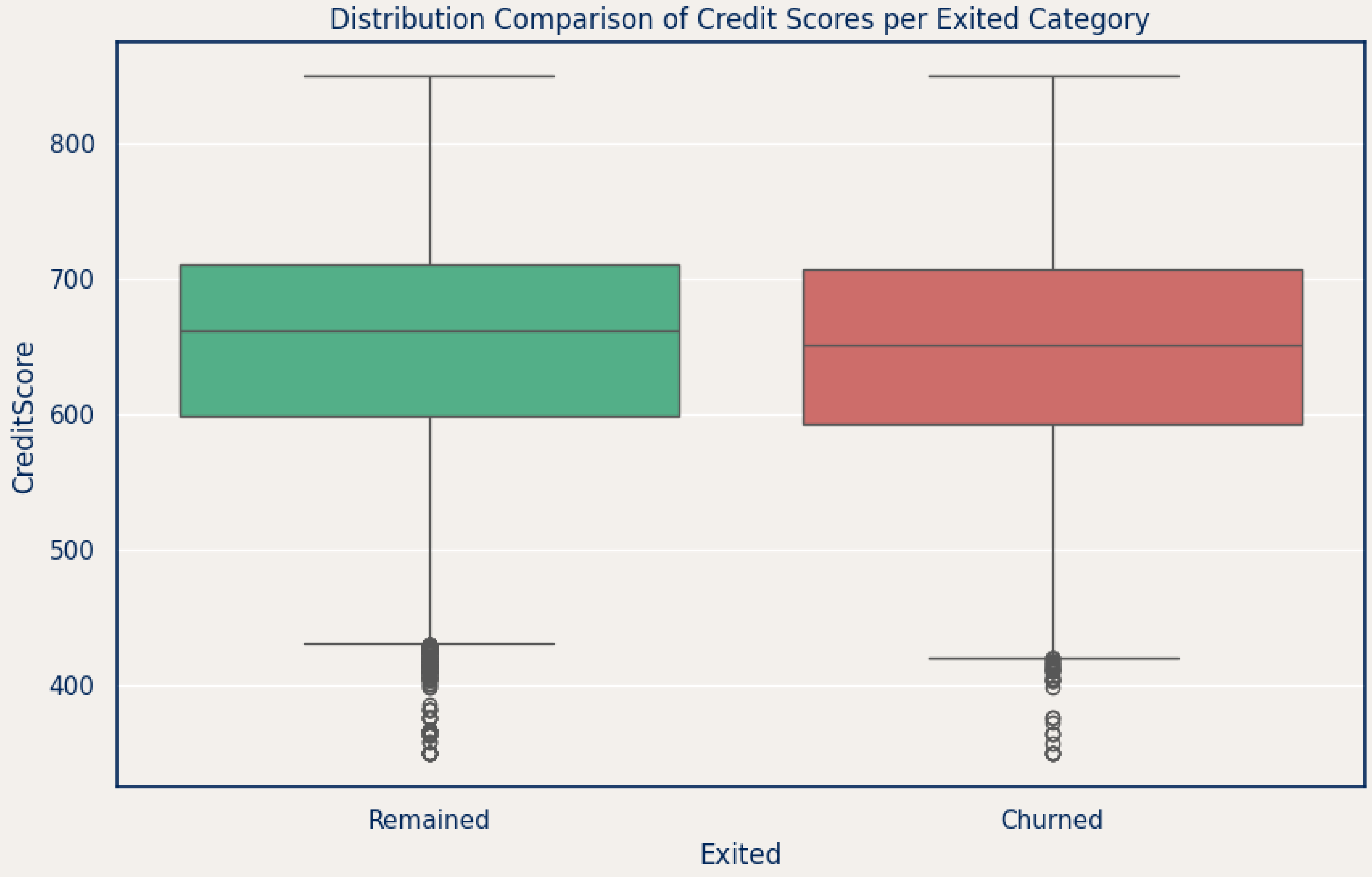
Tenure refers to the length of time that a customer has stayed with the bank. For Mark, he thinks that customers that has spent lesser years with the bank are more prone to exit.



Not much difference between the Tenures of remaining vs exited customers.

ON CREDIT SCORE

A **credit score** is a three-digit number that represents your creditworthiness. It's like a snapshot of your financial reputation. Mark hypothesizes that people with low credit score are more prone to churn than those with high credit score.



The credit scores of both groups were quite similar.

SUMMARY AND SUGGESTED ACTIONS

Dani disproved Mark's hypotheses about the factors he thinks affects customer churn:

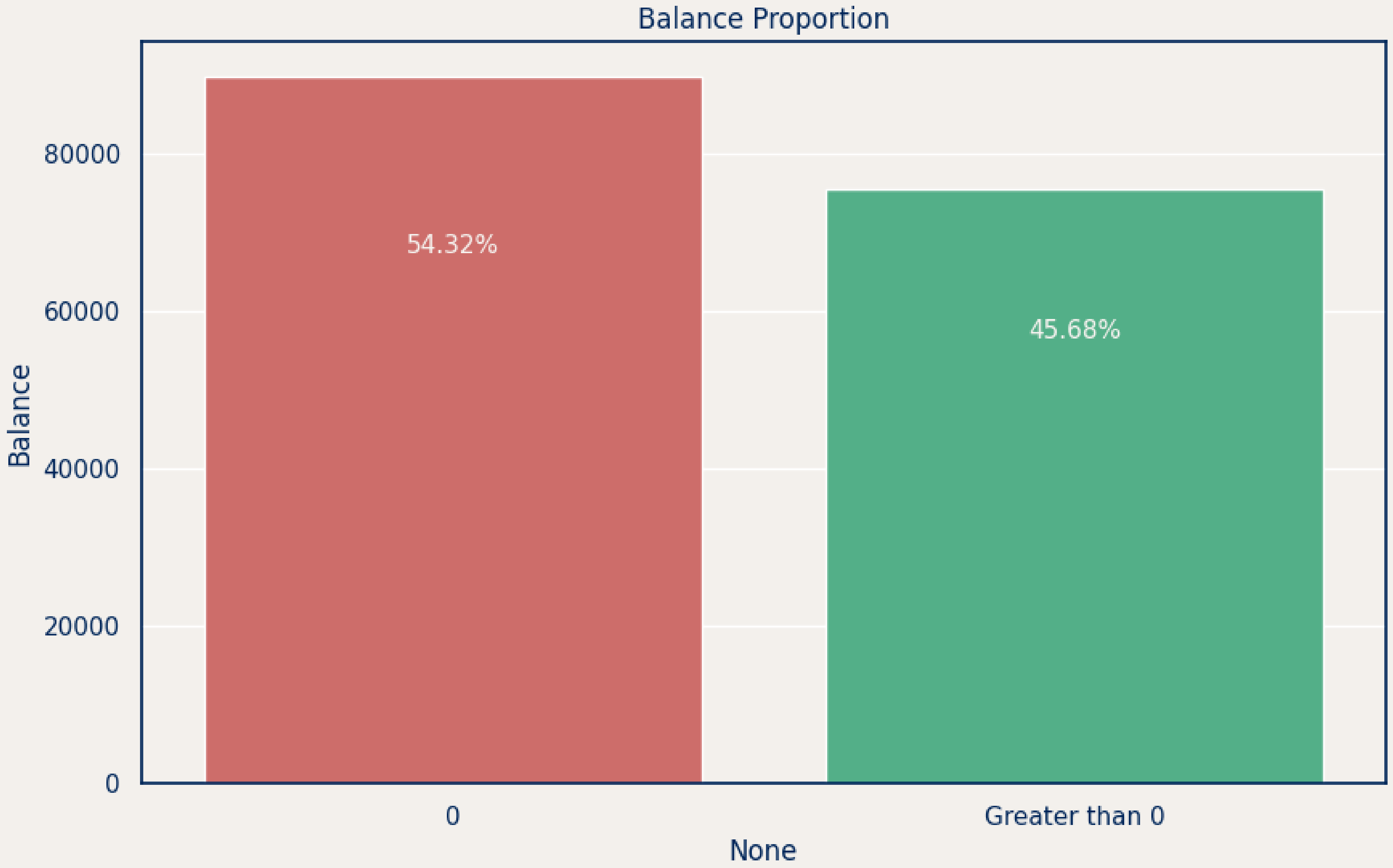
Credit Score and Tenure
Both are not exactly associated with the decision of customers to leave the bank.

Suggestion:

- "Perhaps it will do us good to take a look at the different factors instead?"

ON BALANCE

Balance is pretty much self-explanatory. For Mark, he thinks that customers with lesser balances are more likely to churn.



Most of the customers in the dataset have 0 as their balance!

ON BALANCE

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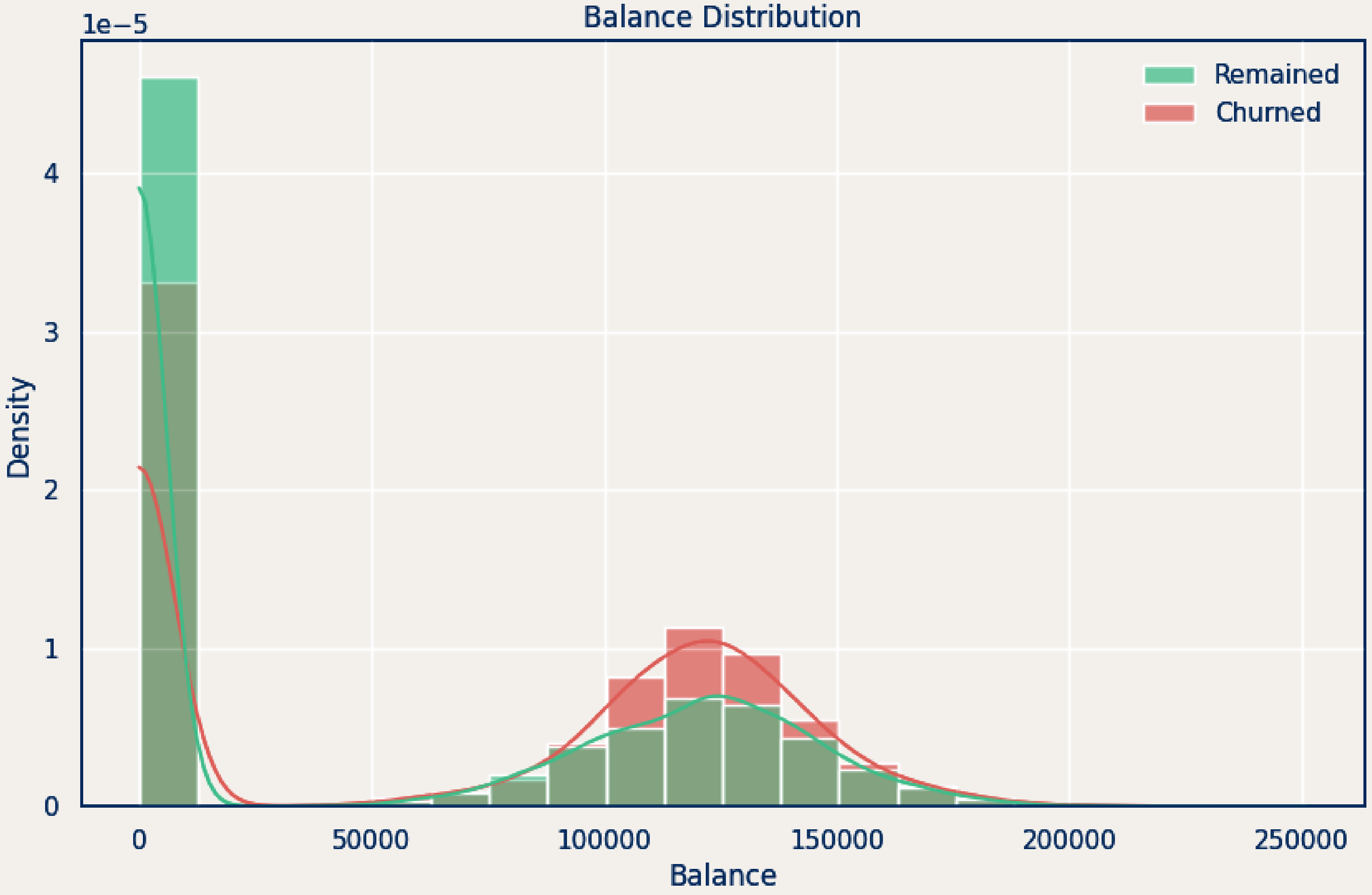

Customers with higher balances were more likely to leave the bank compared to those with no balance.

ON BALANCE

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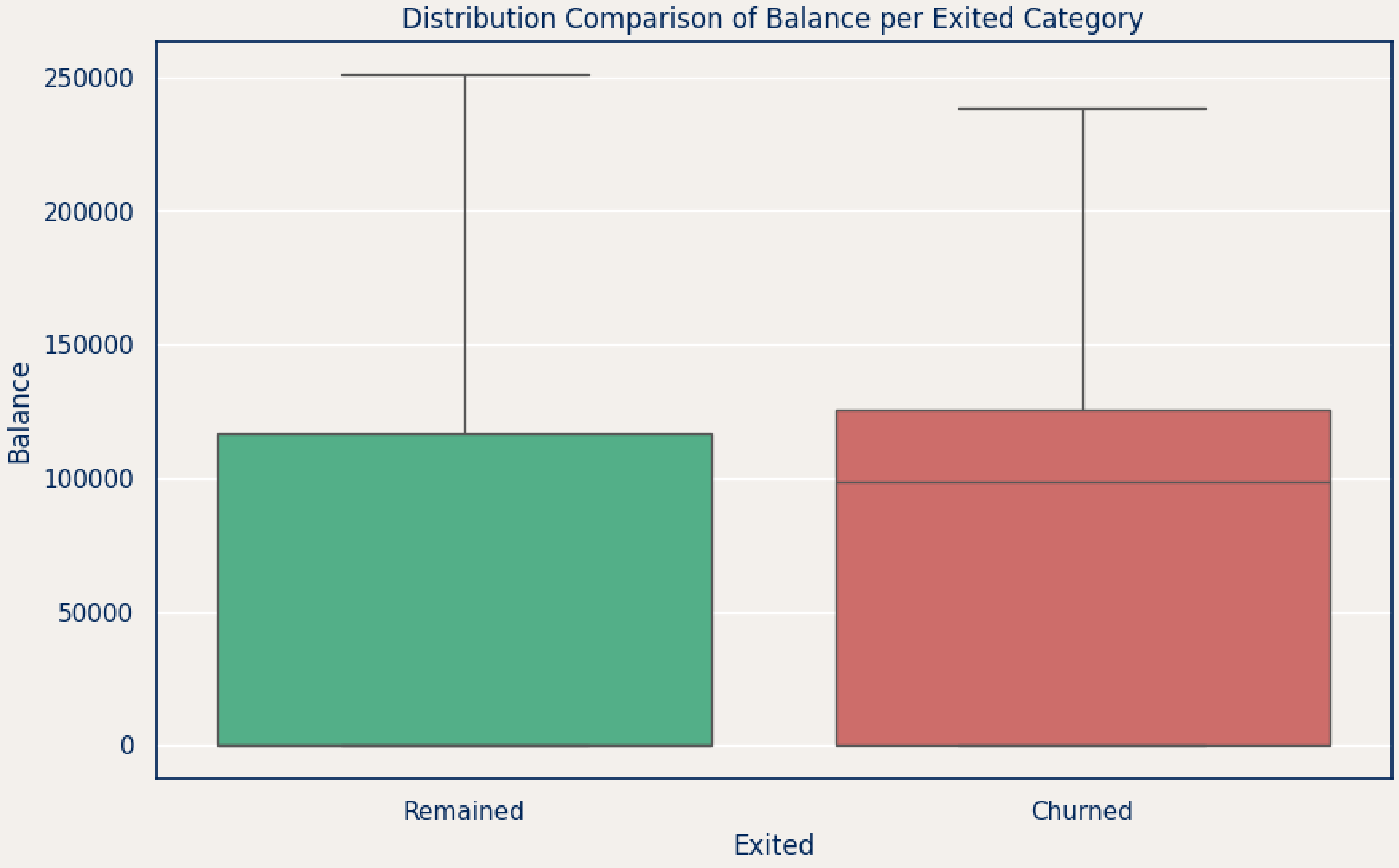


The statistical test she performed concludes that there is indeed a difference between the two, although it is not that large. Moreover, the box plot on the left also supports finding.

SUMMARY AND SUGGESTED ACTIONS

Dani disproved Mark’s hypothesis and proceeded to discuss her uncovered insights on the Balances of the churned group.

Balance

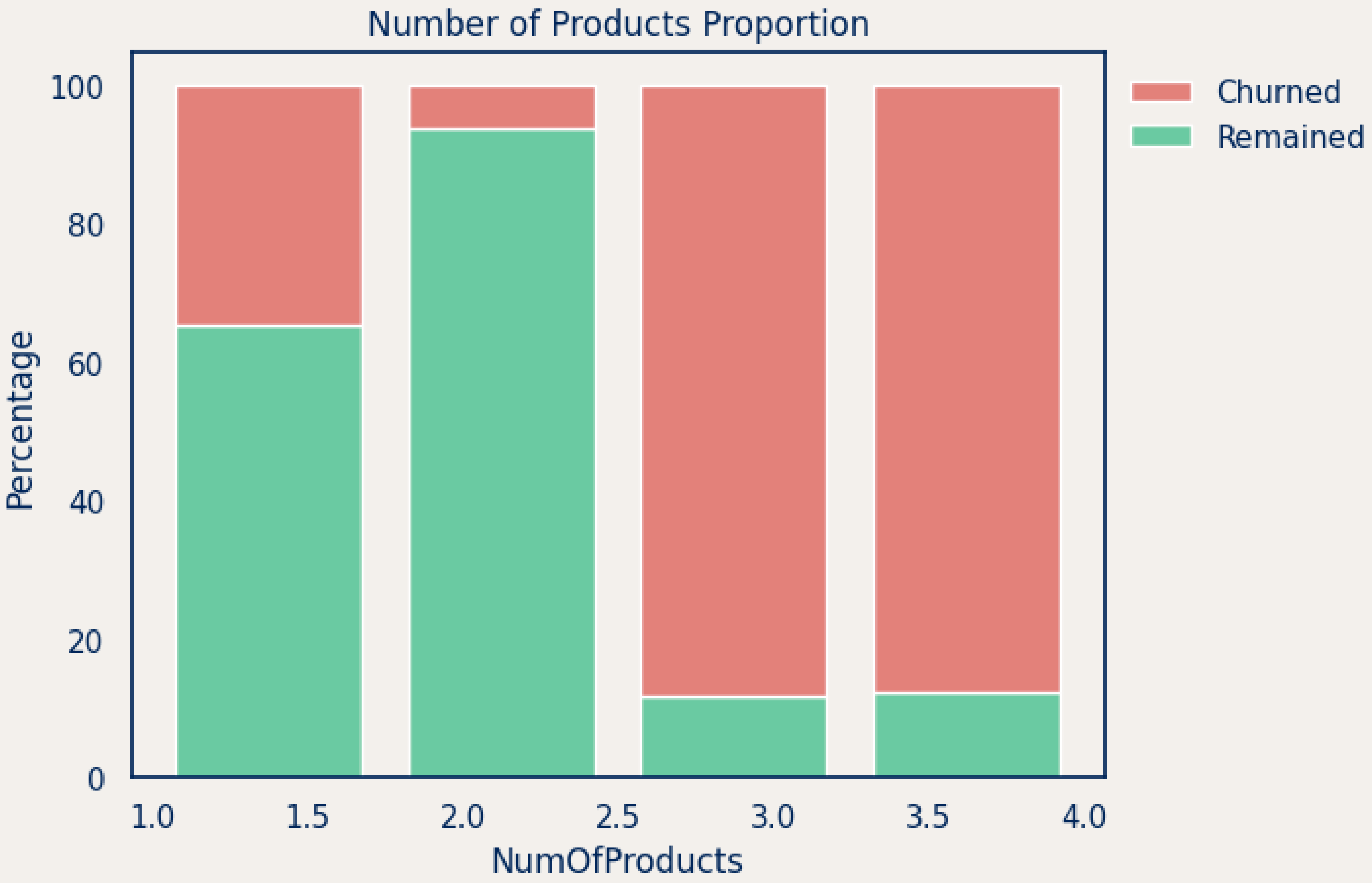
Customers with more balance are more likely to leave the bank.

