Why My Customers Are Leaving?

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Contents

Introduction

Customer attrition, or churn, is a critical challenge for businesses, especially in competitive industries like telecommunications.**"Becuase retaining existing customers is more profitable than acquiring new customers, primarily due to savings in acquisition costs, higher volume of service consumption, and customer referrals."**

For a telecom company based in Iran, building an effective customer retention program can reduce churn.To do so they can use their **Dataset**, to uncover patterns to understand why customers leave and identify those at high risk of leaving by accurately predicting customer churn so they can target them. By carefully analyzing and digging deeper into the dataset, we can predict and understand customer churn.

Methodology

Data Cleaning

Consistency of the dataset is important for meaningful data analysis, and we will make sure of it.

Here is a snapshot of the original dataset:

Table 1: A snapshot of the orginal dataset

Call..Failure	Complains	Subscription..Length	Charge..Amount	Seconds.of.Use	Frequency.of.use
8	0	37	0	4255	65

Call..Failure	Complains	Subscription..Length	Charge..Amount	Seconds.of.Use	Frequency.of.use
0	0	37	0	0	0
0	1	34	0	0	0
0	0	15	0	1275	14
13	0	40	1	6413	102

Here is a snapshot of the dataset after cleaning:

Table 2: A snapshot of the cleanded dataset

Call Failure	Complains	Subscription Length	Charge Amount	Seconds Of Use	Frequency Of Use
6	No complaint	38	0	5918	95
11	No complaint	36	0	2858	65
15	No complaint	13	0	6313	139
7	No complaint	28	0	1320	17
22	No complaint	36	2	15025	220

Table 3: A snapshot of the cleanded dataset

Frequency Of Sms	Distinct Called Numbers	Age Group	Tariff Plan	Status	Age
7	12	3	Pay as you go	Acitve	30
360	22	2	Pay as you go	Acitve	25
75	38	1	Contractual	Acitve	15
37	8	4	Pay as you go	Non-active	45
56	33	3	Pay as you go	Acitve	30

Table 4: A snapshot of the cleanded dataset

Customer Value	Churn
268.520	non-churn
1751.535	non-churn
767.360	non-churn
125.925	non-churn
833.800	non-churn

Exploratory data analysis

- Identifying a criteria that distinguishes customers is our goal in this section.

Although we will not explore every avenue of the dataset, we will start by asking a few questions and then refine our questions as we dig deeper:

1. What are the most and least common values within the data?
2. Are there any unusual patterns?
3. Are there any correlations within the data? Will start with calculated customer value in customers who left.

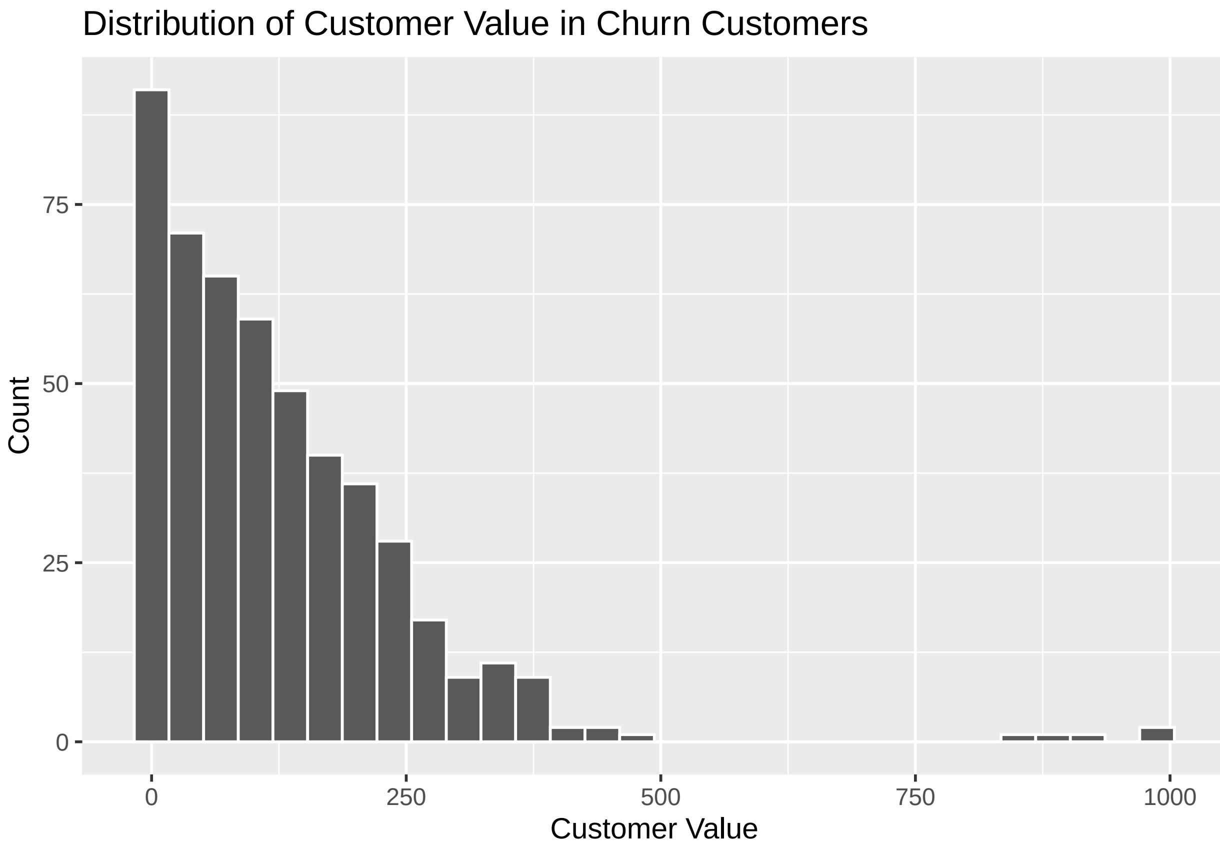
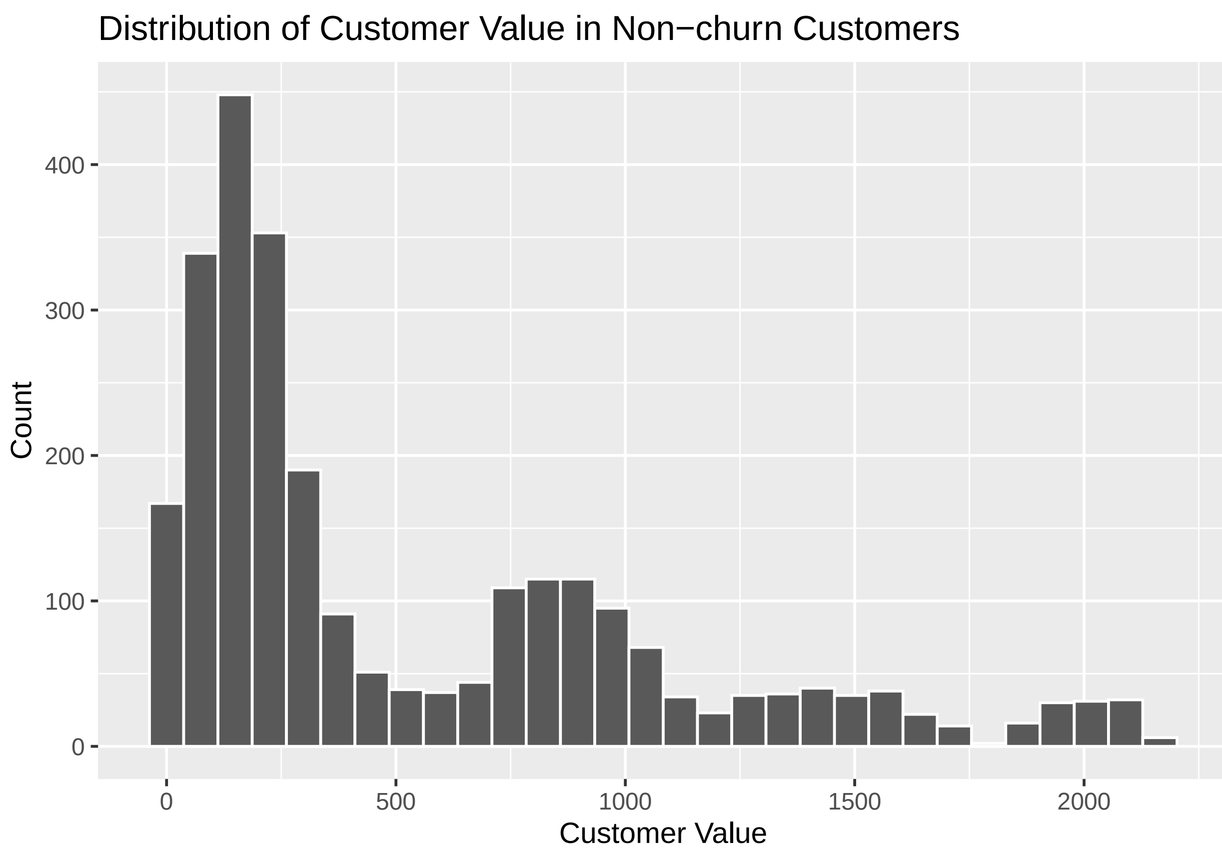


Figure 1: Figure 1 The Distribution of Calculated Customer Value and Churn

- Figure 1 shows that the most common values is zero which is not expected here it could be due to a missing value or real effect. Something to notice here that the figure is skewed to the right which in return might not represent the customers as they are we will address this problem later.
- Next we will see the most common values in non-churn customers.



- Figure 2 shows clustering or subgroups of customers with same values the most common value seems to be less than 500.