Suggestion:

- Identify the pain points of customers with more balance. Perhaps it all lies on the benefits that we offer?

ON # OF PRODUCTS

Number of Products refers to the number of products/services offered by the bank that a certain customer uses. Mark hypothesizes that customers with a lower number of products are more prone to churn.



Customers with 3 or more products are more likely to churn than to remain as compared with other groups!

Probable reason? ***Dissatisfaction with the bank's products/services.***

SUMMARY AND SUGGESTED ACTIONS

Dani, once again, disproved Mark's hypothesis. She then proceeded to discuss her vital findings about the customer's number of products.

Number of products

Most customers have 1 or 2 products. They're more likely to stay with the bank, especially those with 2 products. However, customers with 3 or more products are more probable to leave than stay.

Suggestion:

- It's important to understand why these customers leave through in-depth surveys to identify issues with our products and services.

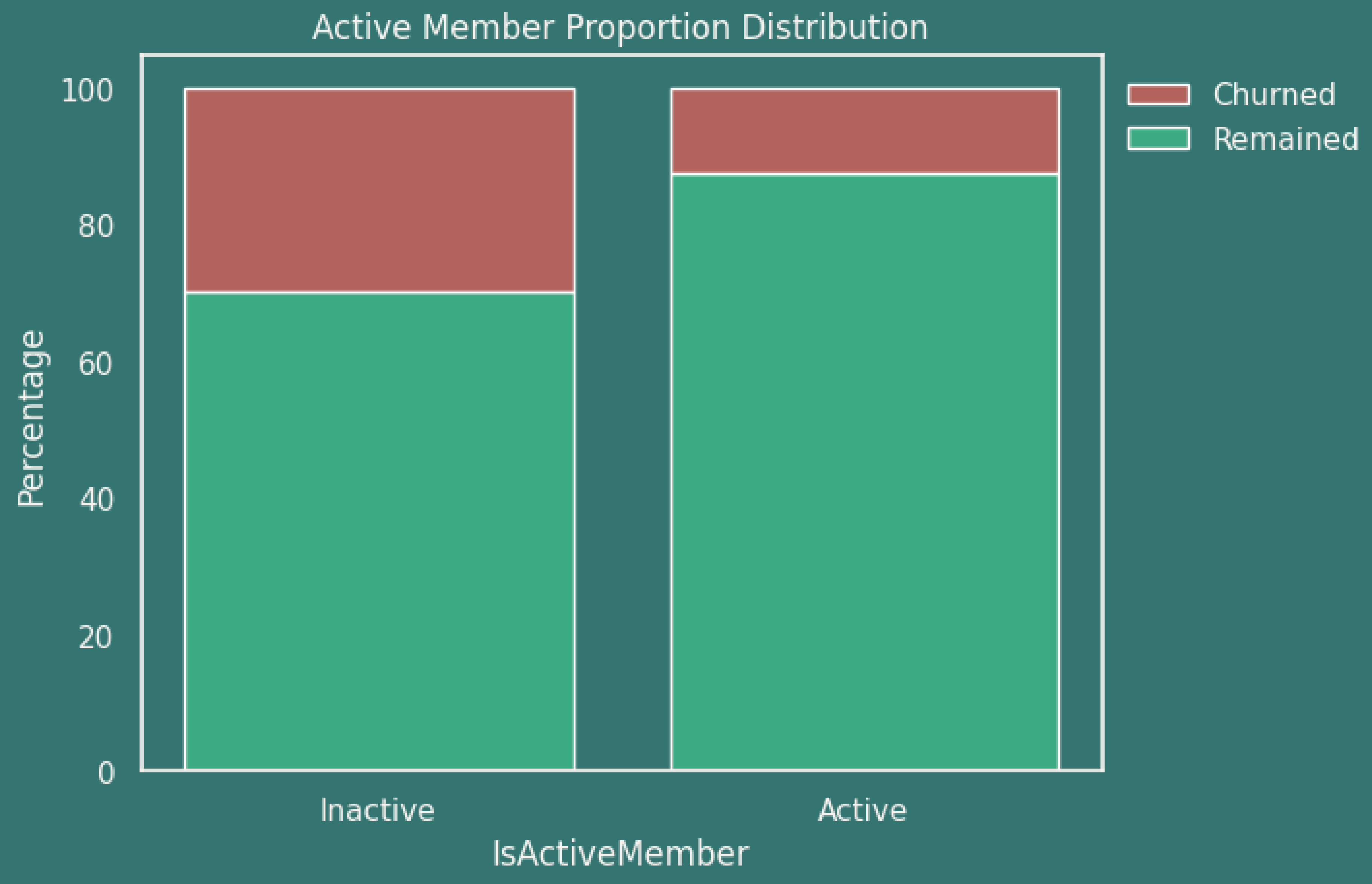
DANI'S HYPOTHESES

Dani has also formed several interesting ideas (hypotheses) while exploring the data. She believes that it is important to investigate how factors like **customer inactivity, age, gender,** and **location** (geography) might be connected to customers leaving the service (customer churn).

With these hypotheses in mind, Dani carefully performed her exploration and immediately communicated the results with Mark.

ON CUSTOMER INACTIVITY

As mentioned earlier, Dani thinks that customer inactivity is a by-product of poor, unusable services/products which eventually leads to churn.



Inactive customers are **3x more likely to get churned than active members!**

SUMMARY AND SUGGESTED ACTIONS

Dani communicated her findings with Mark.

Customer Activity

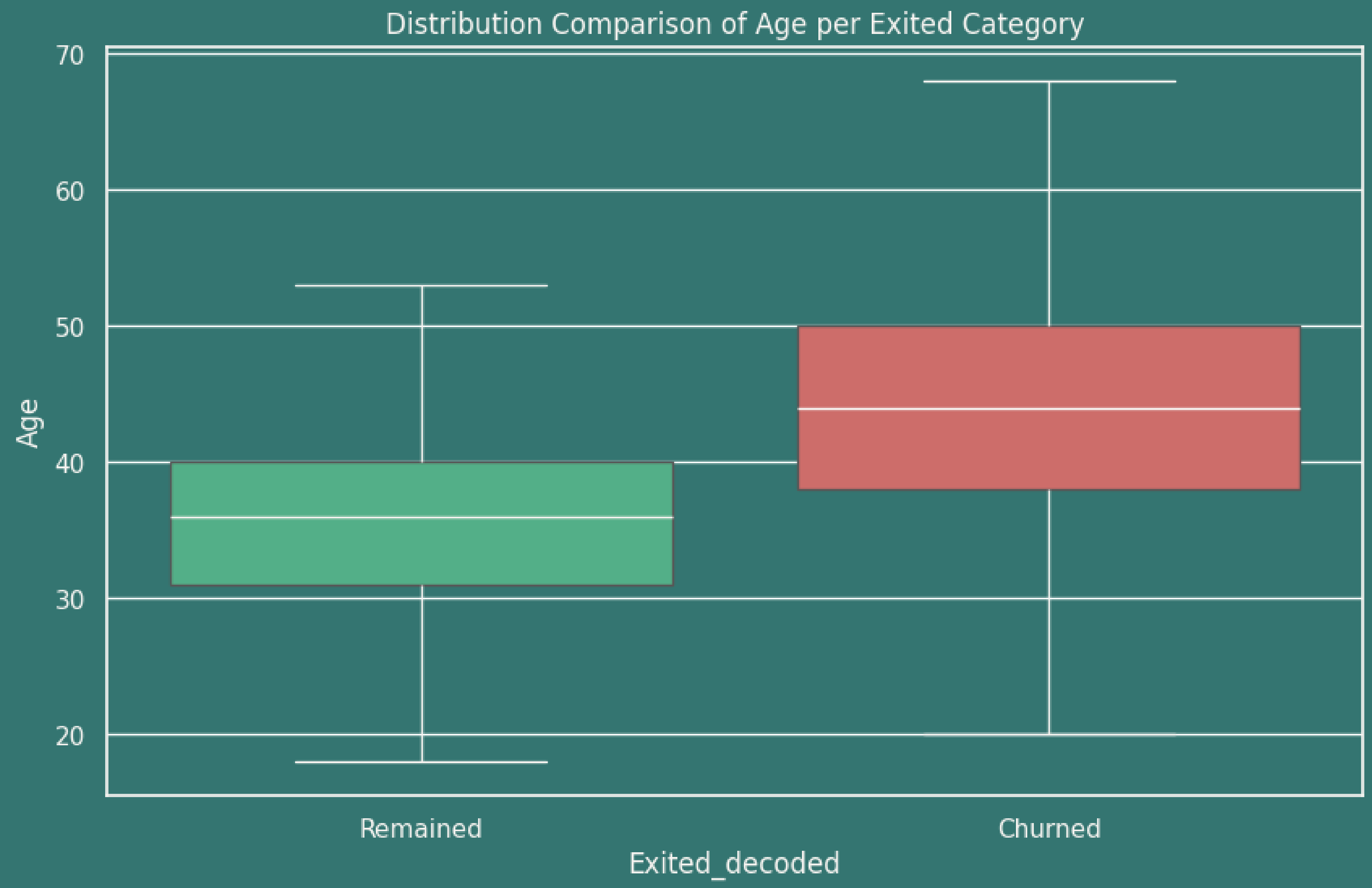
Inactive customers are more likely to leave the bank (churn) than active customers.

Suggestions:

- Understand the reasons behind customer inactivity.
- Implement strategies to re-engage inactive customers.

ON AGE

Age-wise, Dani was thinking that perhaps, there is some age group that is more likely to get churned than to remain. After all, each age group has different priorities in life.



The box plot shows that the **age distribution is different for each group of customers**, “Remained” and "Churned".

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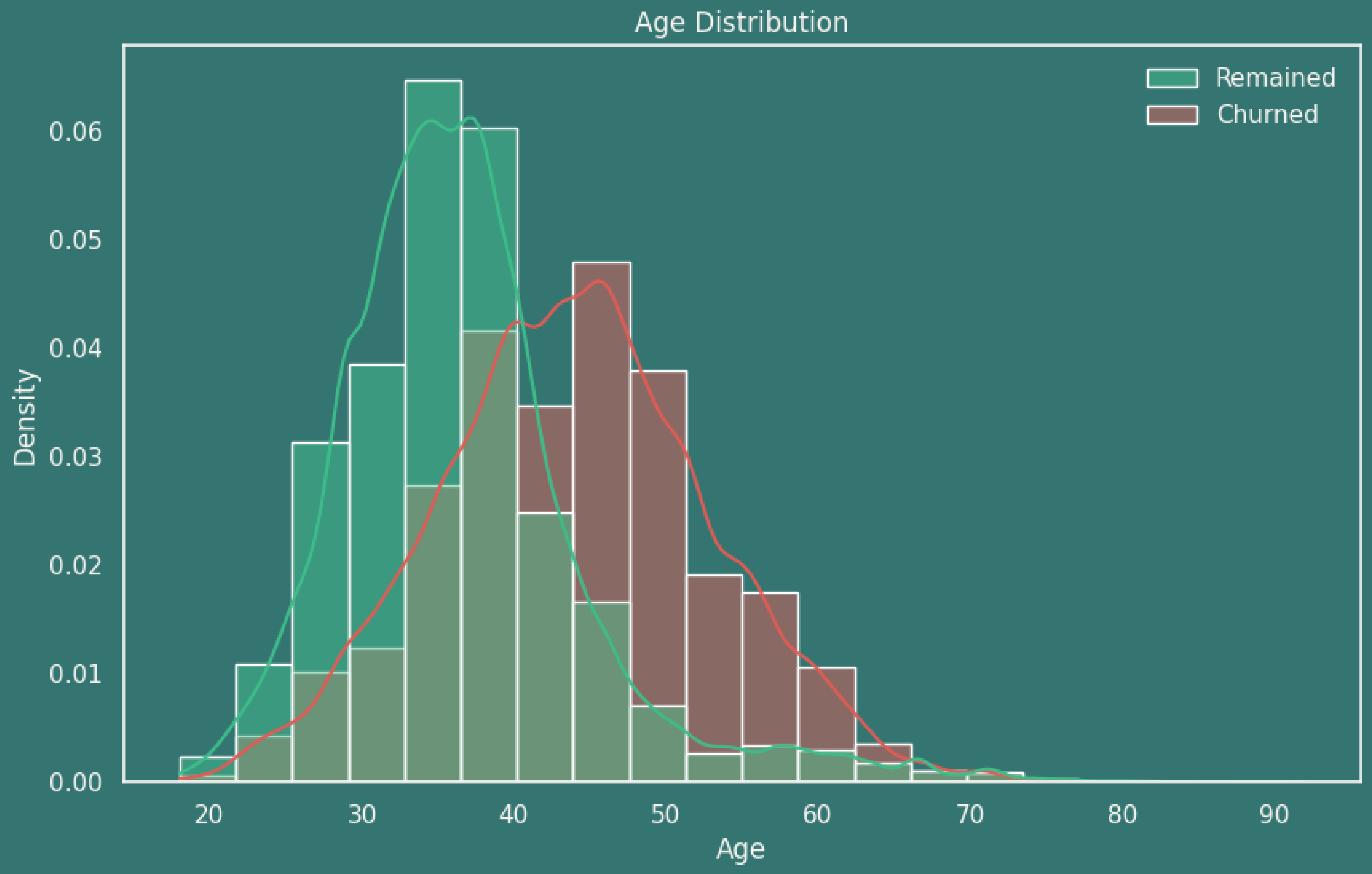
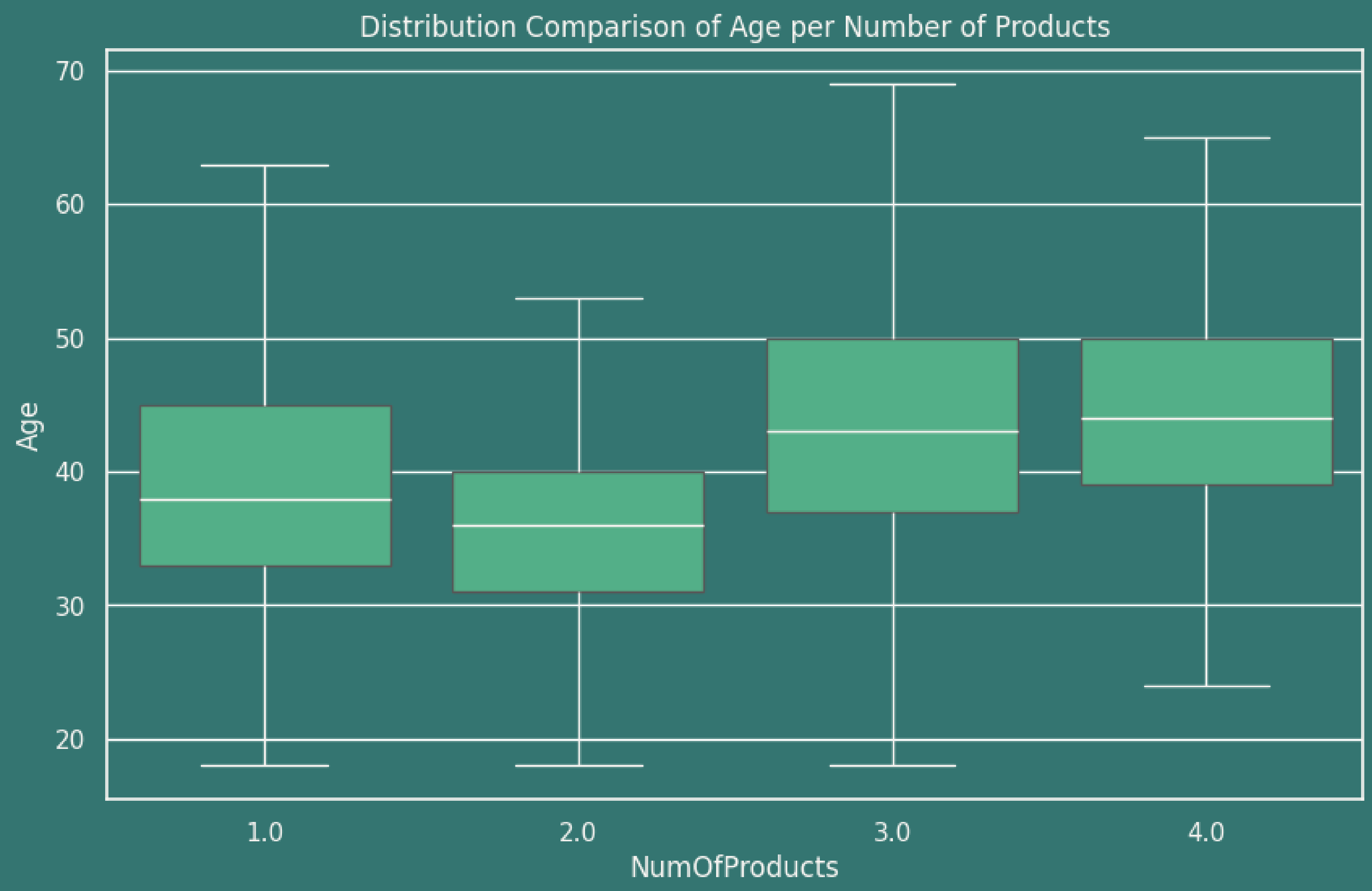


Customers belonging to the age group of 40 and above are more likely to churn than to remain!

ON AGE & # OF PRODUCTS

Dani previously discovered that the number of products a customer has affects their likelihood of leaving. She also wondered if the age of customers with different numbers of products might be another factor to consider.



Summary of the previous analyses:

- Age group 40 onwards are more likely to exit.
- Customers with 3 or more products are more likely to exit.

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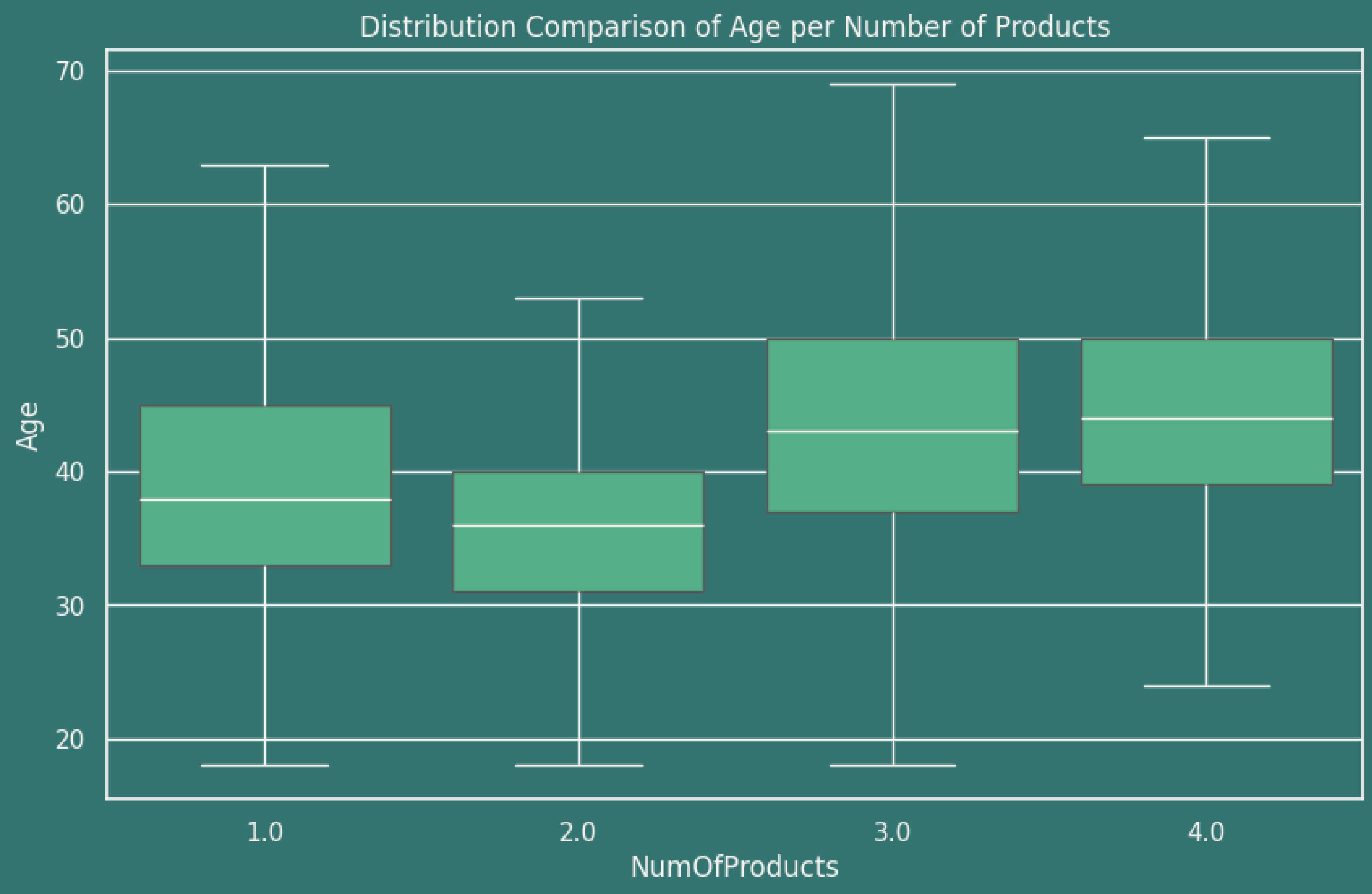


Key observation:

- Most customers with 3 or more products (who are more likely to leave) fall within the 40-50 age range (also a group more likely to leave).

SUMMARY AND SUGGESTED ACTIONS

Dani communicated her findings with Mark.

Age

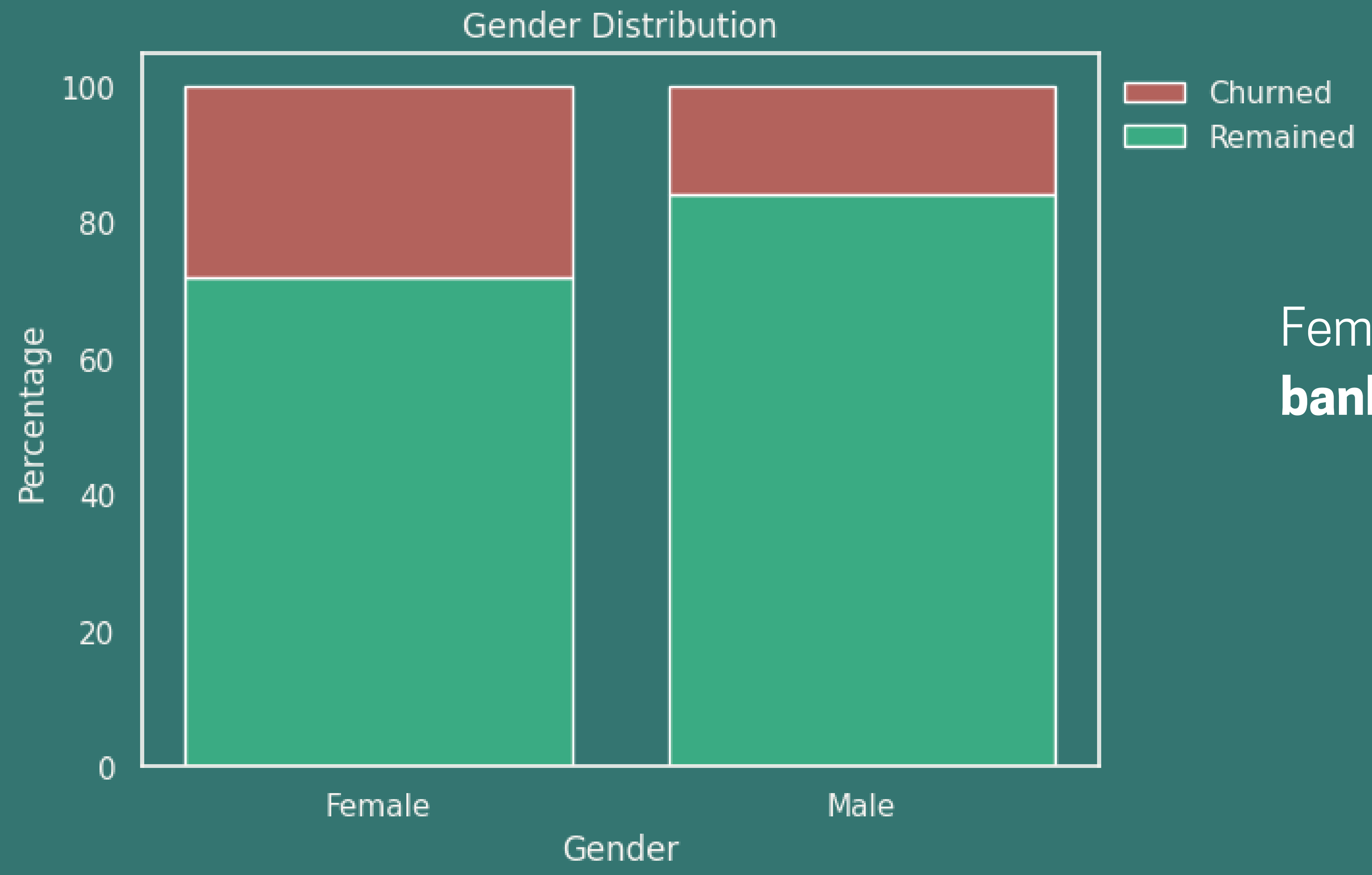
Older customers are more likely to exit the bank!

Suggestions:

- Consider the digital divide in the product design. Let's identify their pain points when using our products. Are they overwhelming? Too complex?
- Offer incentives and perform tailored marketing for older demographics. Perhaps what we are offering is not suitable for their present and future needs.

ON GENDER

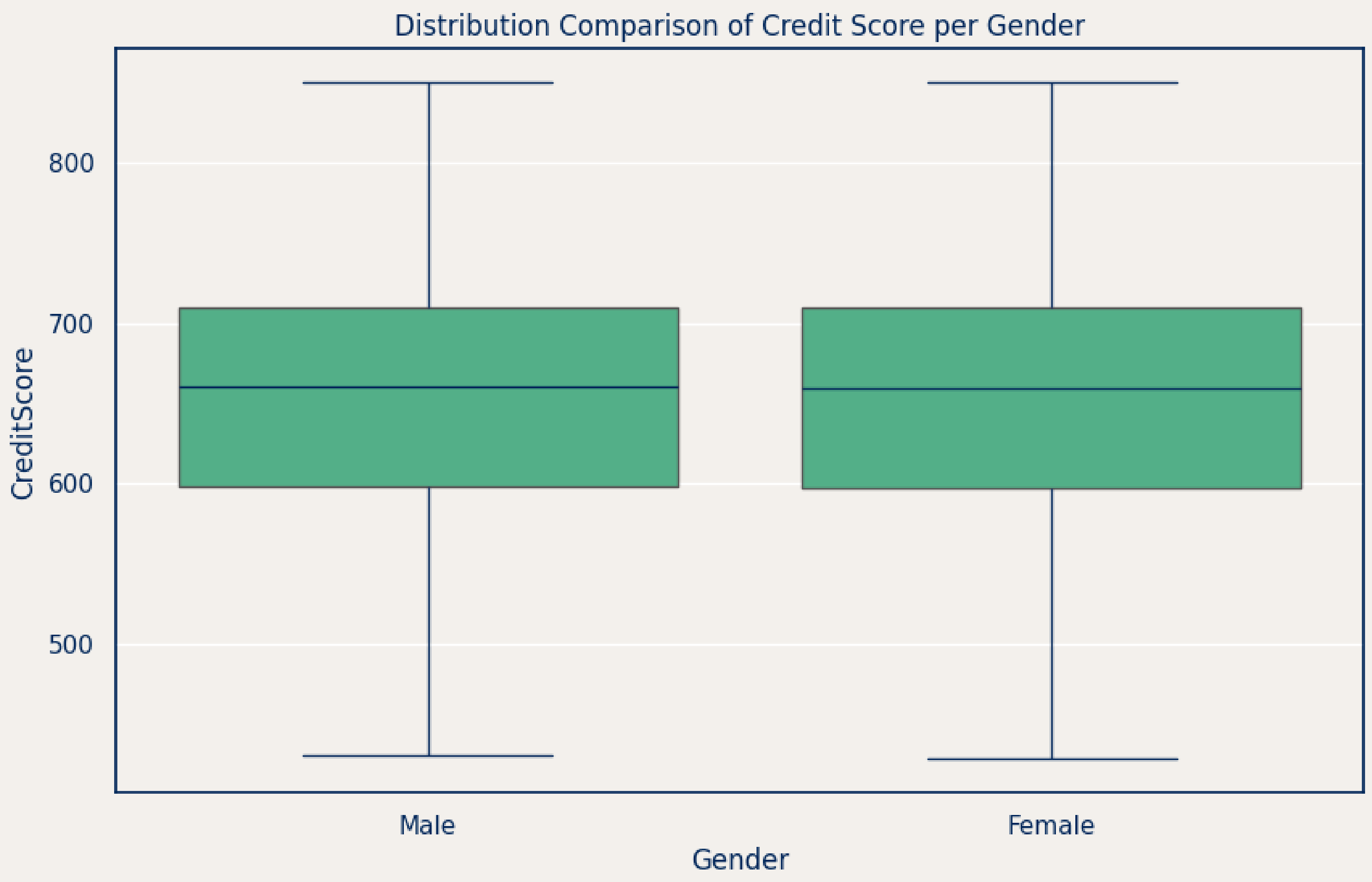
In this analysis, Dani wanted to investigate whether female customers are more likely to leave the bank than male customers. She believed that considering gender disparity is vital when discussing financial opportunities, ensuring that it's not overlooked.



Female customers are **2 times more likely to exit the bank than male customers!**

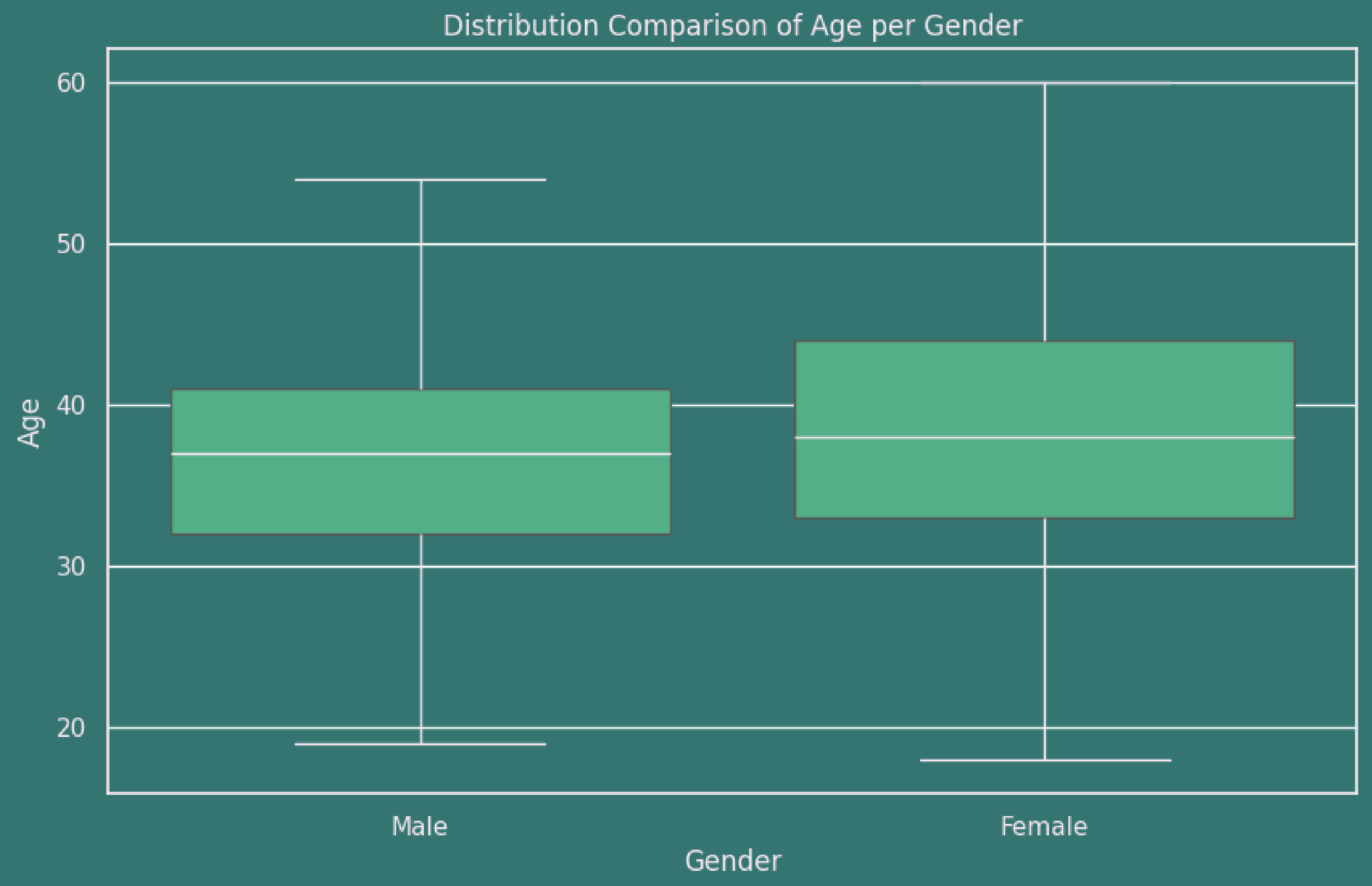
FEMALE DEMOGRAPHIC: AN INDEPTH LOOK

Following her findings on gender, Dani decided to delve deeper into other potential differences between male and female customers, such as credit score, age, activity, and more.



Credit Score and Age

On Credit Score and Age, it appears that there really is no observable difference between the Male and Female.



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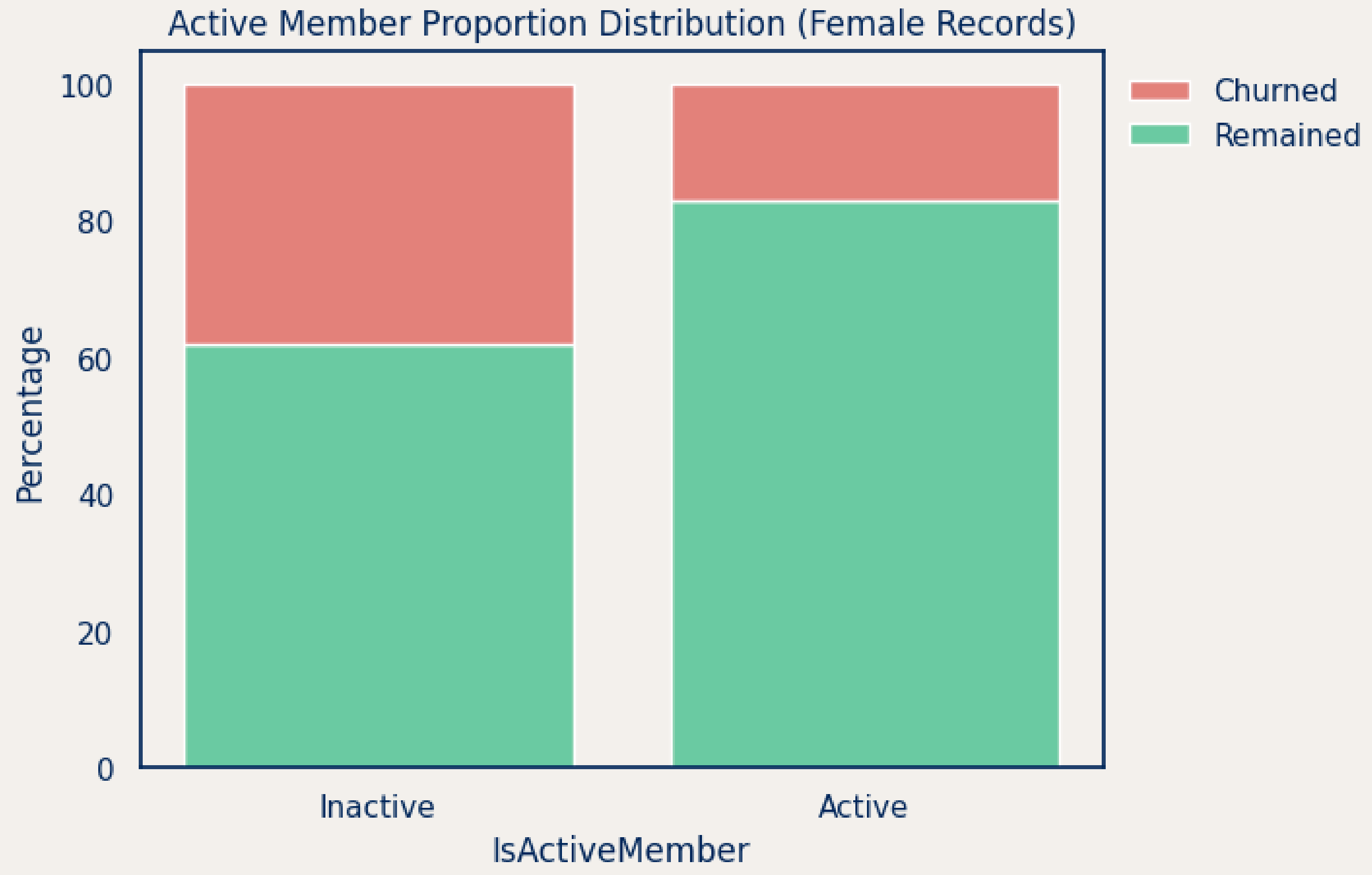
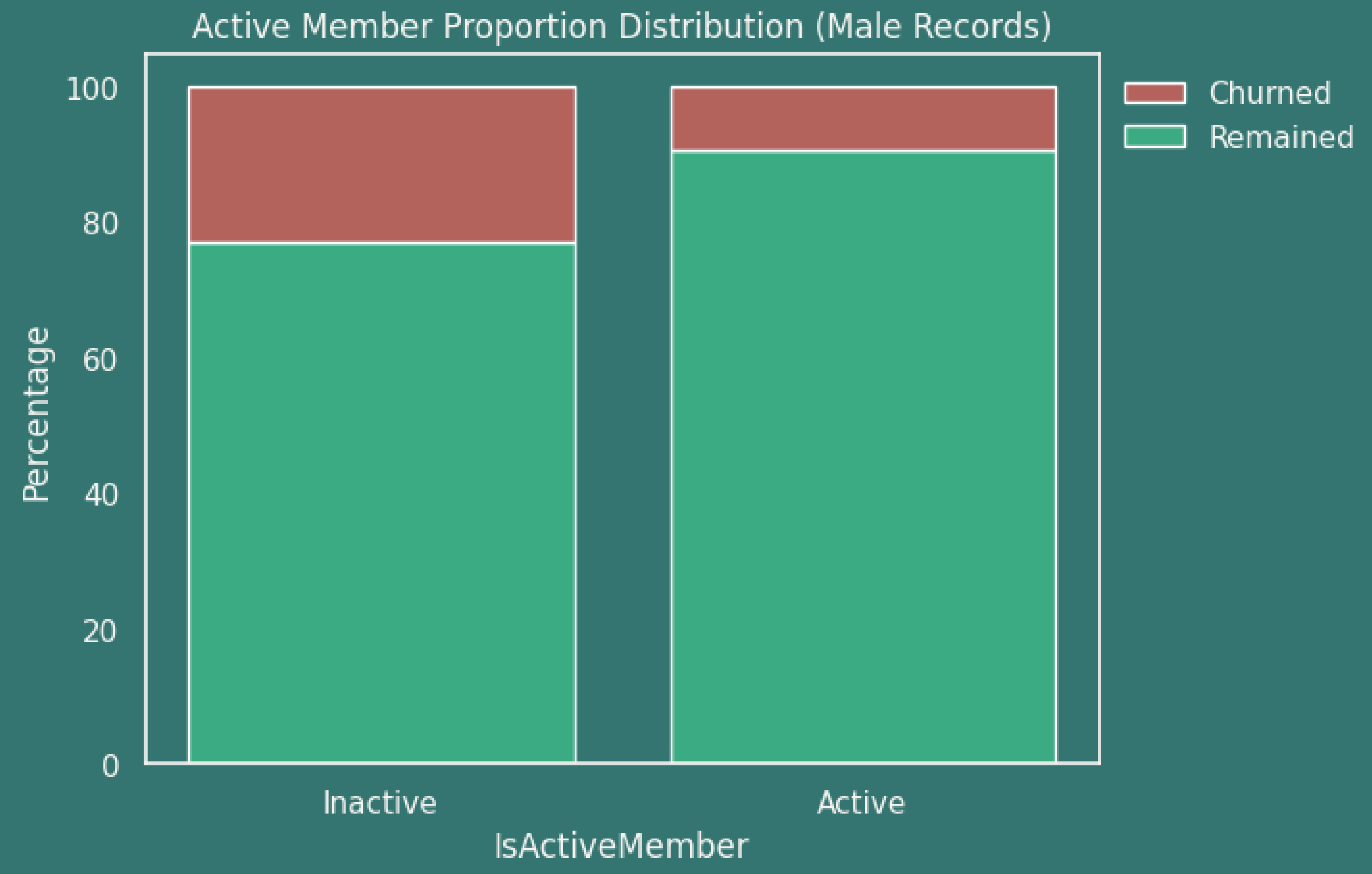


Customer Activity vs Genders

For customer activity, however, it appears that the inactive female customers have churned more than its male counterpart in proportion.