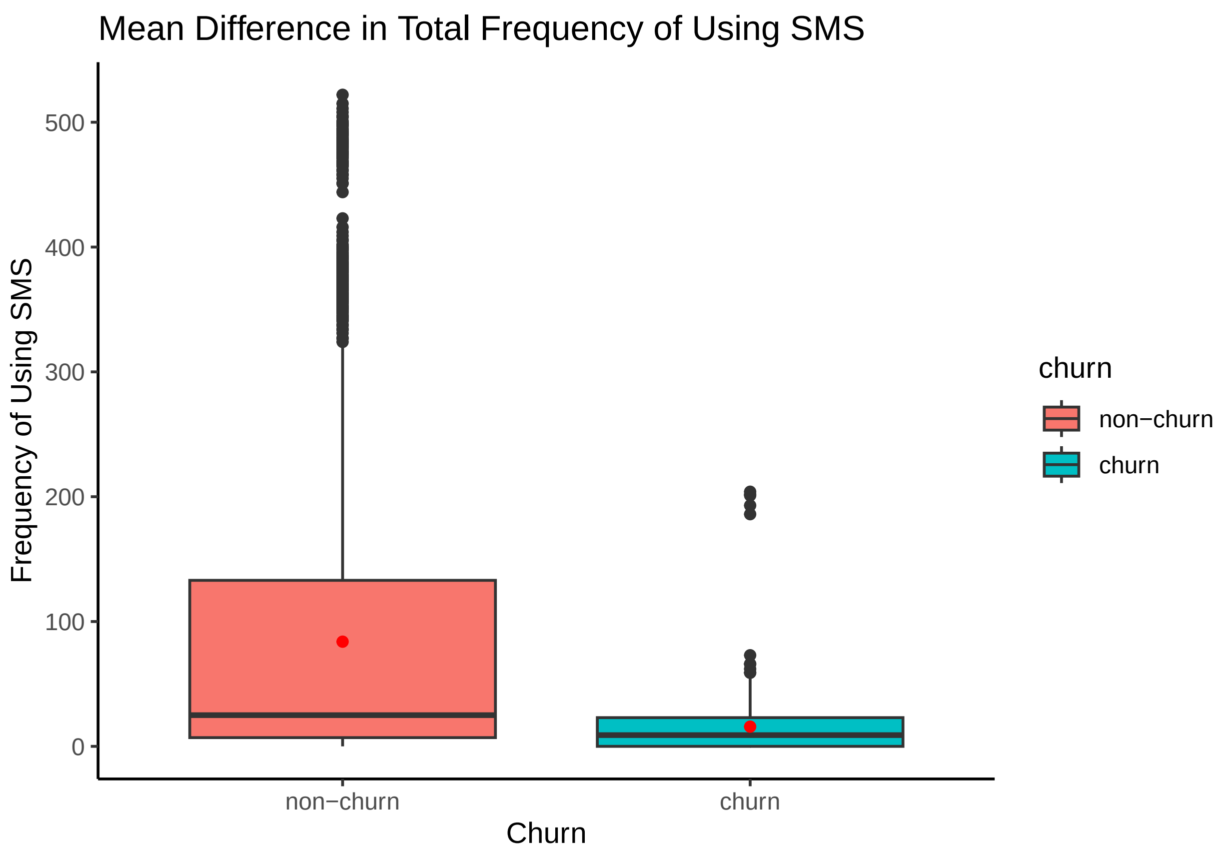


Figure 2: Figure 3 Mean ifference in frequency of using sms between churn and non-churn customers