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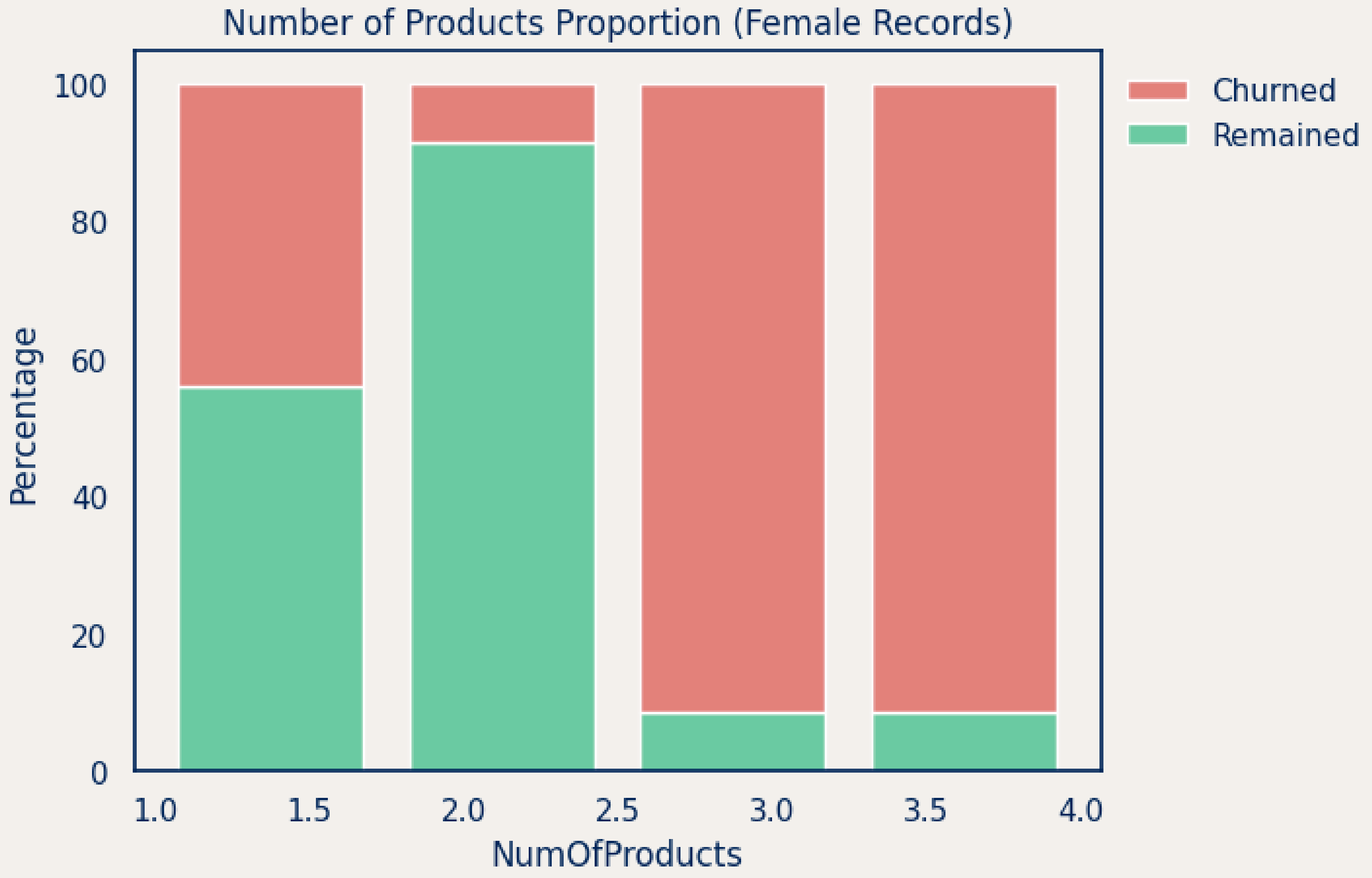
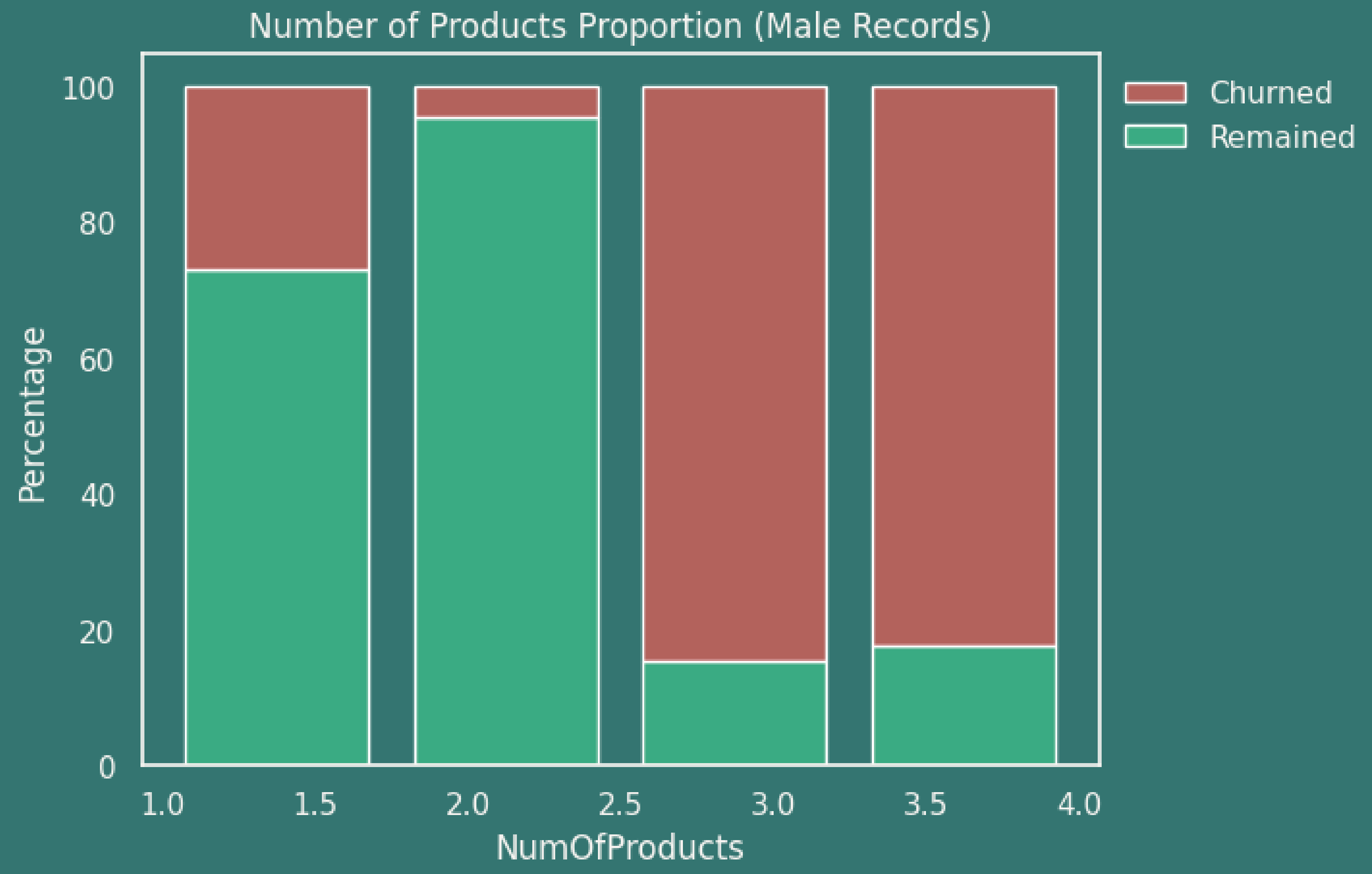


Number of Products vs Genders

Dani found out that **women with only 1 product were more likely to churn** than men with the same number of products. However, for 2 or more products, the proportion appears to be the same for both genders.



SUMMARY AND SUGGESTED ACTIONS

Dani communicated her findings with Mark.

Gender

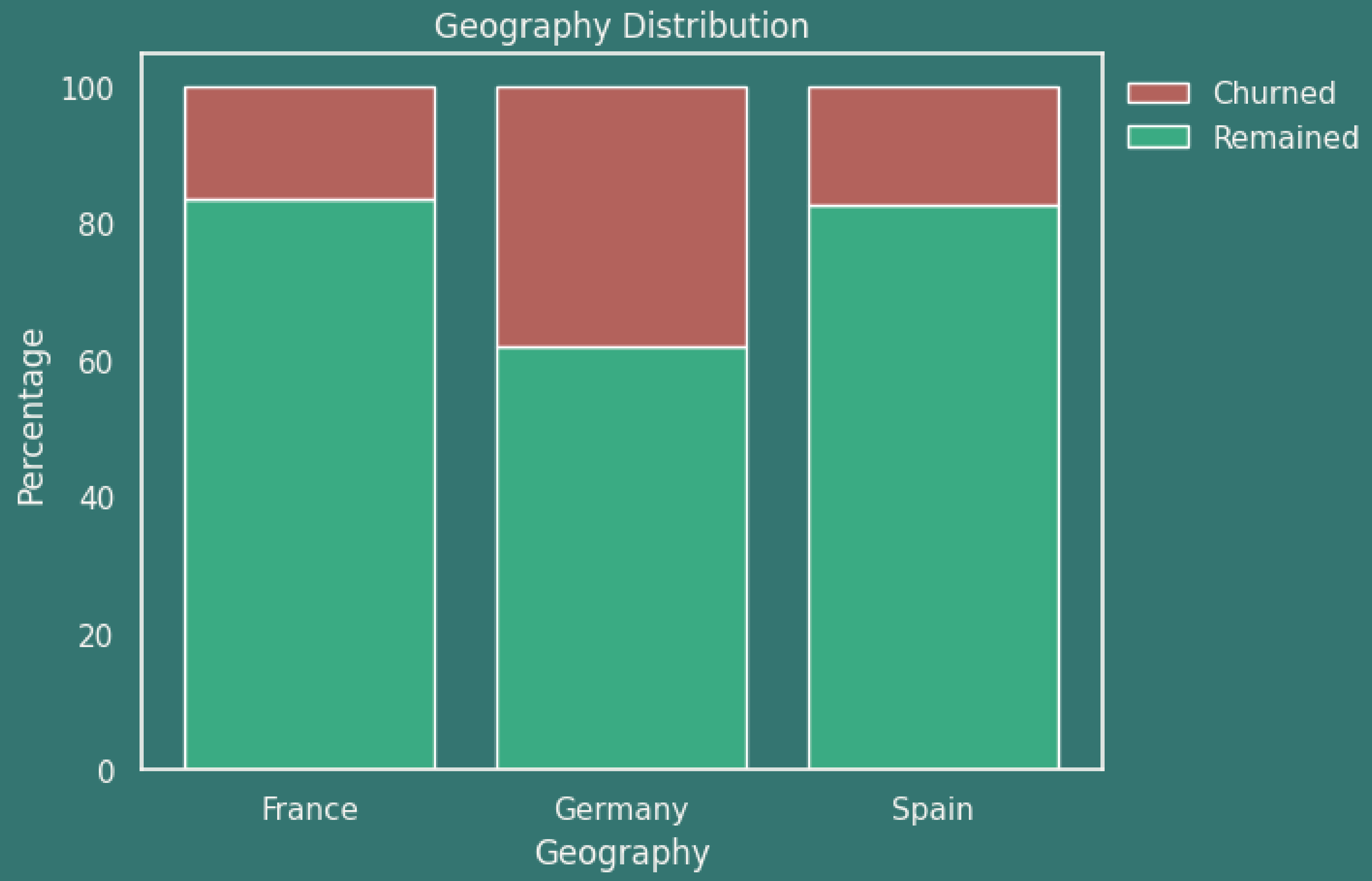
Female customers are 2x likely to exit than male customers.

Suggestions:

- Since the dataset we are working on is limited, we should conduct further analysis on the pain points of female customers so that we can create tailored strategies for them.

ON GEOGRAPHY

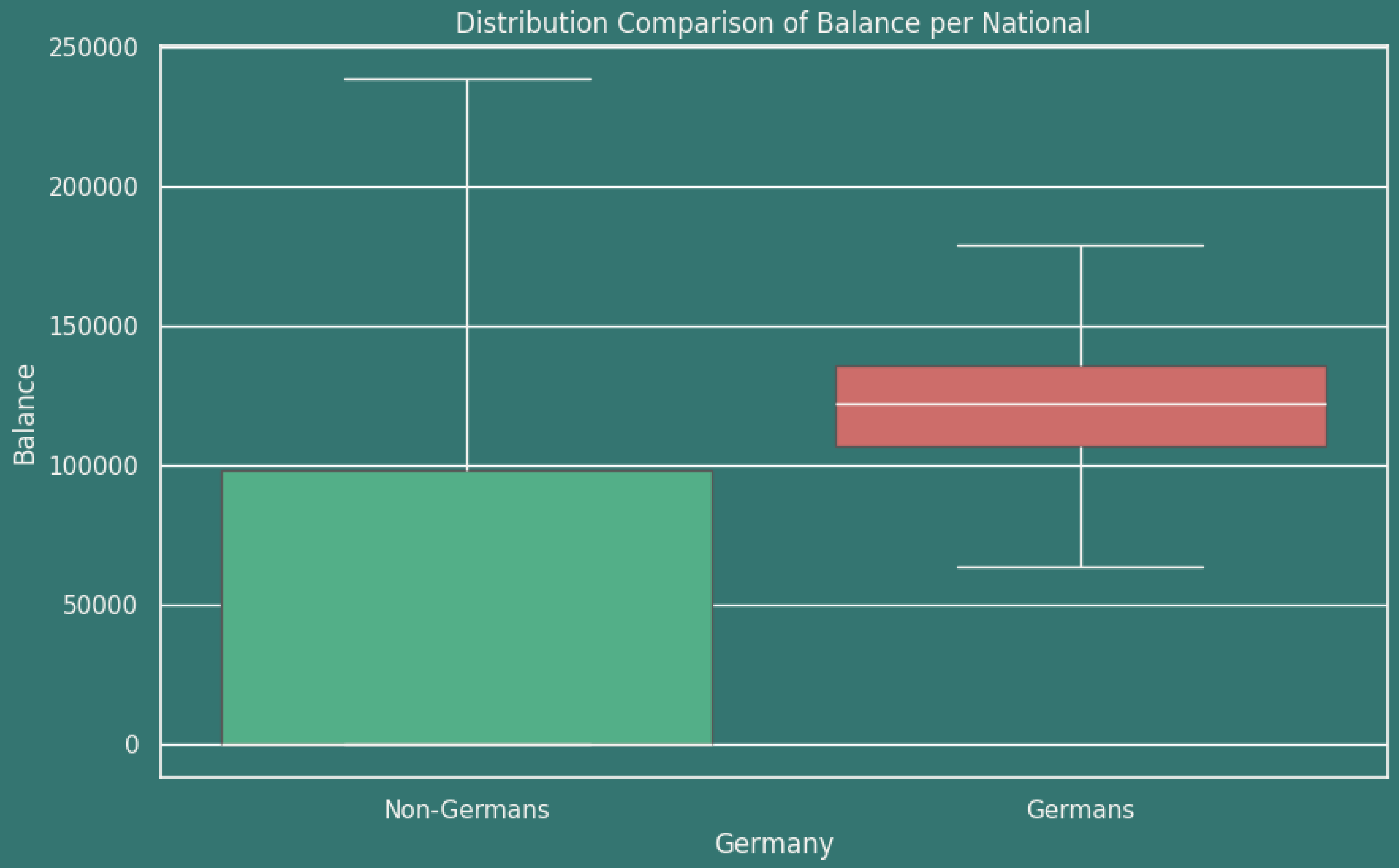
During her initial investigation, Dani noticed that the "Geography" information only listed three countries: France, Germany, and Spain. She then wondered if customers from a specific country were more likely to leave the bank than others.



Visualizations and advanced statistical tests showed that **German customers were 3x more likely to leave the bank!**

GEOGRAPHY AND BALANCE

Since Dani found that most customers who left the company were German, she decided to investigate further and see if there were any differences between German and non-German customers. In particular, she found something interesting about the way account balances were distributed for each group.



Earlier, we saw that customers with higher balances tend to exit more. Here, Dani uncovered that **most German customers have high balances.**

SUMMARY AND SUGGESTED ACTIONS

Dani communicated her findings with Mark.

Geography
German customers are 3x likely to exit the bank than French nor Spanish customers. They also have larger balances than non-German customers.

Suggestions:

- Analyze the market positioning of ABC Bank in Germany.
- Offer tailored marketing for German customers. Like higher interest rates?
- Conduct surveys, and identify pain points.

ON MARK'S ACCEPTABILITY

After sharing her findings and suggestions all along the way, Dani finally presented her conclusions to Mark. He was thrilled that they had finally identified the key factors leading to customer churn (customers leaving the bank).

However, Dani, being the extra innovator that she is, wasn't satisfied. She believed they could do even more with the historical data they now had. So, she made a suggestion that surprised Mark: ***"What if we could create a system that automatically identifies customers who might leave the bank?"***

MODEL BUILDING

As suggested by Dani, the ABC Multinational Bank can actually create a system that will automatically detect customers that are likely to leave. But how will Dani do just that? Let's find out!

SUPERVISED MACHINE LEARNING

Machine learning is something that Mark has not heard of before, let alone a supervised one. With this, Dani gave Mark a basic explanation:

"**Supervised machine learning** is like teaching a computer with lots of examples so it can learn to predict new things on its own."