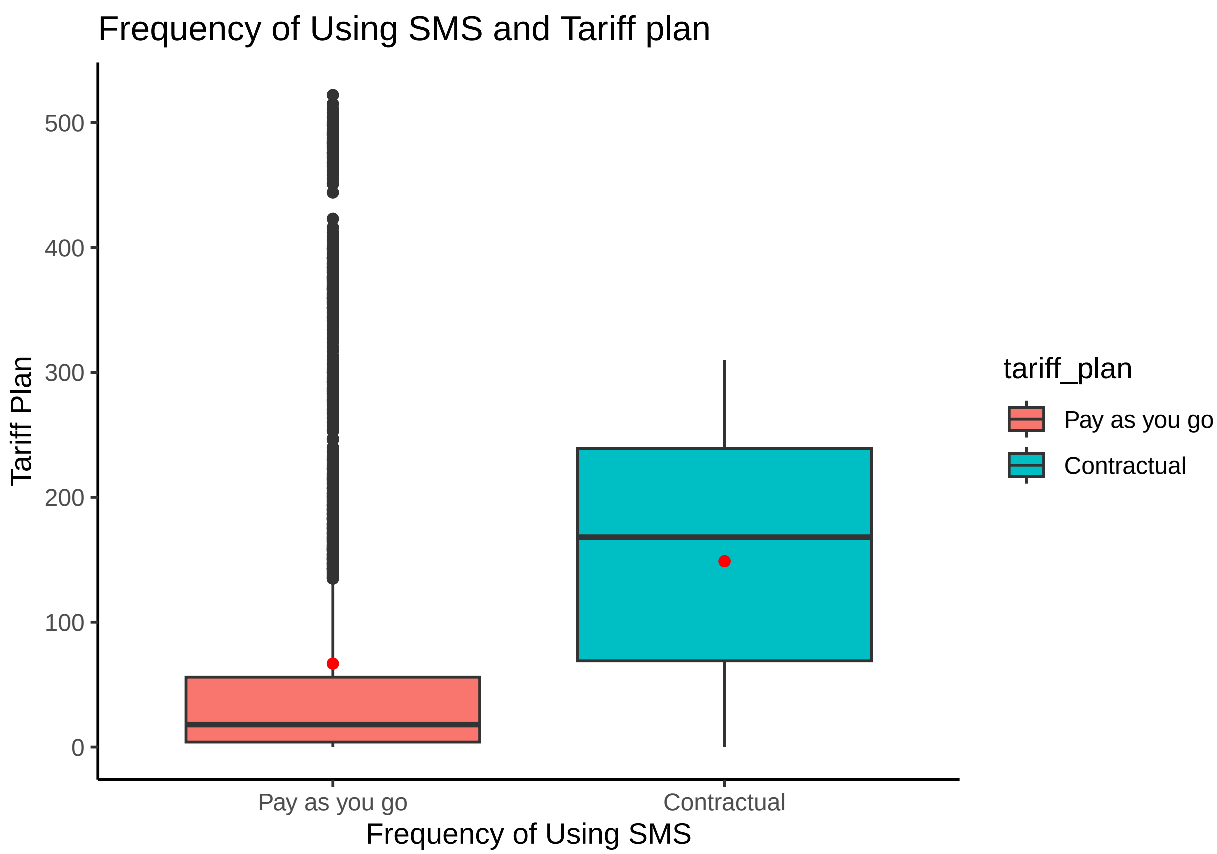


Figure 3: Figure 4 Mean total frequency of using sms and tariff plan

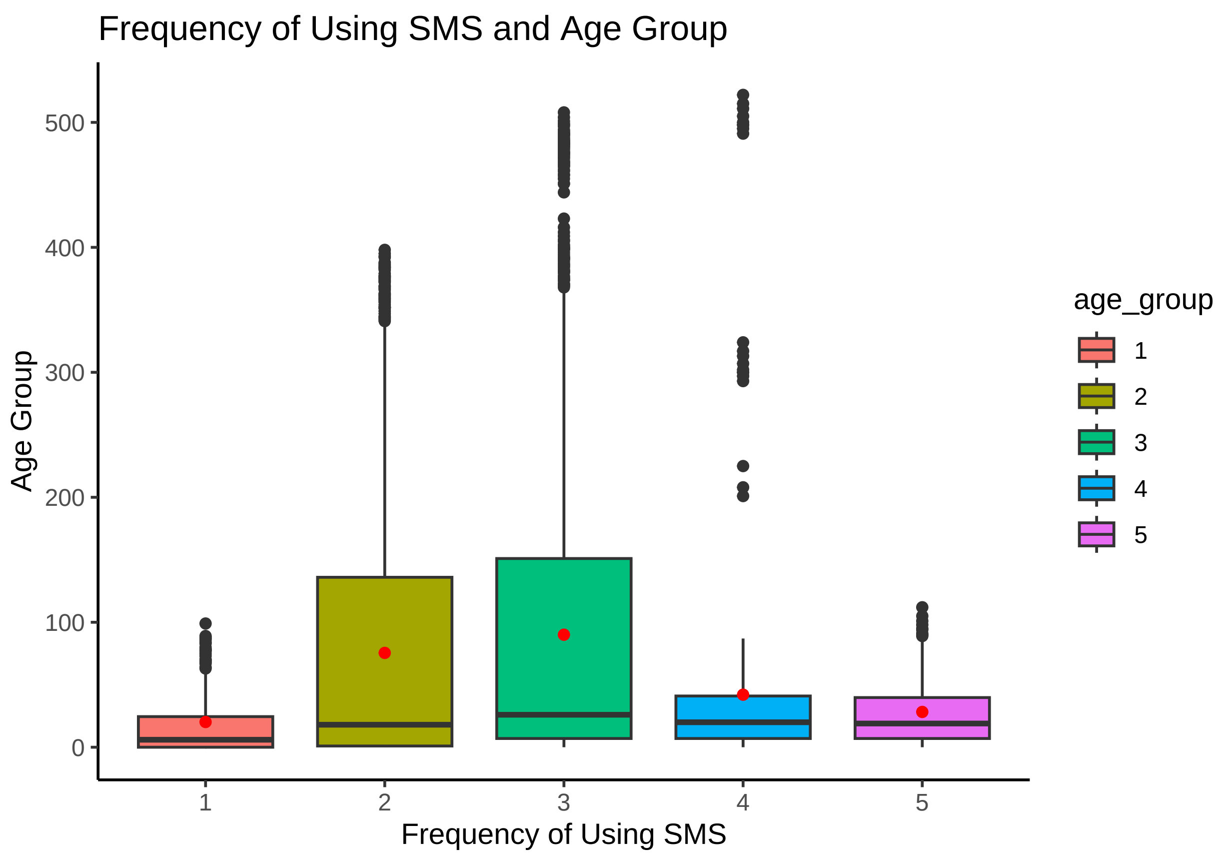


Figure 4: Figure 5 frequency of using sms and age group

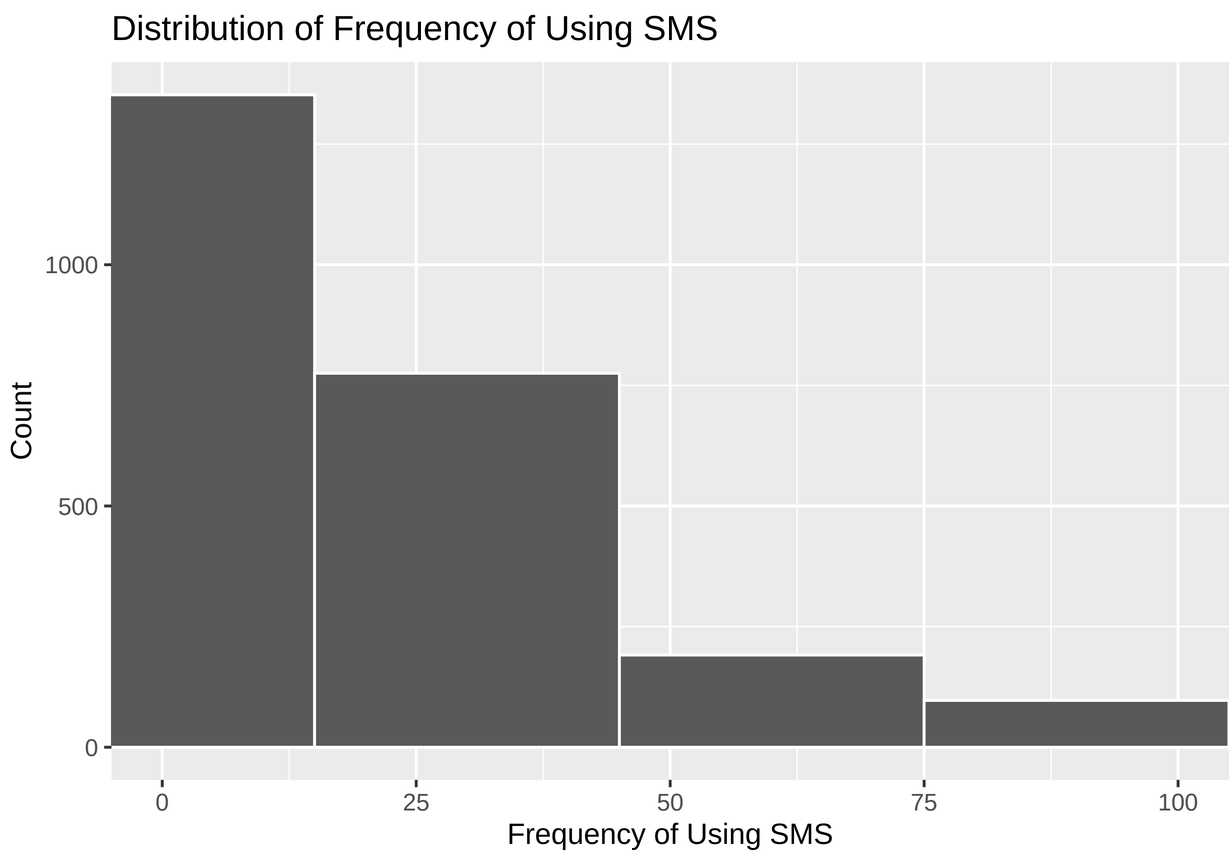


Figure 5: Figure 6 Distribution of Frequency of Using SMS

- **Could there be a difference in SMS usage?** Figure 3 compares the average SMS usage between churning and non-churning customers and shows a noticeable difference in average usage.
- **Tariff plan and SMS usage** In Figure 4, despite some overlap between plans in average SMS usage, there is still a difference, suggesting a potential link between plan and churn, but deeper analysis is required to determine if plan is a significant factor.
- **Age, usage and churn** As we have seen in Figure 5, there appears to be a relationship between usage frequency, SMS usage, age groups (as in this figure) and the decision of customers to either leave or stay. Further analysis is needed here to confirm whether the company needs to improve its messaging system, tariff plans and perhaps tailor its marketing strategy more towards certain age groups.
- **Zero SMS usage?**. In Figure 6 we can see that the most common value is zero, which raises questions such as:

1. Is it plausible that SMS usage is zero for most customers?
2. The figure is skewed to the right, indicating non-normality, what could be the real value?

The zero usage of messages could happen for some customers, so dropping the values will not do much here. But since the data is randomly selected, we can use bootstrapping to see if there is a meaningful difference in the statistical analysis part.