SUPERVISED MACHINE LEARNING

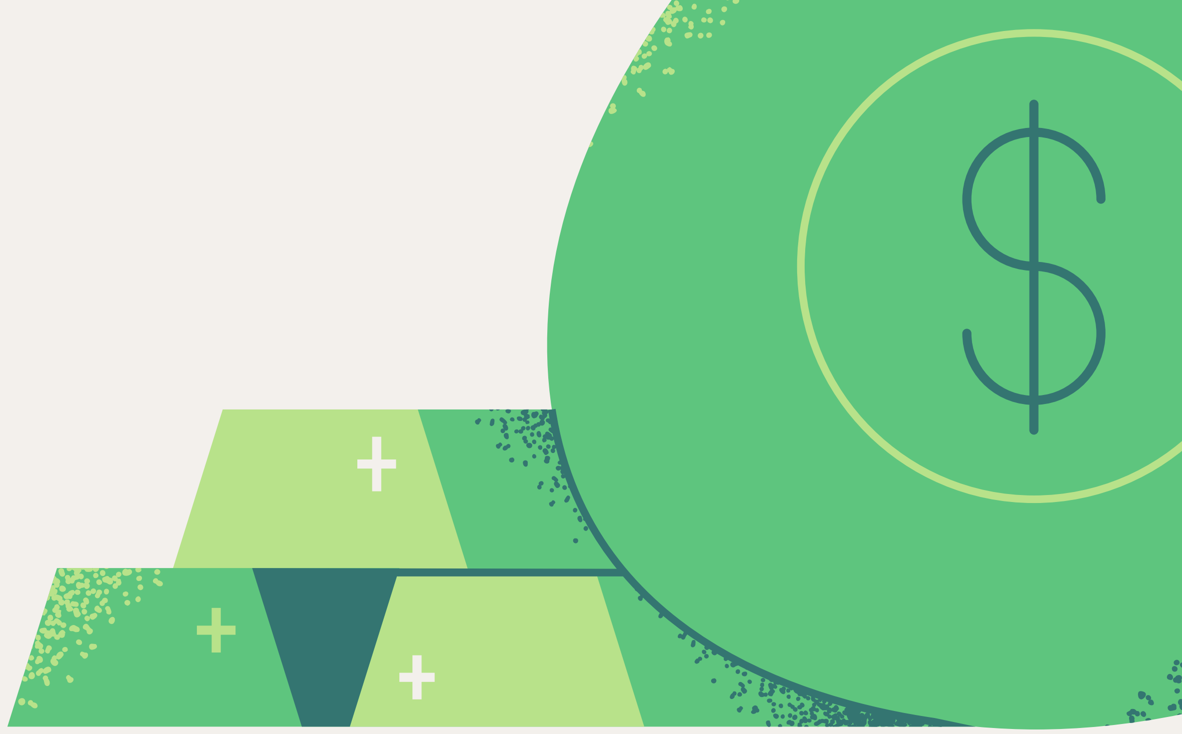
Machine learning is something that Mark has not heard of before, let alone a supervised one. With this, Dani gave Mark a basic explanation:

The key thing we need here is historical data with labels. This means that the dataset needs two things: features and a target.

Features are the different characteristics the model learns from, like age or income.

We use these features to predict the **target**, which is the outcome we're interested in, like whether a customer is likely to leave the bank.

ON MODEL BUILDING



With the current data that she have, Dani selected several algorithm that she thinks fits the process that she want to do. She wants to classify customers that are likely to churn vs remain, so she chose algorithms that are perfect for classification tasks.

MODELS, MODELS, MODELS!

Dani modeled the problem that she is trying to solve (classification) based on the algorithms that she chose. *How did she do that?*

- **Data Cleaning:** Done!
- **Encode Values:** Not all data is numerical. Convert them!
- **Engineer Features:** Combine features to capture more information, or remove ones that don't help the model learn.

WHAT ARE WE WILLLING TO MISS?

Before presenting the results of the machine learning models to Mark, Dani decided to be transparent about their limitations. She emphasized that **these models are not perfect and will inevitably miss some data points.**

Dani inquired about Mark's priorities. Specifically, she wanted to understand which type of error he aimed to minimize: failing to identify customers who are highly likely to churn (leave) or misclassifying customers who are likely to stay.

Mark's preference was clear: **he would rather the model mispredict customers who would ultimately remain loyal, rather than miss those who were genuinely at risk of leaving.**

BEST EVALUATION METRIC

The question that Dani asked is actually very vital. This will allow her to choose which metric should she prioritize when evaluating the performance of the models that she created. Taking Mark's priority into account, the priority metric is:

Recall. This measures how well a classification model correctly identifies true positives. In the context of bank churning, this answers the question: *"Out of all the customers who left, how many did the model found?"*

BEST MACHINE LEARNING MODEL

LIGHTGBM

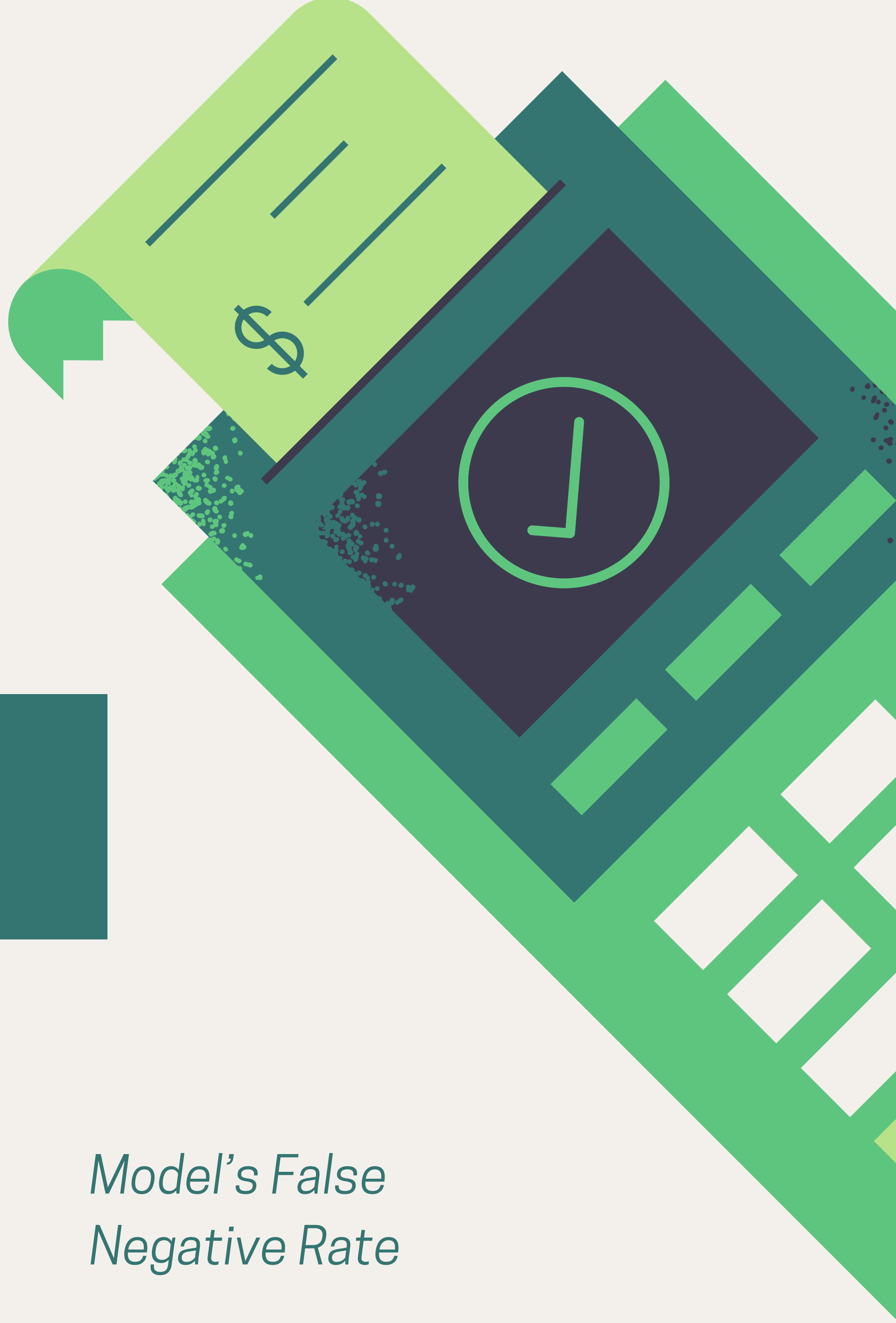
Recall: 79.63% (highest among all models trained.)
ROC-AUC: 80.54% (highest among all models trained.)

HIGHLIGHTED BUSINESS VALUE

Original Churn Rate **21%** VS **4.3%** *Model's False Negative Rate*

- If we could perfectly **identify all <u>new and remaining</u> customers the model predicts will leave** and **successfully prevent them from churning**, then the churn rate would be equivalent to this model's false negative rate.

BEST MACHINE LEARNING MODEL



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HIGHLIGHTED BUSINESS VALUE

Original Churn Rate **21%** VS **4.3%** *Model's False Negative Rate*

17%! This means that if ABC Multinational Bank decides to deploy this model in real life, we are projected to reduce the churn rate of existing customers by a stagerring 17%!

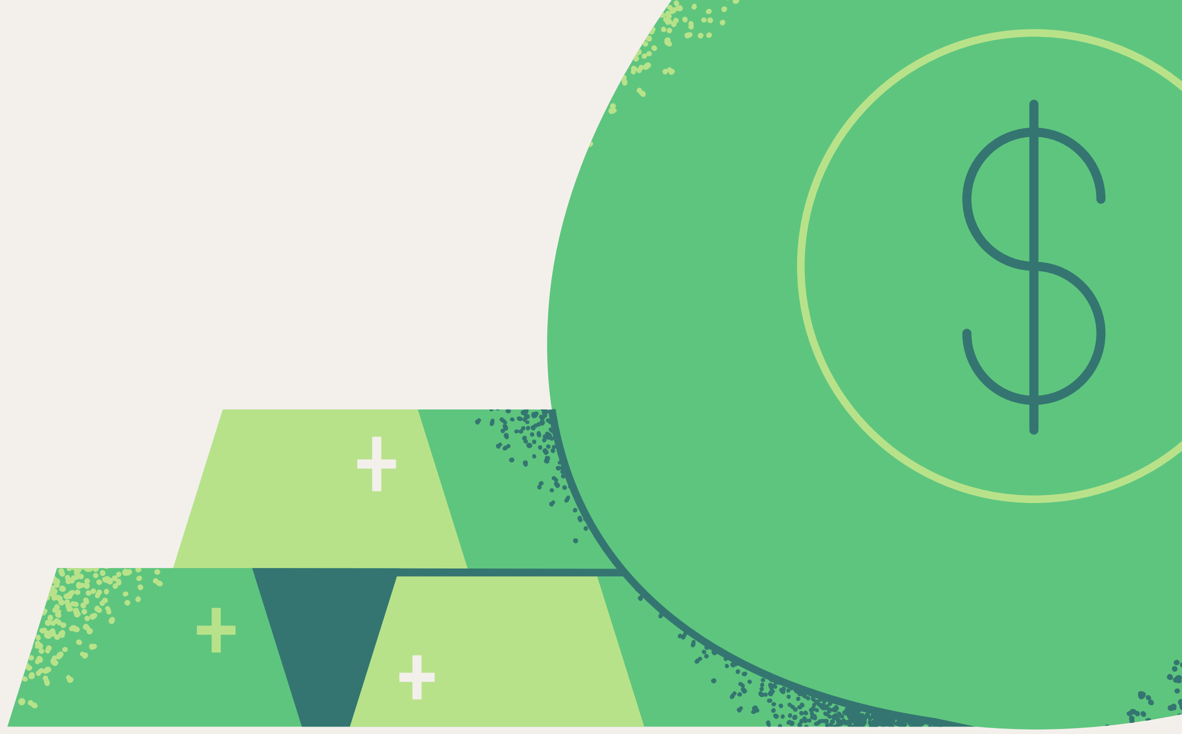
OKAY, BUT HOW?

After explaining the best model her experiment produced and the business benefits it offered, Mark was understandably impressed, yet *curious*. Known for his inquisitiveness, he asked Dani **how the best model generated its predictions** and **what made it so successful**. He wanted to understand **why he should trust these predictions** enough to make important business decisions.

Prepared as always, Dani had an answer ready.

MODEL EXPLAINA-BILITY

The questions of Mark actually does make sense. Why should we even trust this model in creating business decisions for us? In this portion, we introduce the concept of model explainability.



ON MODEL EXPLAINABILITY

Dani may not know the inner workings of every machine learning she uses, but she's an expert at choosing the right tool for the job. This skill is what helps her succeed. Besides, there are a lot of tools out there that allows here to investigate the decision-making aspect of the models that she builds, like:

SHAPLEY ADDITIVE EXPLANATIONS (SHAP)

SHAP acts like a light on each part of a customer's data and shows how much that specific part contributed to the model's prediction.

Why is it helpful?

- **Trust** - we can see why the model is making a certain prediction, leading business leaders to have more confidence in the results.
- **Fairness and Bias** - we can see which problematic features actually affects our predictions.

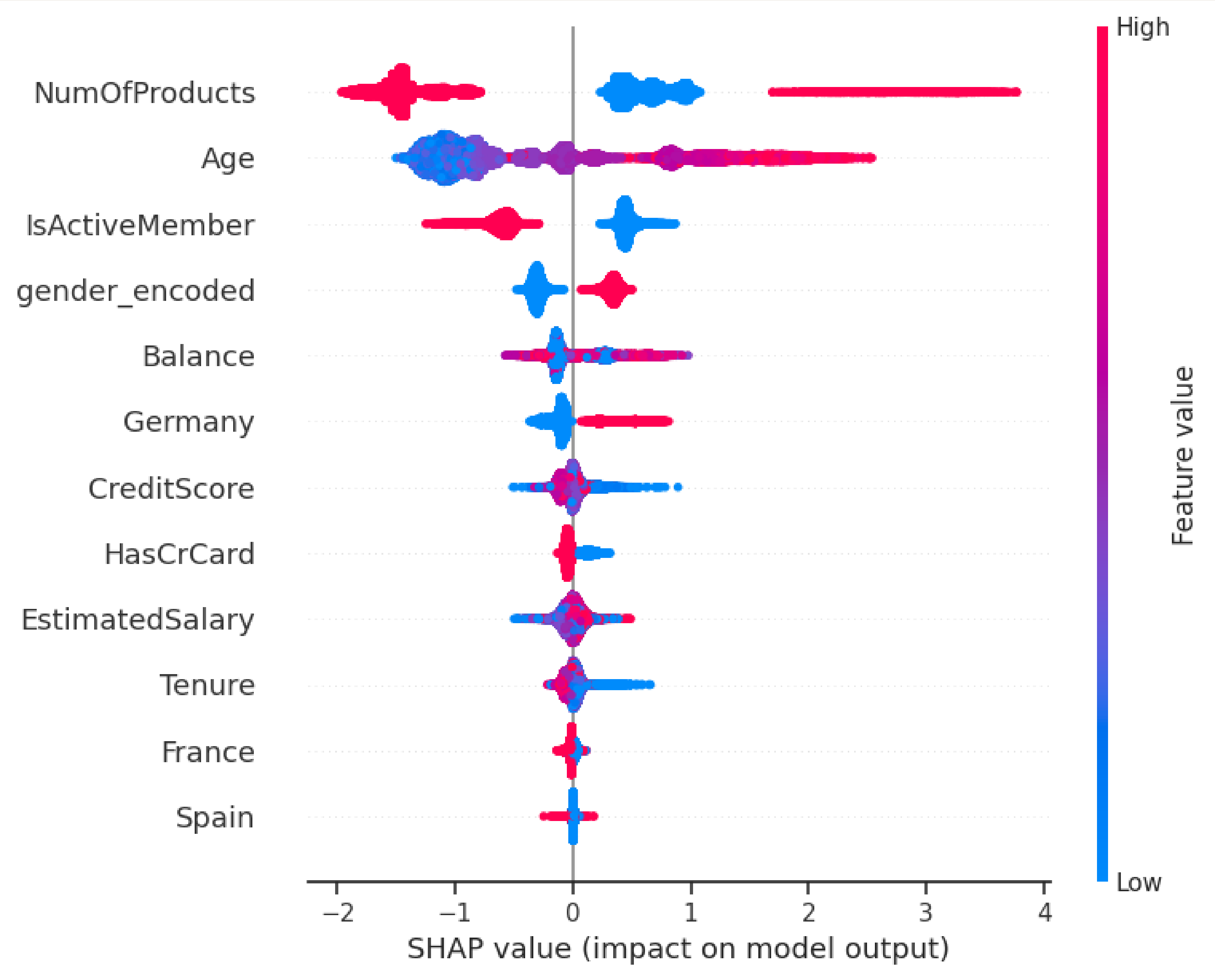
RECALL: IMPACTFUL FEATURES BASED ON EDA

Dani and Mark decided to take a look back at the major features that affects customer churn during the Dani's exploratory analysis of the dataset.

- **Customer Activity** (inactive are more likely to churn)
- **Number of Products** (customers with higher number of products are more likely to churn)
- **Age** (older people are more likely to churn)
- **Geography** (Germans are more likely to churn)
- **Gender** (Female customers are more likely to churn)
- **Balance** (Customers with high balance are more likely to churn)

Dani would like to check if her findings during her data analysis makes sense with the predictions made by the model.

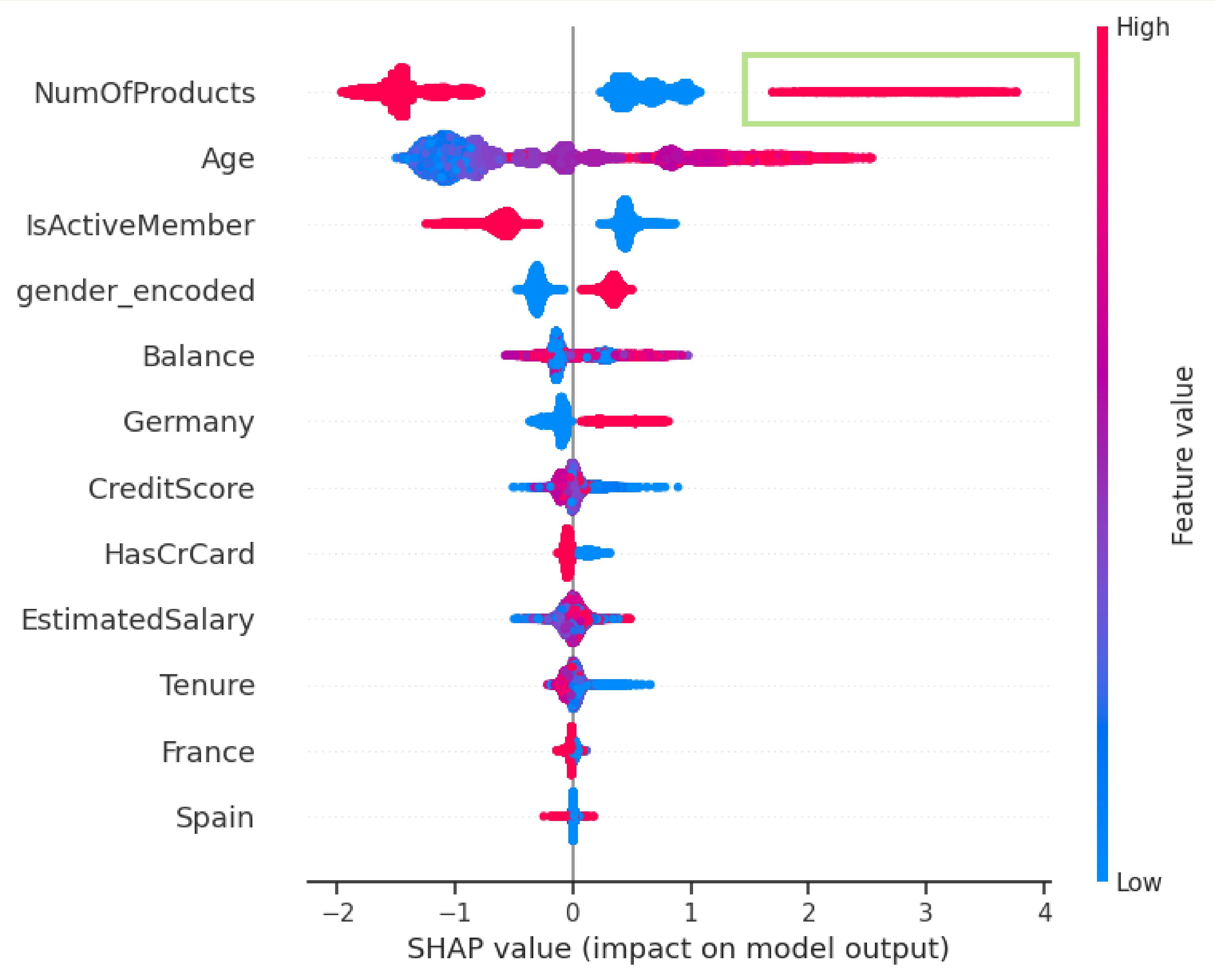
SHAP BEESWARM PLOT



This plot summarizes **how the top features of the dataset impacts the model's prediction.**

At first glance at the graph, Dani immediately knew that the predictions made her model does make sense. Nonetheless, she had to communicate her findings with Mark.

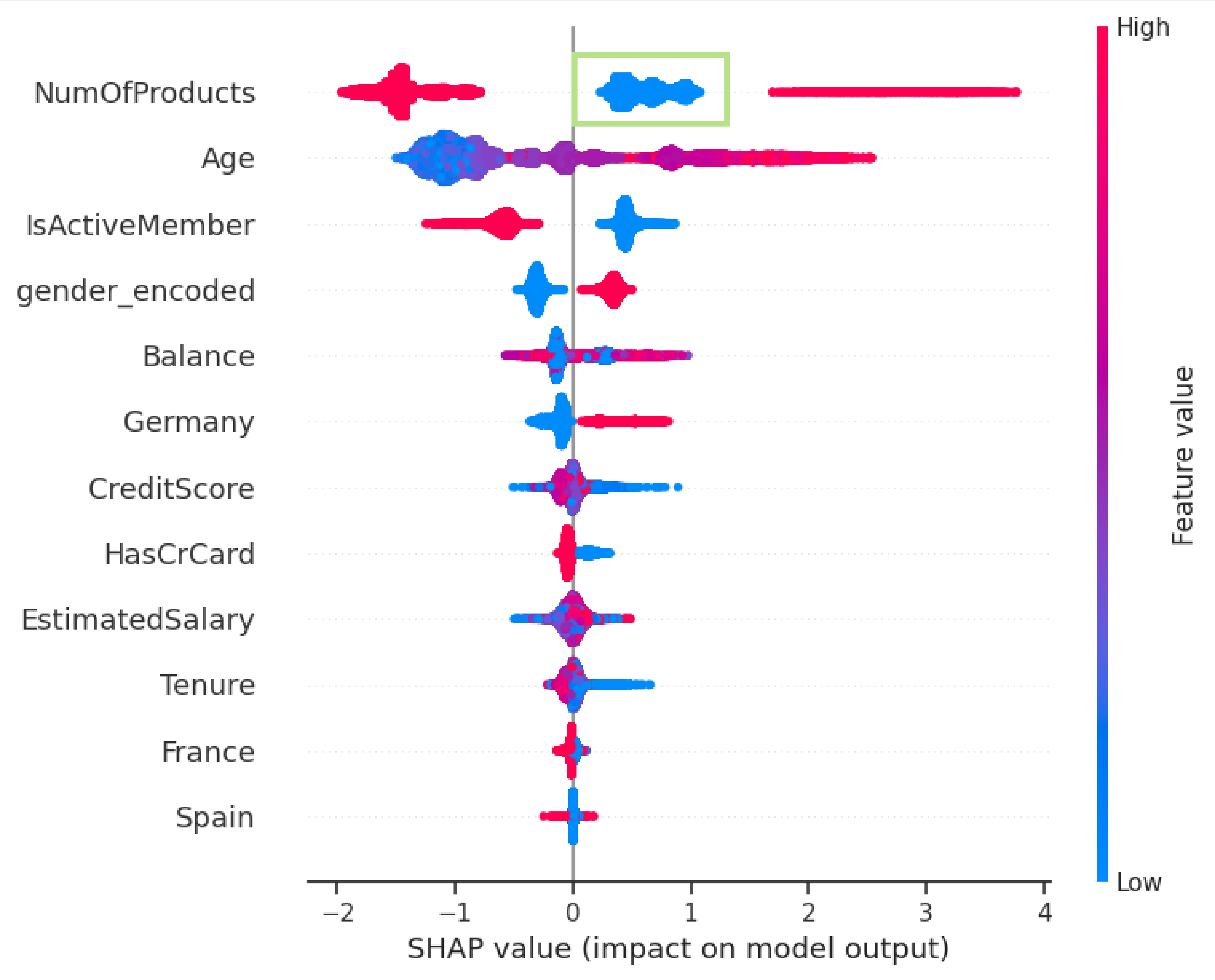
SHAP BEESWARM PLOT



Number of Products

- The higher the value, the redder it gets.
- As indicated by the swarm plot for this feature, higher values for number of products, the higher the SHAP value. **This simply means that customers with higher number of bank products are more likely to get churned.** This makes sense with Dani's findings on her data analysis.

SHAP BEESWARM PLOT



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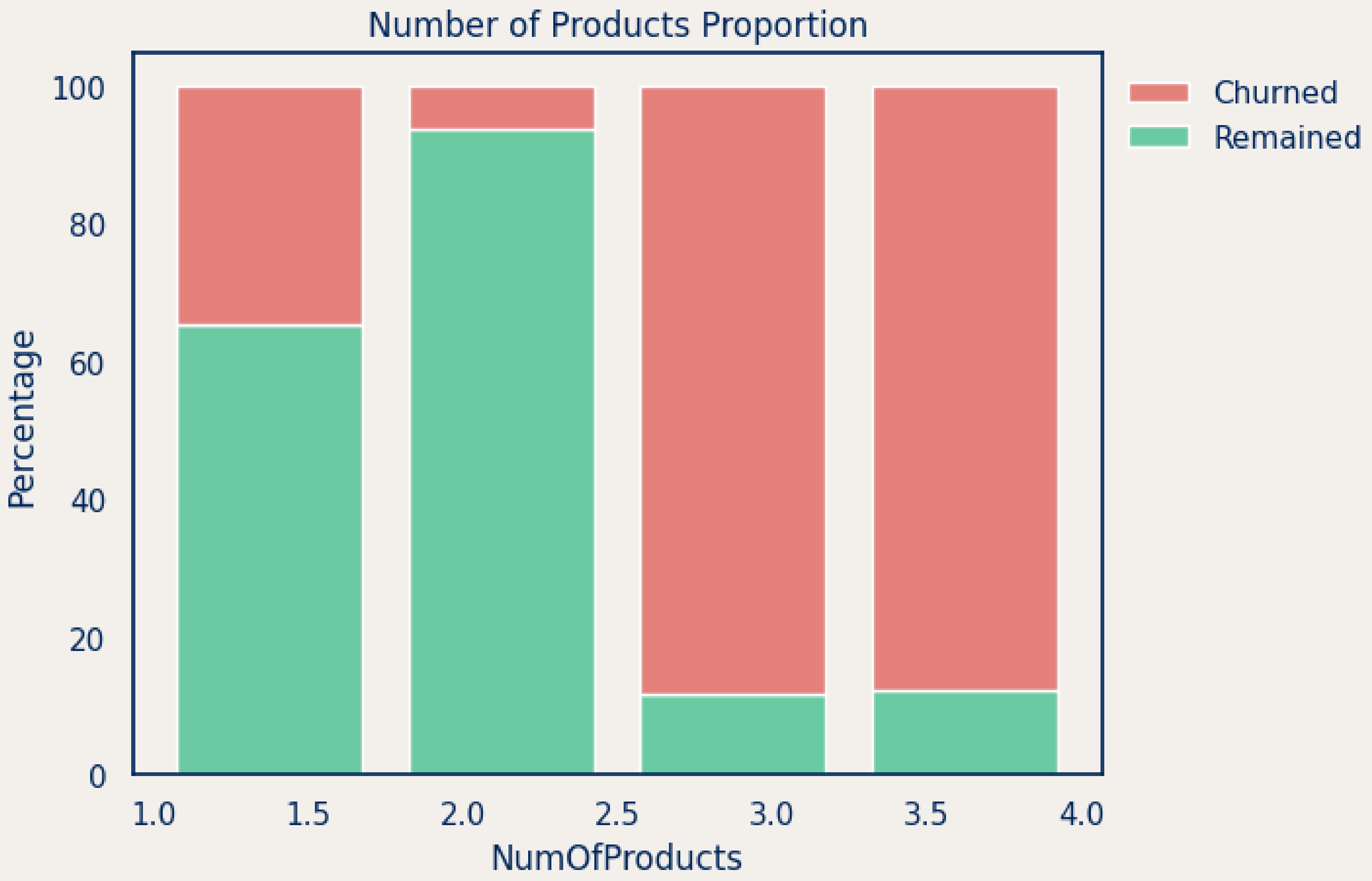
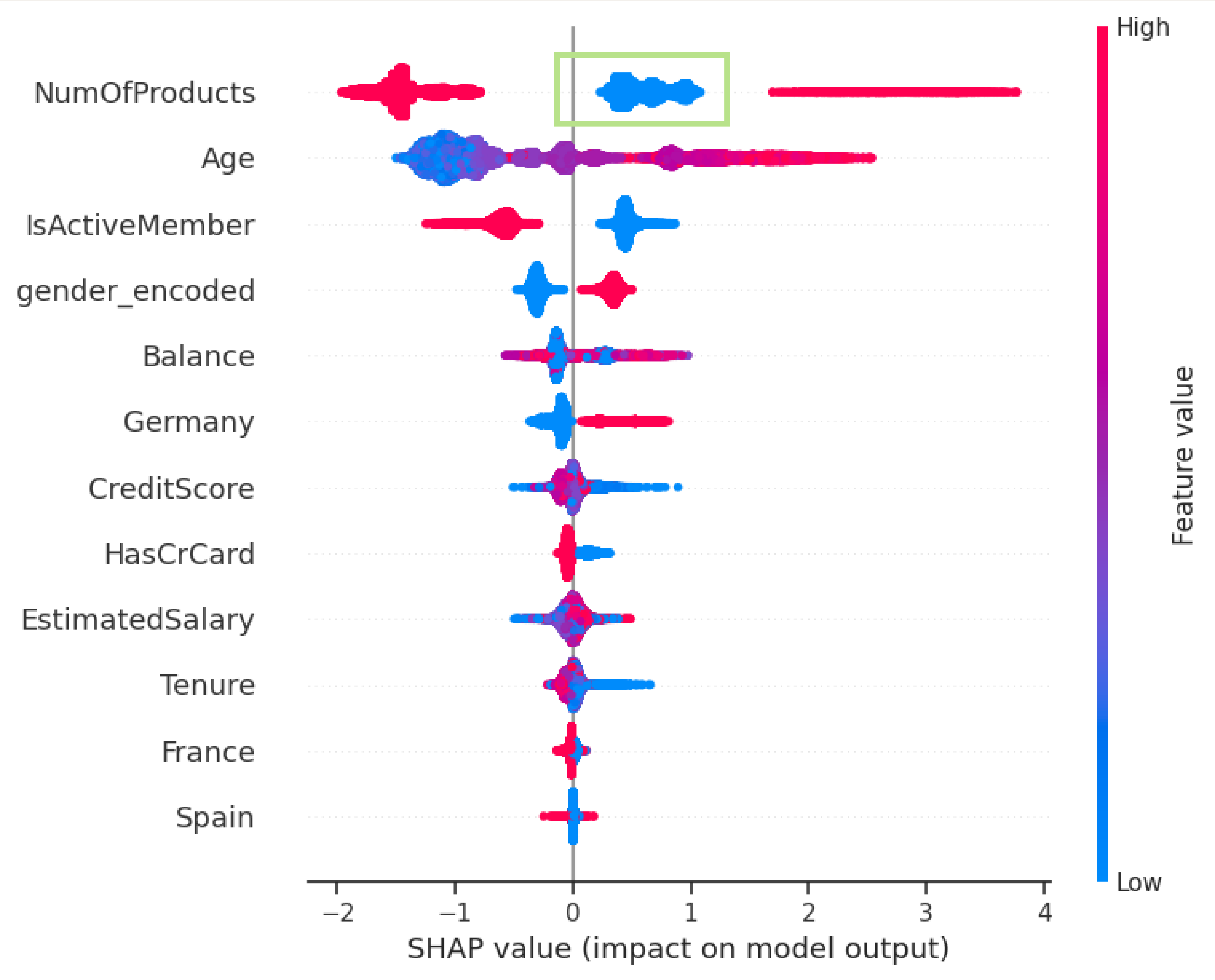
- For this blue part, this simply refers to the customers with 1 bank product.

GOING BACK...

Considerable proportion of customers with 1 bank product have churned (Approximately 35%).



SHAP BEESWARM PLOT



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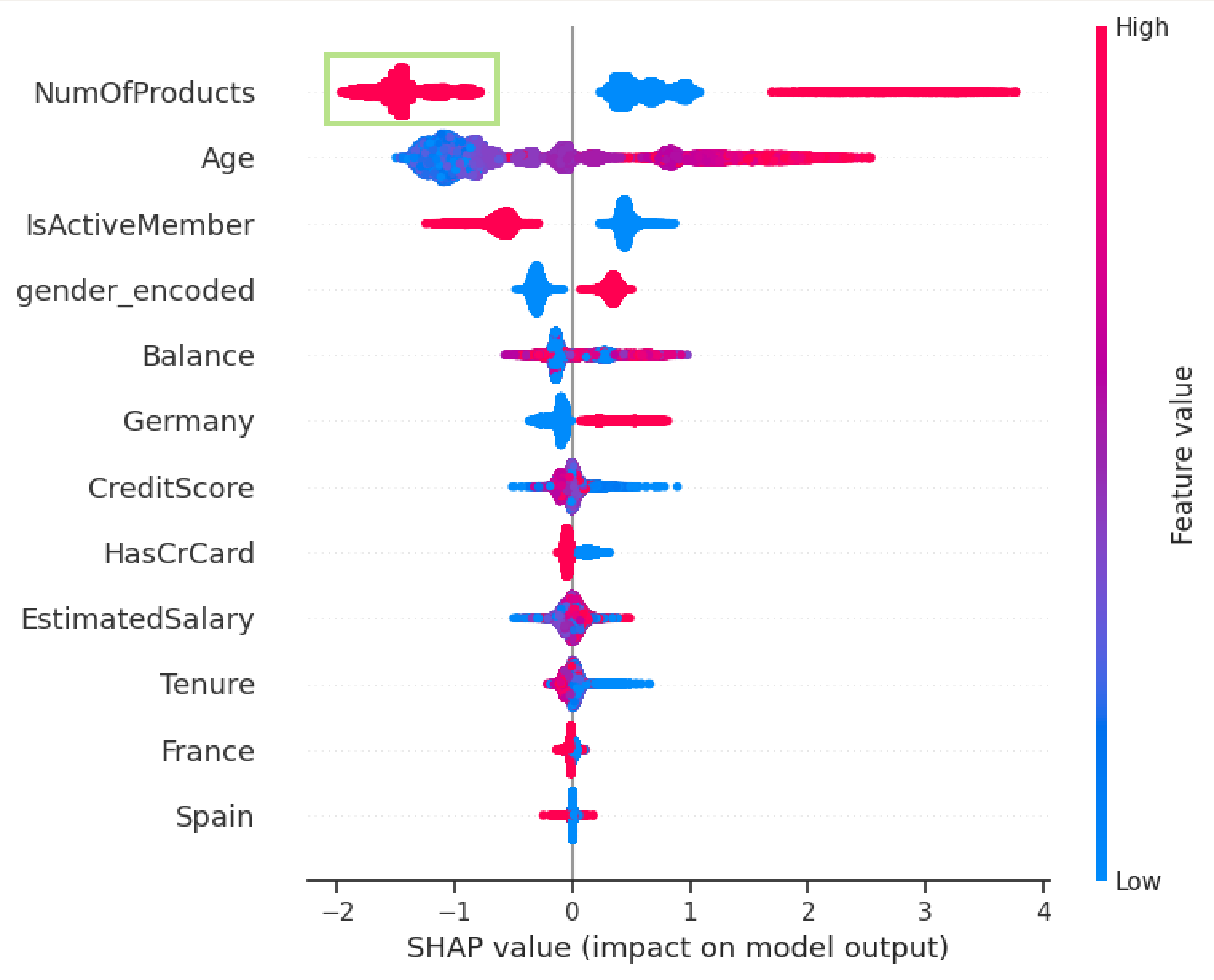
- For this blue part, this simply refers to the customers with 1 bank product.
- This makes perfect sense since there are still churners from the customer group with 1 bank product.