```
## # A tibble: 2 x 2
##   churn       cor
```

```
##   <fct>     <dbl>
## 1 non-churn 0.347
## 2 churn     0.128
```

Table 5: Summary statistics for non-churn customers

Variable Name	mean	sd	p0	p25	p50	p75	p100
call__failure	7.66	7.15	0	1.00	6.00	12.00	36.00
subscription__length	32.66	8.39	3	29.00	35.00	38.00	47.00
charge__amount	1.08	1.60	0	0.00	0.00	2.00	10.00
seconds__of__use	5014.22	4312.74	0	1819.00	3530.00	6892.50	17090.00
frequency__of__use	76.98	58.50	0	32.00	63.00	104.00	255.00
frequency__of__sms	83.87	118.81	0	7.00	25.00	133.00	522.00
distinct__called__numbers	25.58	17.39	0	12.00	23.00	36.00	97.00
age	31.07	9.15	15	25.00	30.00	30.00	55.00
customer__value	535.51	536.21	0	142.06	268.07	864.55	2165.28

Table 6: Summary statistics for churn customers

Variable Name	mean	sd	p0	p25	p50	p75	p100
call__failure	7.48	7.83	0	0.00	5.00	11.00	34.00
subscription__length	31.89	9.47	3	31.00	35.00	37.00	45.00
charge__amount	0.23	0.62	0	0.00	0.00	0.00	4.00
seconds__of__use	1566.63	1539.20	0	318.00	1182.00	2391.50	6123.00
frequency__of__use	29.13	26.32	0	6.00	25.00	45.50	100.00
frequency__of__sms	15.80	23.52	0	0.00	9.00	23.00	204.00
distinct__called__numbers	12.39	10.87	0	2.00	10.00	20.00	48.00
age	30.64	6.89	25	25.00	30.00	30.00	55.00
customer__value	124.81	129.43	0	38.38	96.84	181.32	987.26

Table 7: The correlation between frequecy of use and charge amount

churn	cor
non-churn	0.35
churn	0.13

- The summary in table 5 and 6 shows a difference in means between customers who stayed in the company for example the mean for frequency of using **SMS** is higher in customers who stayed.

Statistical analysis

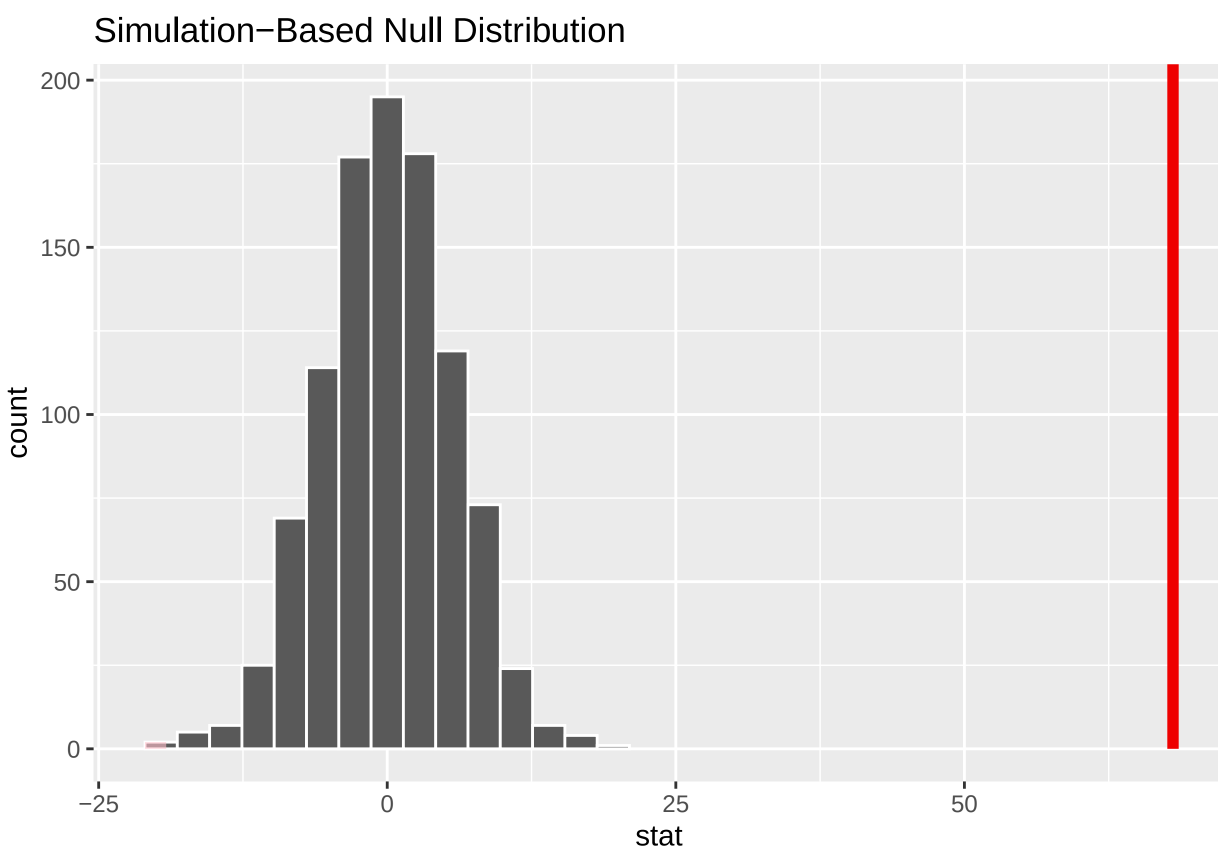
- **Assessing the significance in differences**
- Since we are going to conduct a hypothesis tests here we set our level of rejection (i.e meaning that the risk of rejecting the null hypothesis when it is true) to be 5%.

Figure 3 illustrates the difference in frequency of SMS usage between churn and non churn customers.Before drawing any conclusions, we will check if the difference is statistically discernible (i.e significant).

As this will inform us about the customer behavior.

The Testing Framework :

1. **Null hypothesis**$\{H_0\}$ There is no difference in mean of frequency of SMS usage between churn and non churn customers.
2. **Alternative hypothesis**$\{H_0\}$ There is a difference in mean of SMS usage between the churn and non churn customers.




```
## # A tibble: 1 x 1
##   p_value
##     <dbl>
## 1       0
```

Here the the p-value is 0 that i.e (the compatibility of data and the null hypothesis), we can conclude that we have a convincing evidence to reject the null hypothesis.

Indicating that there are real differences between churn and non-churn in frequency of SMS usage.

- To quantify the difference, we will construct a confidence interval for the difference in **SMS usage** :