SHAP BEESWARM PLOT

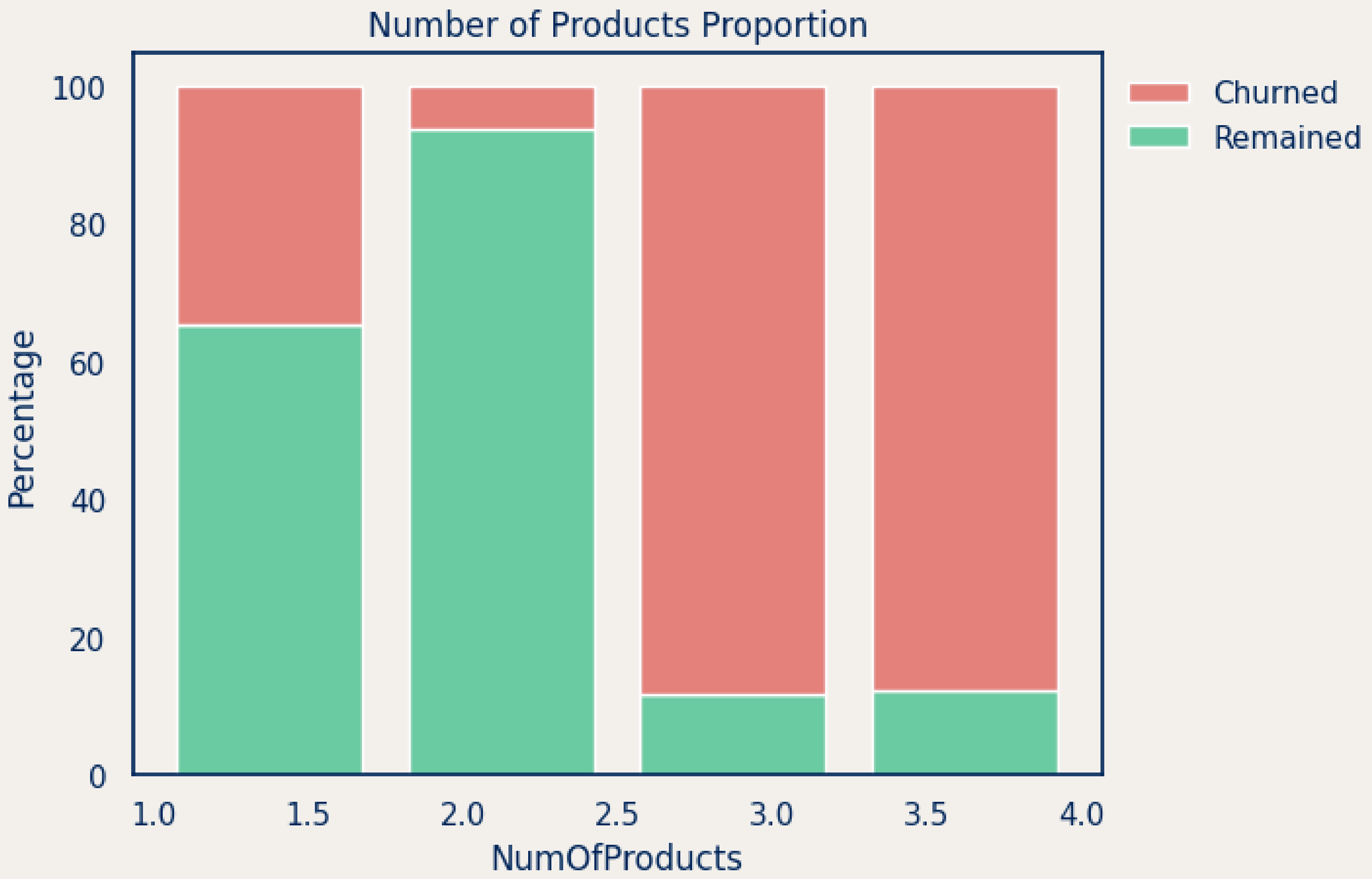


Number of Products

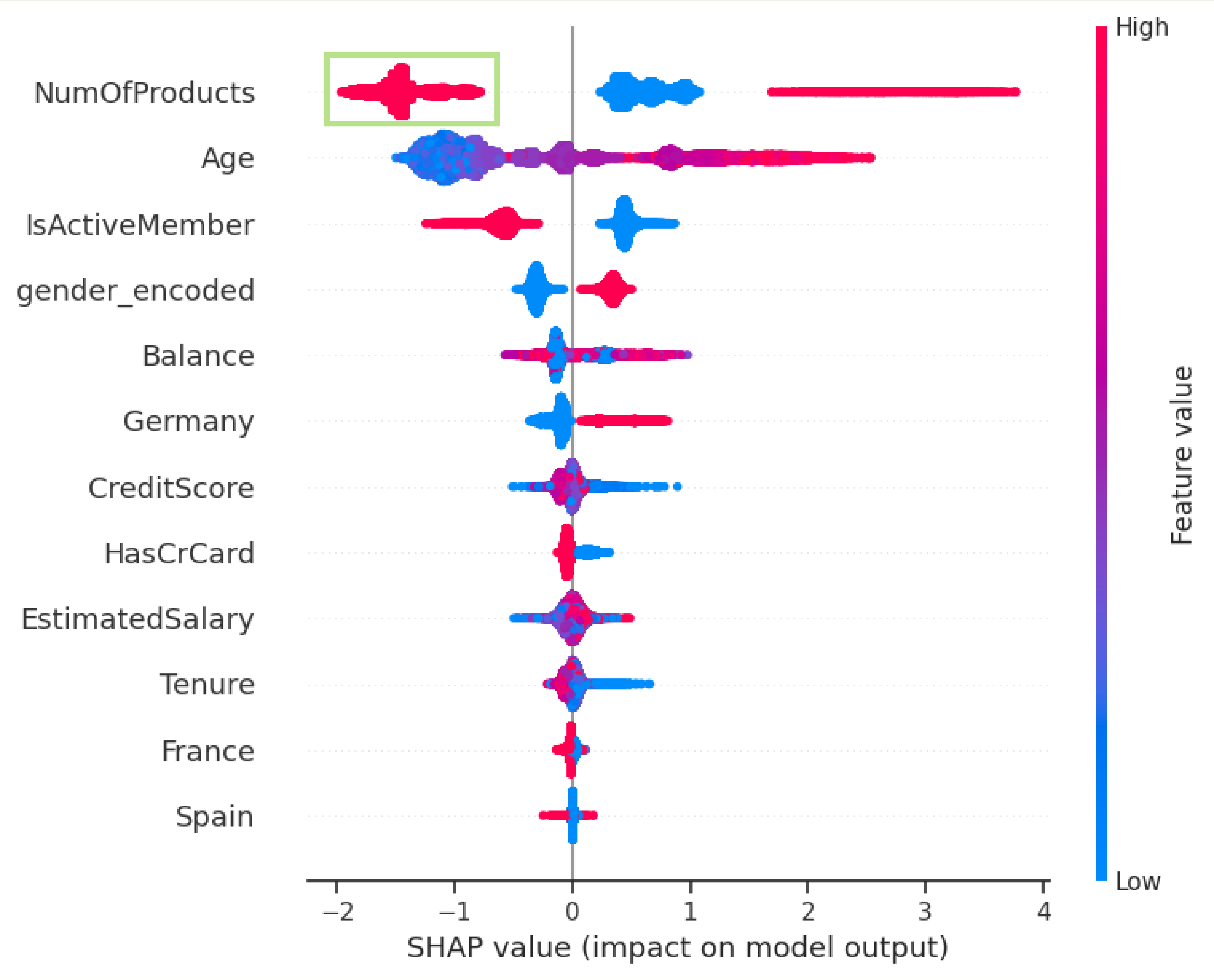
- However, this portion of the plot seems off. Dani was certain that customers with 3 or 4 products are most likely to positively contribute to the churn factor.
- Dani speculated that this may be the customer group with 2 bank products.

GOING BACK...

Most of the customers with just two bank products remained with the company.



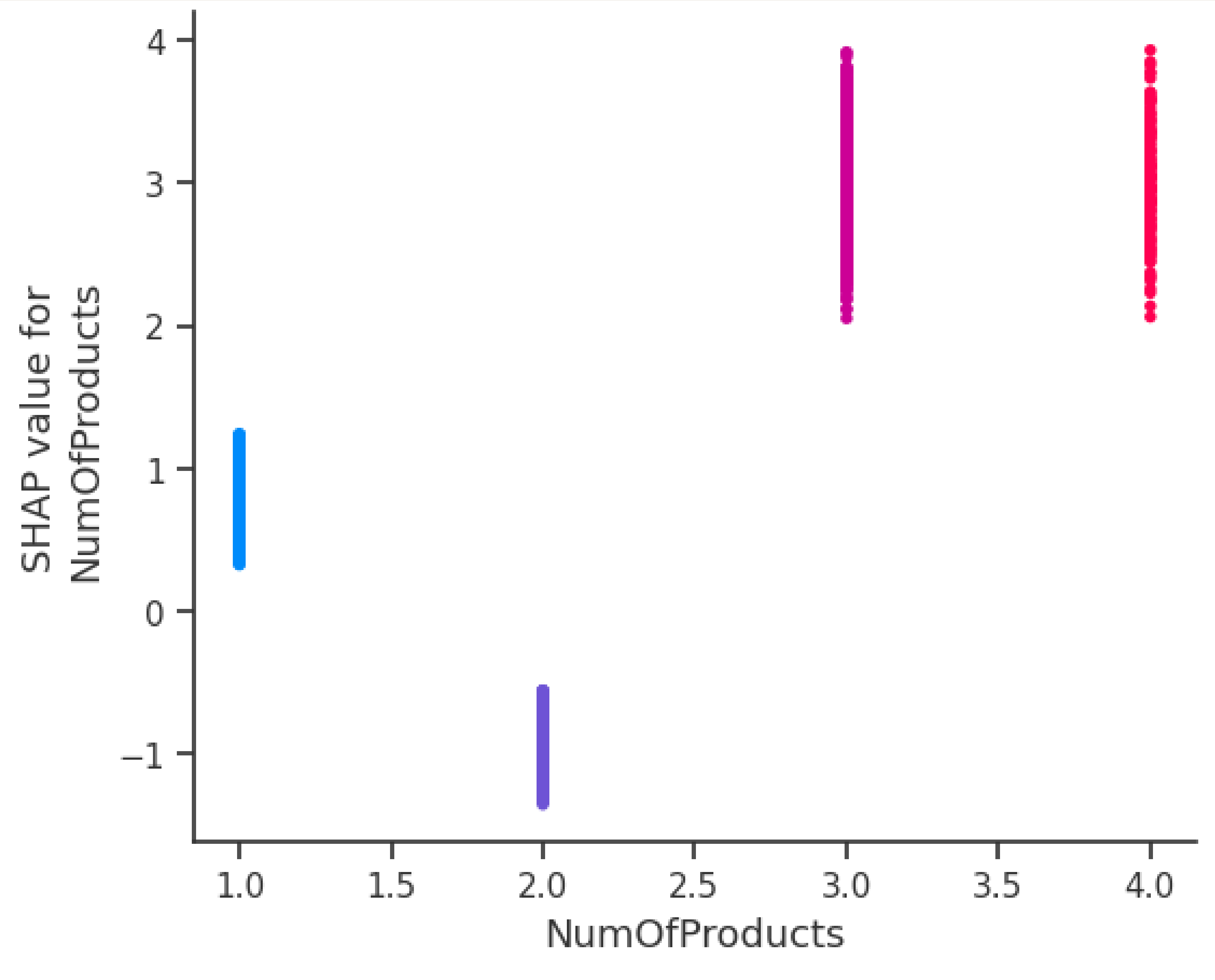
SHAP BEESWARM PLOT



Number of Products

- However, this portion of the plot seems off. Dani was certain that customers with 3 or 4 products are most likely to contribute to the churn factor.
- Dani speculated that this may be the customer group with 2 bank products.
- This is the only explanation that will make sense of this. So Dani decided to explore this even further.

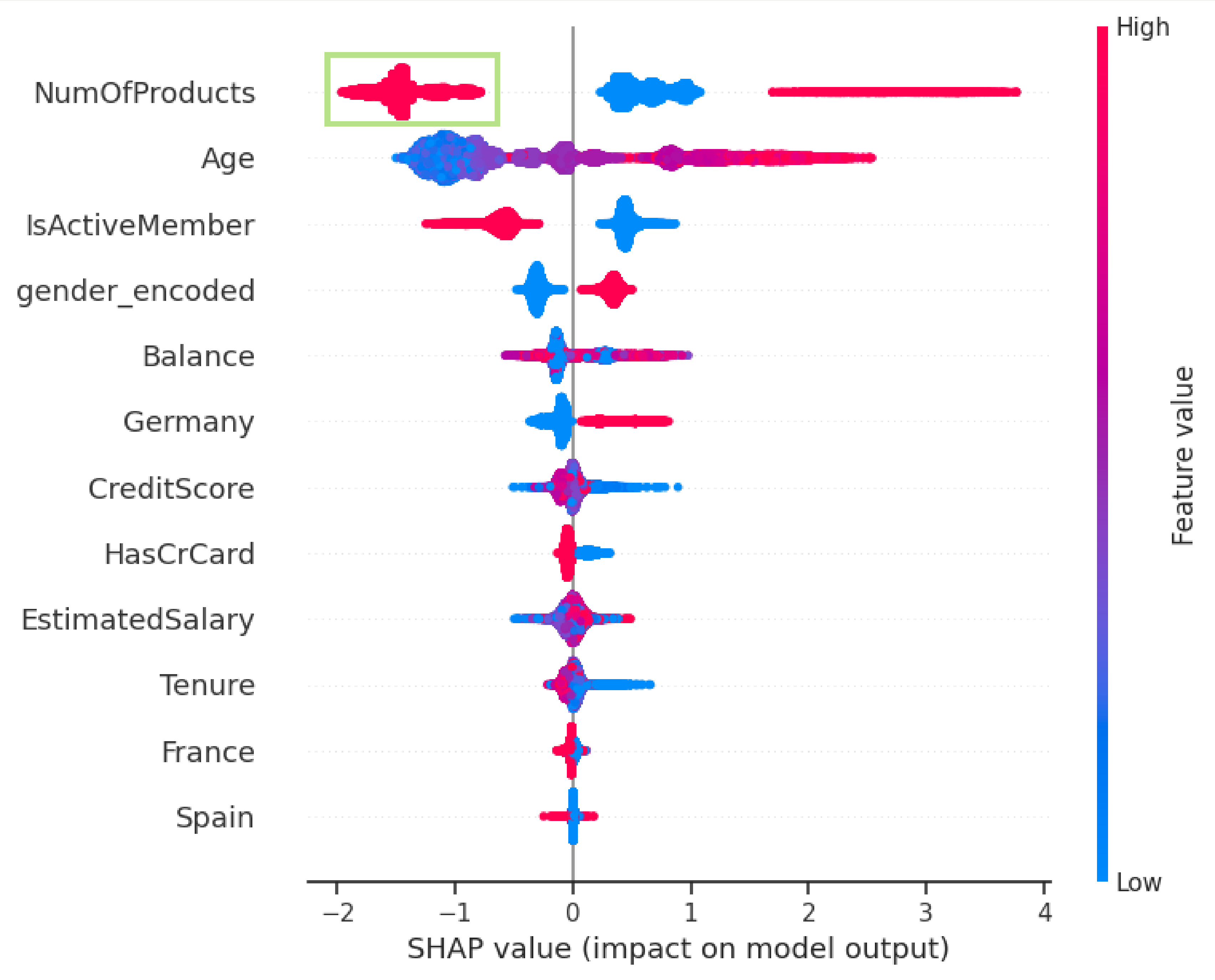
SHAP DEPENDENCE PLOT



Number of Products

- Upon investigating the Dependence Plot of NumOfProducts with itself. Dani's conclusion was indeed correct! Having 2 bank products contributes negatively to the churn factor (SHAP value), while having 3 and 4 bank products contributes positively to the churn factor (SHAP value).

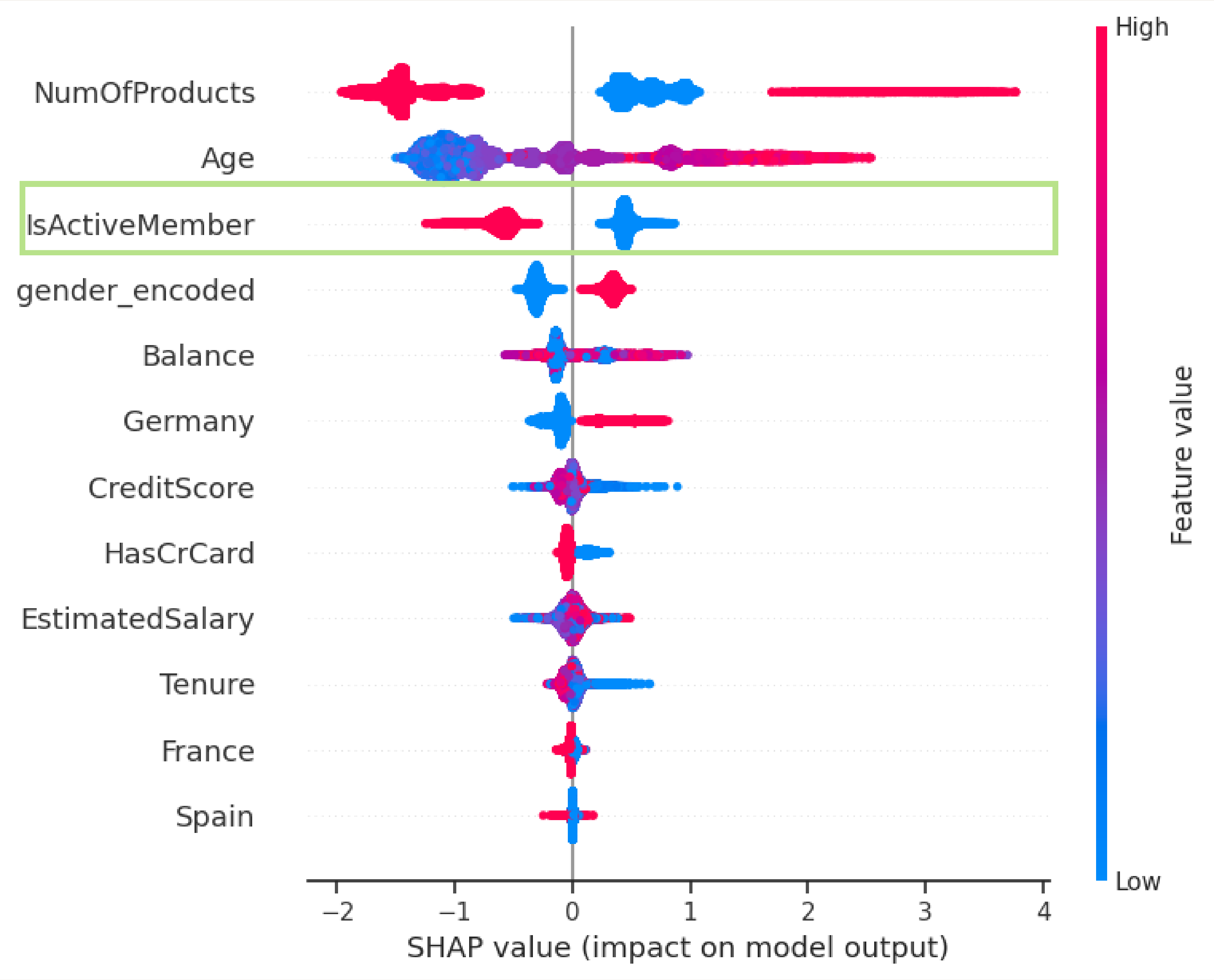
SHAP BEESWARM PLOT



Number of Products

- Investigating the SHAP value for both plots, they are the same.

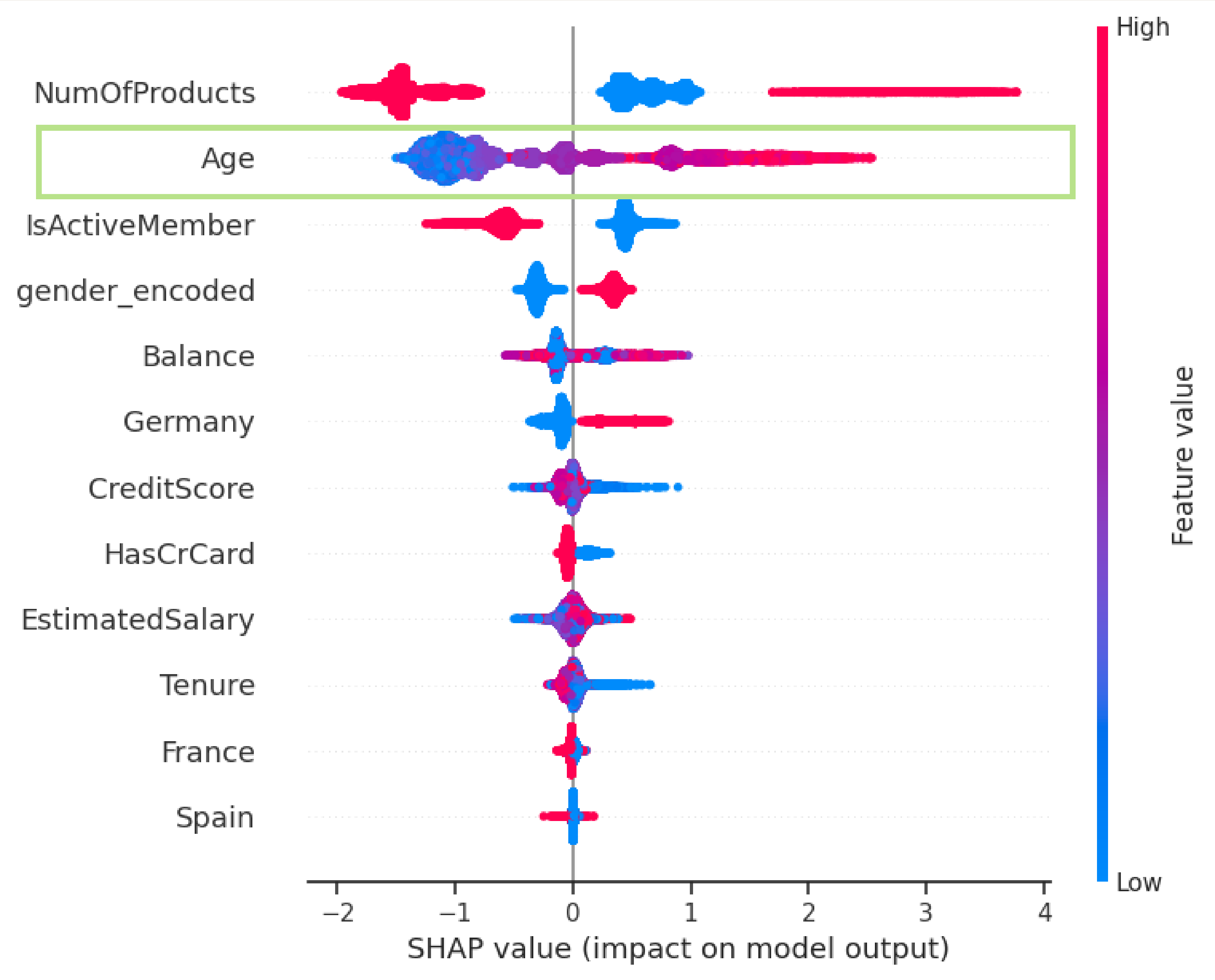
SHAP BEESWARM PLOT



Customer Activity

- For the customer activity feature, the beeswarm plot supports Dani's findings on the data analysis.
- Inactive customers are more like to churn than active members.
- Therefore, inactivity (value of 0) contributes positively to the churn factor while being active (value of 1) contributes negatively.