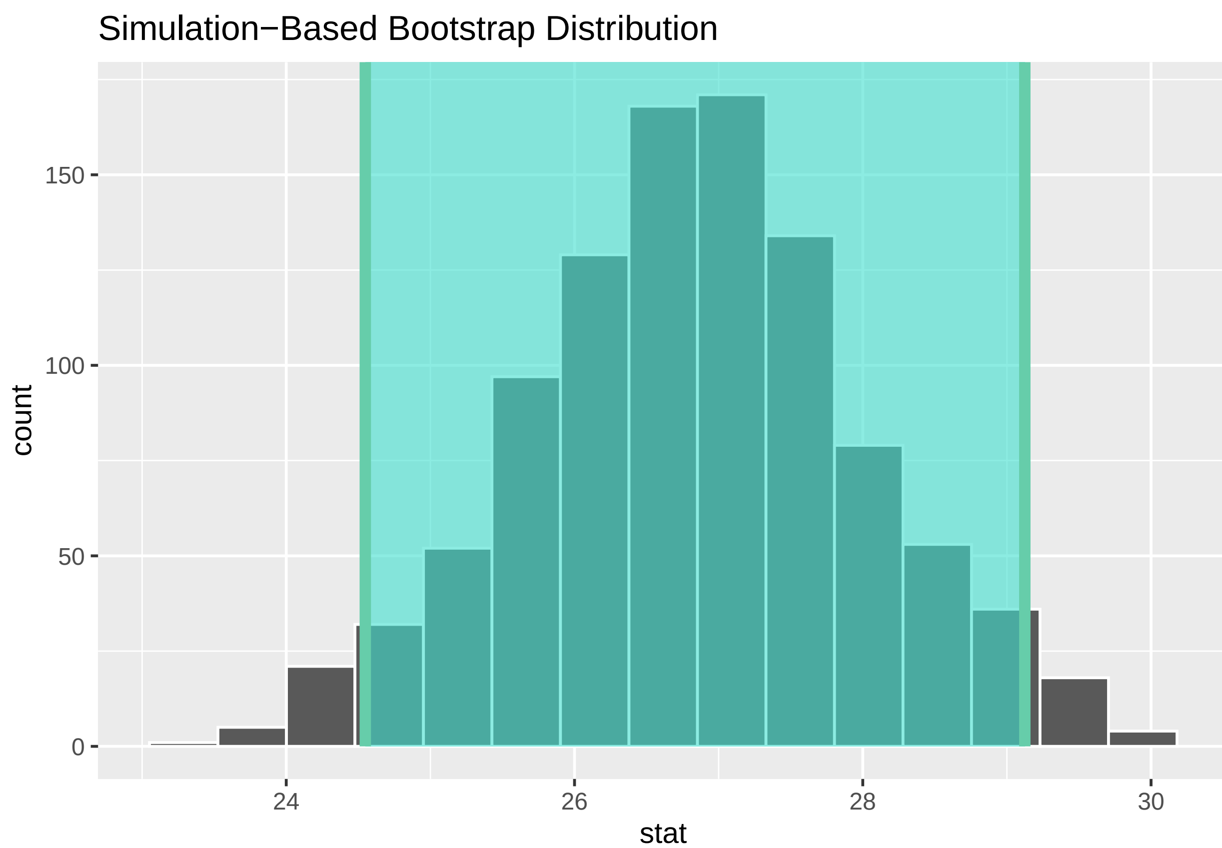


Table 8: 95% level of confidence in the range of differences in churn and non-churn customers

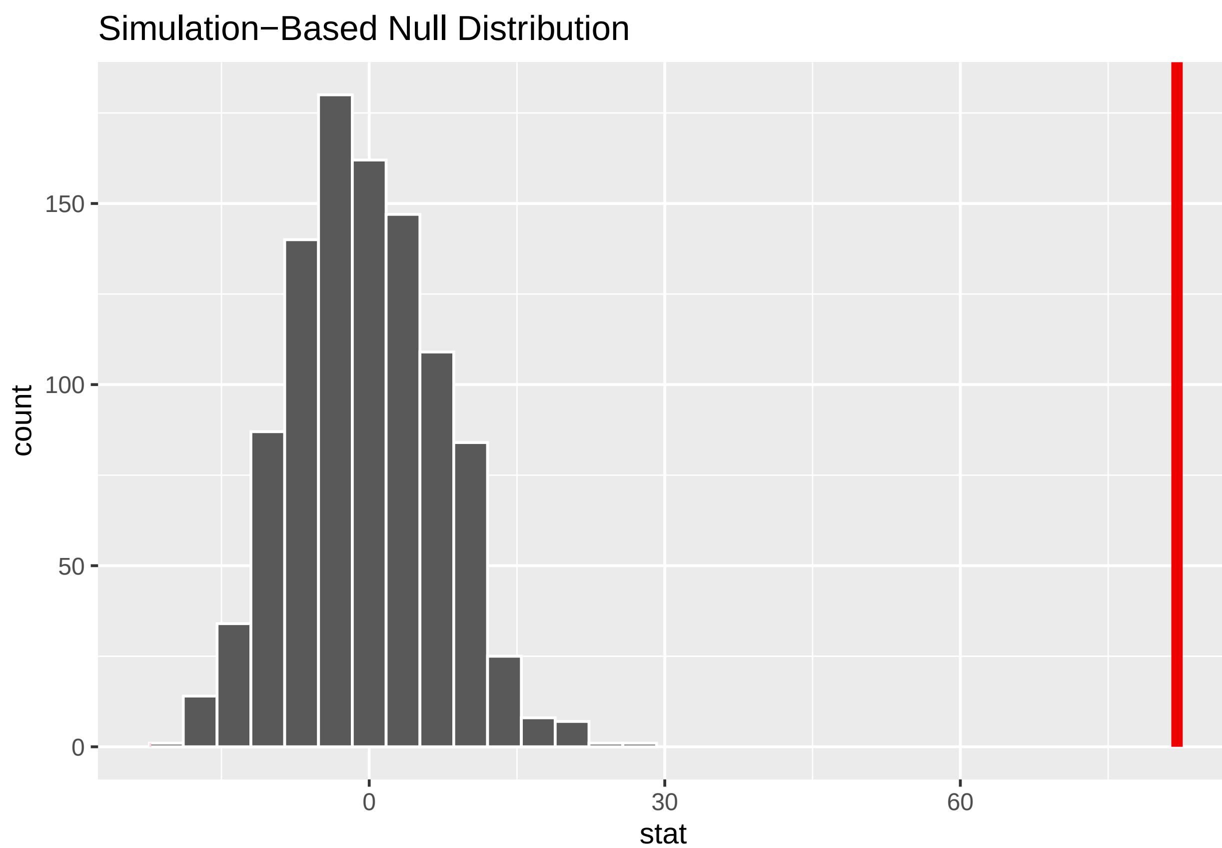
lower_ci	upper_ci
24.55	29.12

- **Assessing the Differences in Tariff Plans**

Figure 4 is showing a difference in frequency of SMS usage between tariff plans before continuing we will check if the difference is statistically discernible (i.e significant).

To do so we will conduct a hypothesis test :

1. **Null hypothesis**$\{H_0\}$ There is no difference in mean of frequency of SMS usage between the two tariff plans.
2. **Alternative hypothesis**$\{H_A\}$ There is a difference in mean of SMS usage between the two tariff plans.




```
## # A tibble: 1 x 1
##   p_value
##     <dbl>
## 1       0
```

- Since the p-value is 0, we can say that we have a convincing evidence to reject the null hypothesis.

Indicating that there are real differences between tariff plans in frequency of SMS usage.

An implication for the company might be asking what can make their messaging system more attractive.

Even though there are limitation to this analysis that needs to be considered, we will discuss it later.

Predictive analytics

Knowing in advance which group or subgroup of customers are likely to leave, is our aim here in which we are going to build a model step by step :

1. Fit the model: We use logistic regression for the predictive model and apply backward selection to choose variables with significant p-values.