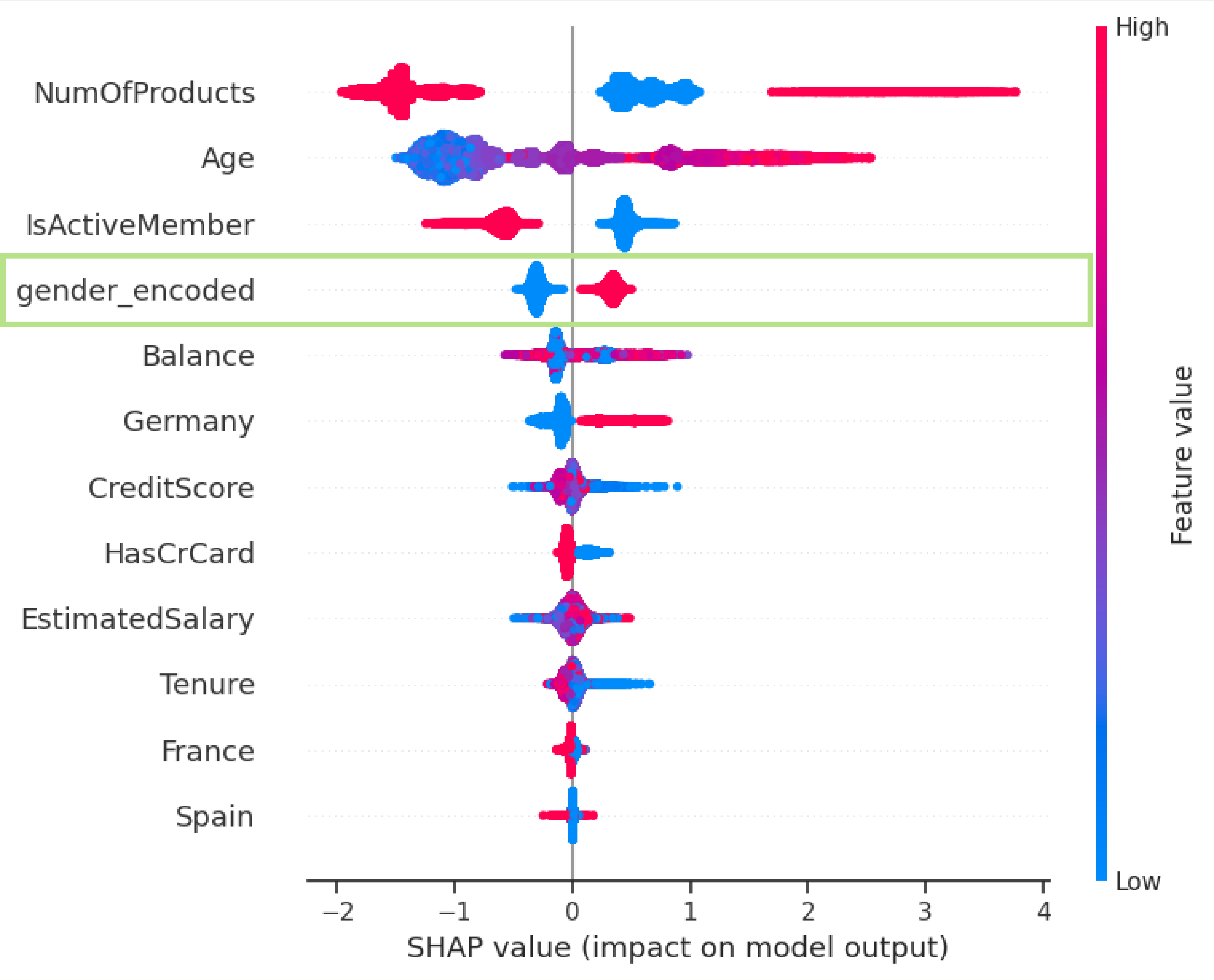
SHAP BEESWARM PLOT



Age

- For the Age feature, the beeswarm plot supports Dani’s findings on the data analysis.
- Older customer really tends to churn more, thus higher age contributes positively to the churn factor.

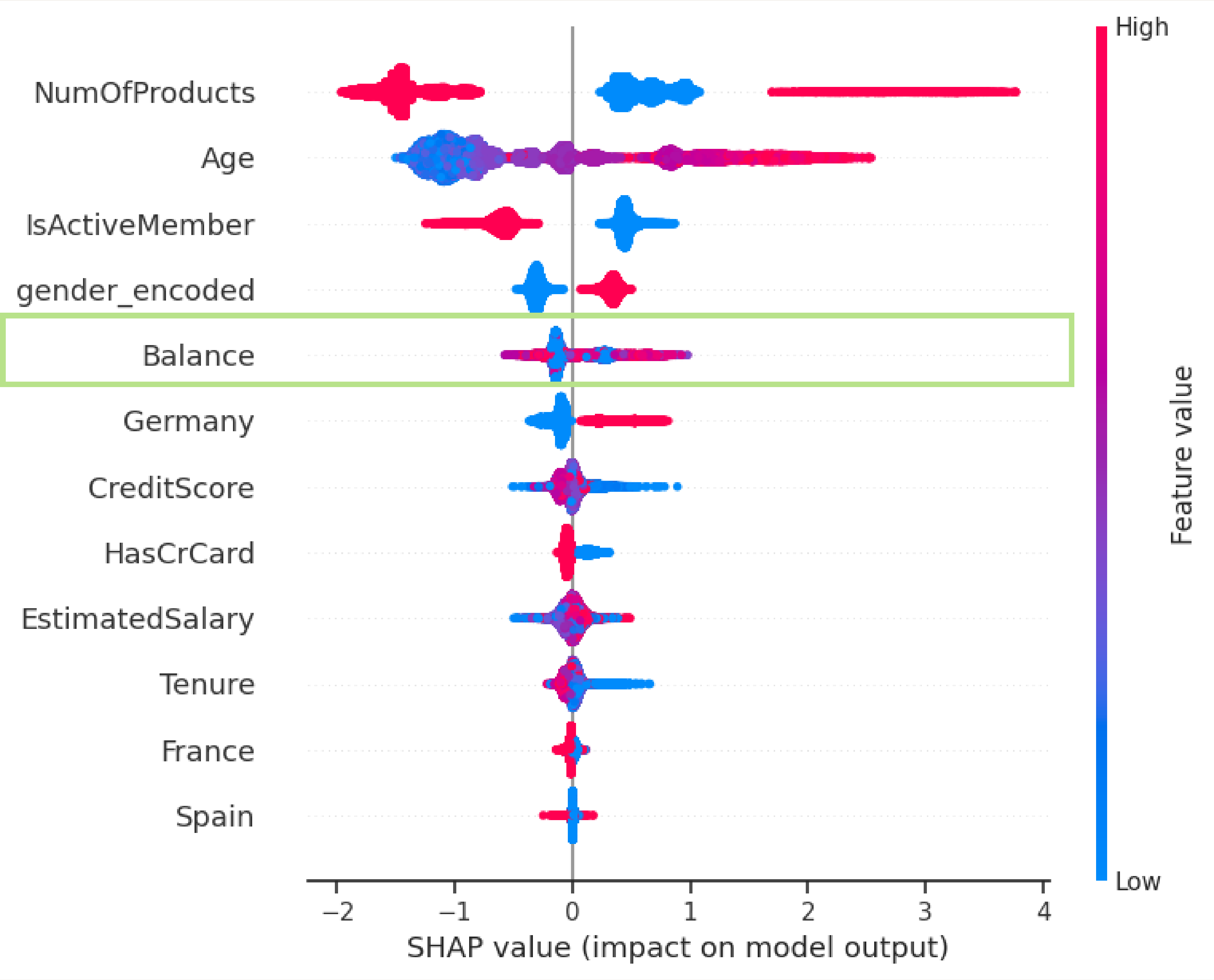
SHAP BEESWARM PLOT



Gender

- During the analysis, we found out that female customers are more likely to quit.
- Here, we can see that female customers (value or 1) do indeed affect the churn factor positively. However, it is not that much.

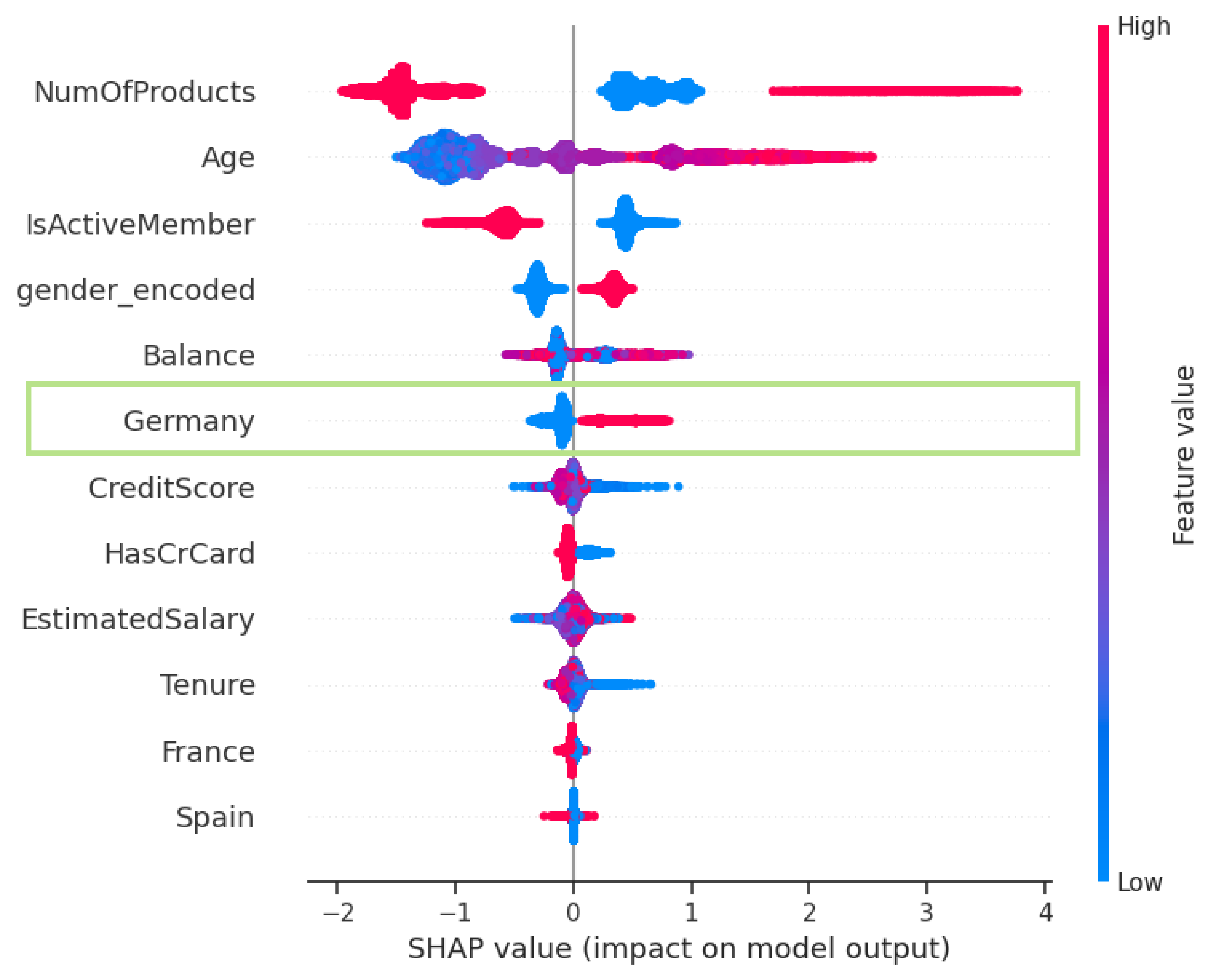
SHAP BEESWARM PLOT



Balance

- Balance, too, is consistent with Dani's findings during the data analysis.
- Customers with more balance than 0 does indeed affect that churn factor positively.
- Although it is also important to note that there are some customers with more than 0 balance that negatively affects the churn factor, but it is definitely not that much.

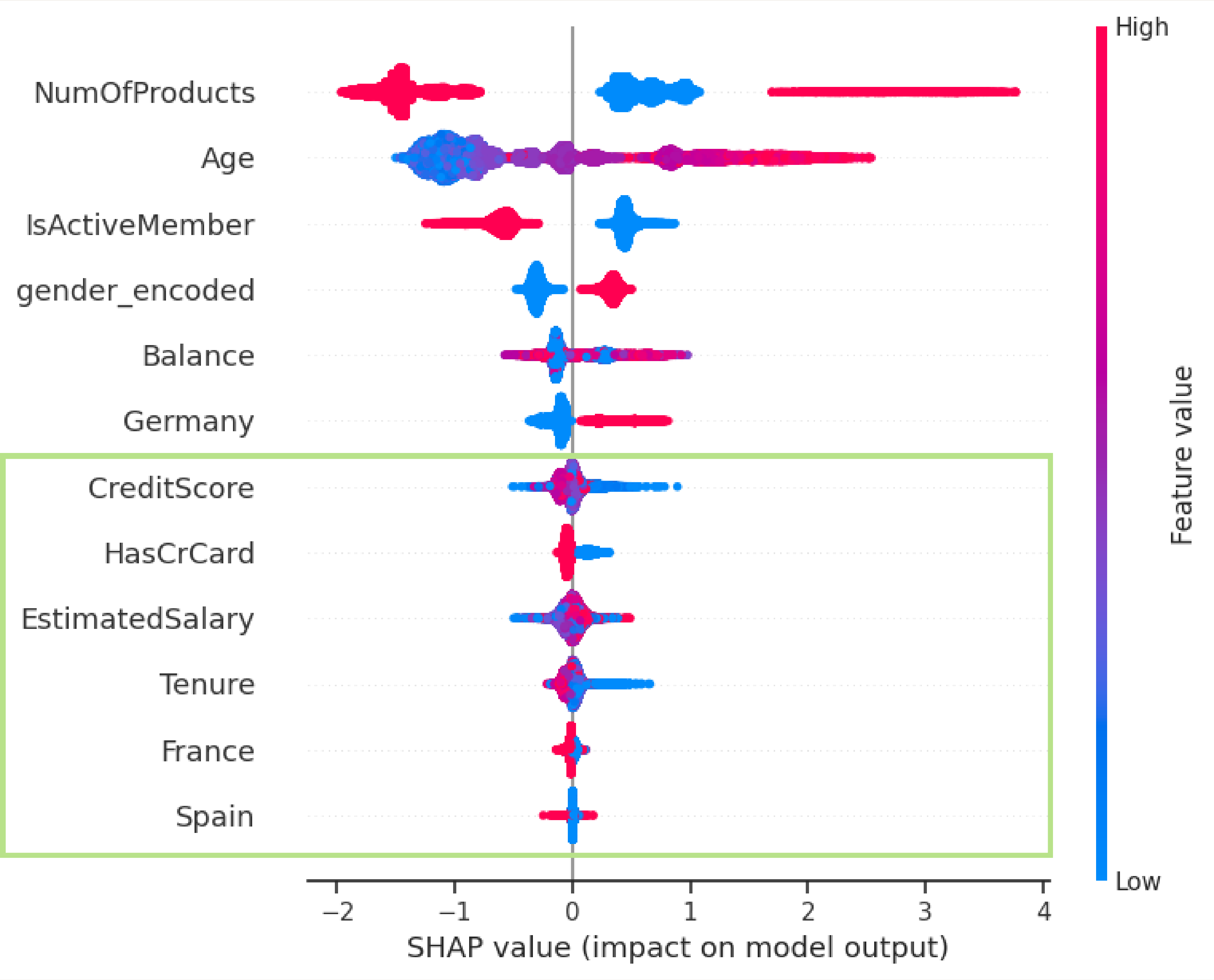
SHAP BEESWARM PLOT



Geography

- During the data analysis, Dani discovered that German customers are more likely to get churn.
- The result of the beeswarm plot is also consistent with that finding since German customers (value of 1, red dots) contributes positively to the SHAP value.

SHAP BEESWARM PLOT



Other features

- For other features, Dani either found them irrelevant or beyond her immediate findings during data analysis.
- For example, customers with lower tenure or lower credit score are more likely to churn.
- While the chosen machine learning algorithm might have uncovered deeper patterns leading to these associations, most of Dani's initial analysis aligns well with this model's predictions.
- This may be enough for Mark to finally place his trust in the model.

FINALLY!

After presenting the explainability portion of the best model generated by Dani, Mark was finally contented. He thinks that Dani definitely did a great job with her work, and her model is definitely worth deploying in their systems to further improve ABC Multinational Bank’s market positioning.

“Kudos, Dani! You absolutely smashed it!”

CONCLUSION

Let's end Dani's and Mark's story by summarizing what happened, and what they should do next!

SUMMARY OF DANI'S FINDINGS AND SUGGESTIONS

CUSTOMER ACTIVITY

- **50%** of the customers are inactive.
- **Inactive** customers are **more likely to leave**.
- **Female customers are more inactive** than male customers.

Suggestions	Let's **track customer inactivity and re-engage them** by letting them know we're here for them! We can achieve this through push notifications, emails, or text messages. To grab their attention, let's introduce compelling deals, offers, or new products that address their specific needs.

SUMMARY OF DANI'S FINDINGS AND SUGGESTIONS

AGE AND NUMBER OF PRODUCTS

- **Older customers are more likely to leave.**
- The **greater the number of products**, the **more likely they are to quit**.
- Having only 2 bank products seems to be the sweetest spot.
- Older people tend to have more products, and so they tend to leave more.

Suggestions

Let's identify pain points! The most probable reason here is customer dissatisfaction with our products. If they are overwhelmed with too many products (such as accounts), provide them with seamless ways that will allow them to manage their products. Perhaps the design of the products is too complex? Consider investing in User Experience (UX) then!

SUMMARY OF DANI'S FINDINGS AND SUGGESTIONS

AGE AND NUMBER OF PRODUCTS

- **Older customers are more likely to leave.**
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- Having only 2 bank products seems to be the sweetest spot.
- Older people tend to have more products, and yet they tend to leave more.

Suggestions

Other than identifying pain points, let's back it up by **offering incentives and tailored benefits for older customers.** It is important to understand their future plans and we, as a financial institution, must be able to evolve with our customer needs. Perhaps benefits suited for their retirements will work well?

SUMMARY OF DANI'S FINDINGS AND SUGGESTIONS

BALANCE	• Customers with more balance are more likely to churn than those with 0 balance.
Suggestions	Offer better benefits, such as higher interest rates.

SUMMARY OF DANI'S FINDINGS AND SUGGESTIONS

GEOGRA-PHY

- German customers are more likely to leave than French and Spanish customers.
- German customers generally have more balance than non-German customers.

Suggestions	**Let's further analyze the bank's market positioning in Germany**. Perhaps competitors provide better benefits? Since German customers have more balance, perhaps they also want greater interest rates.

SUMMARY OF DANI'S FINDINGS AND SUGGESTIONS

GENDER

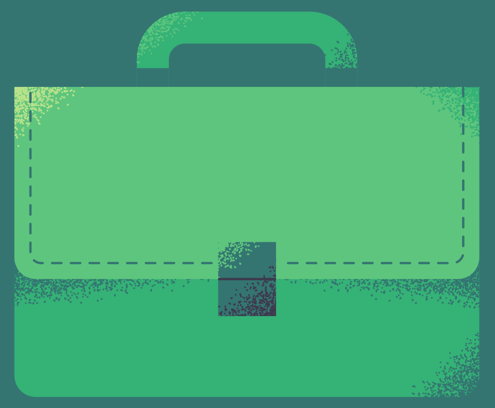
- Female customers are 2x more likely to churn than male customers.
- They are also more likely to become inactive.
- A lot of female customers with only 1 bank product have left.

Suggestions	**We need to develop products that cater to a diverse range of customers, including women.** By understanding and addressing the needs of different groups, we can create products that resonate with a wider audience.

AN IMPORTANT REMINDERS FOR MARK

Identify real causes

The dataset she worked on was limited. Talk to our valued customers and provide surveys to know their pain points.



Align strategies with business

Create strategies that are anchored to the business goals, objectives, and values.

AN IMPORTANT REMINDERS FOR MARK

Iterate and adapt

Monitor the progress of the implemented plans, and adapt to the evolving needs of customers to avoid increase in churn rate.

Continuous collaboration with Data Scientists

Resolve different issues other than churn rate in a data-driven manner.

AT LAST!

With Dani's help, Mark successfully identified the key factors behind customer churn. Their combined efforts also led to the development of an automated system that predicts potential churners, making it easier to implement intervention strategies.

This data-driven approach empowers Mark to tackle ABC Multinational Bank's churn rate head-on. Armed with these insights, he can now develop effective strategies to solidify the bank's market position.
素晴らしい!


THANK YOU!
以上です、ありがとうございました!