Table 9: A table for logistic regression based-model

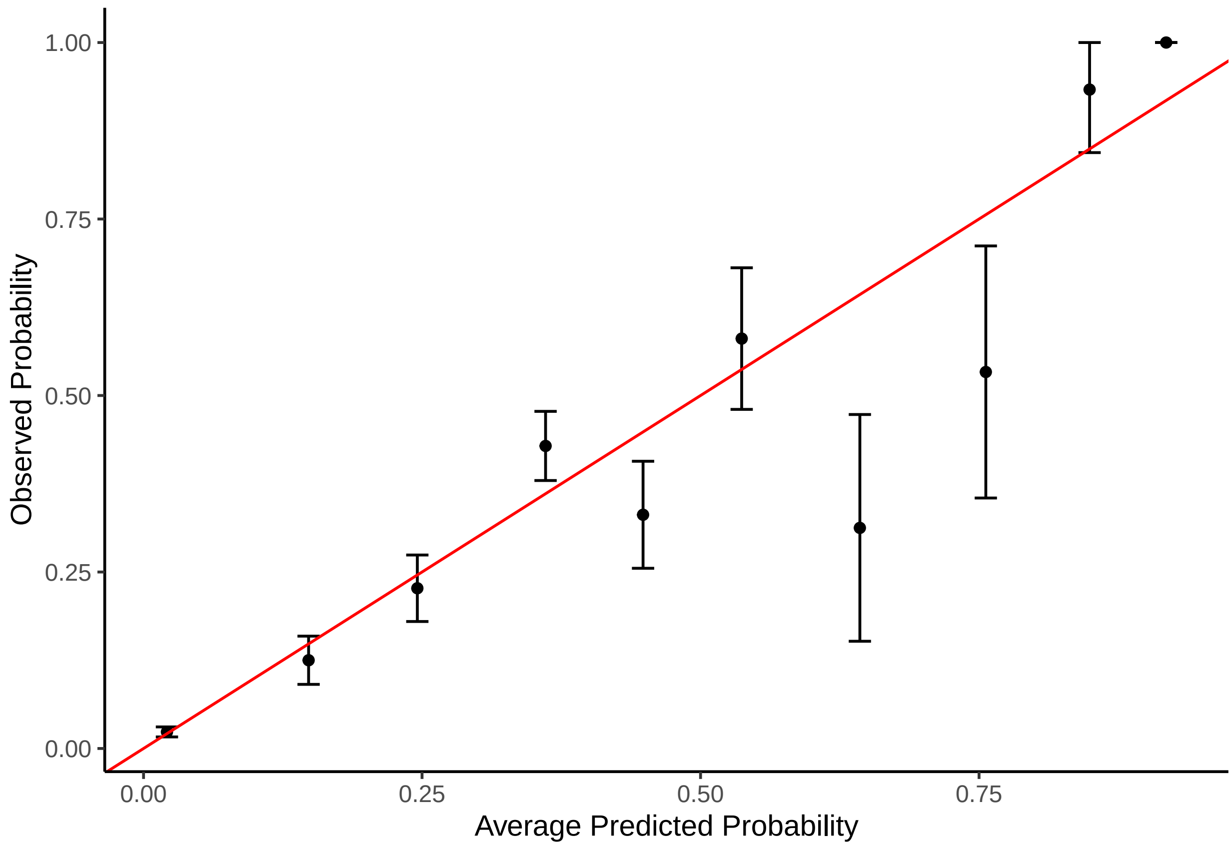
term	estimate	std_error	statistic	p_value	conf_low	conf_high
(Intercept)	-0.43	0.03	-14.64	0	-0.49	-0.38
call_failure	0.17	0.00	62.25	0	0.17	0.18
charge_amount	-0.75	0.02	-41.12	0	-0.79	-0.72
frequency_of_sms	-0.01	0.00	-68.63	0	-0.01	-0.01
frequency_of_use	-0.03	0.00	-55.96	0	-0.04	-0.03

- Table 5 summarizes the logistic regression model after backward selection, showing only the variables with significant p-values.

2.For the logistic regression model to provide valid results, certain assumptions must be satisfied :

Independecy: The data has been collected randomly, so we assume suffeciency in this condition.

Linearity: Which for this condition to work linear relationship between logit and predictor variables needs to exist:



The plot compares predicted probabilities (x-axis) with observed probabilities (y-axis). The points should cluster around the red diagonal line (representing perfect predictions). This indicates that the model's linearity assumption holds since the observed probabilities match predicted values closely.

3. After checking the conditions, we check the accuracy of the model (i.e how much the model can explain the churn variable).

To do so we will use 5-fold cross-validation

The accuracy of the model is **0.86**.

- We can evaluate the model in another way here it is :

```
##
##              non-churn churn
##   churn             77   123
##   non-churn       2578   372
```

The table there is telling true negatives, positives, and false negatives and positives(i.e how many predictions that our model got it right and it was about 0.86).

But this accuracy might be **misleading** because the model was trained and tested on the same data set.

We will take the same steps but training and testing on different data sets.

```
##
## glm.pred    non-churn churn
##   churn              4    26
##   non-churn       1675   285
```

The accuracy rate here is 0.85 and Missclassification rate is 0.15.

4. Model predictions. We can use the model we to apply it only on certain customers :

```
##    1    2
## 0.06 0.07
```

As the task at hand is only to do prediction and not to interpret coefficients, a model that suffers from high multicollinearity will likely lead to unbiased predictions of the response variable. So multicollinearity is likely to not cause any substantial problems.

But we should be careful about **extrapolations**. In other words, just because our model supports a linear relationship doesn't mean that relationship holds for values outside our range. Predictions for such values is far away from the actual range often aren't accurate.

Conclusion

Our model, with an accuracy rate of 0.85, offers valuable predictive power, meaning the company can identify customers at risk of churn and intervene with tailored retention strategies. While some misclassification occurred, the model still provides strong actionable insights.