Data Analysis Project

Spring 2024

Chanyoung Park

Analyzing Insurance Auto Claims

Car Accident

Introduction

This semester we will be working with a dataset of auto claims filed by customers of an automobile insurance company located in the southwest and western regions of the United States.

Insurance companies depend on accurate pricing estimates to maintain profitability. Auto policies must be priced so that the insurance company makes a profit in the long run, given the costs of their customers' payouts for accident repairs, total loss car replacements, medical fees, and legal fees.

The executives at this insurance company have noticed declining profitability over the last several years and have hired you as a data science consultant to evaluate their claims data and make recommendations on pricing, customer behavior, and car insurance policy adjustments.

The objective of this project is to perform an exploratory data analysis on the `claims_df` dataset and produce an executive summary of your key insights and recommendations to the executive team at the insurance company.

Before you begin, take a moment to read through the following insurance company terms to familiarize yourself with the industry: Auto Insurance Terms

Auto Claims Data

The `claims_df` data frame is loaded below and consists of 6,249 auto claims submitted by customers of the insurance company. The rows in this data frame represent a single claim with all of the associated features that are displayed in the table below.

Data Definitions

Variable	Definition	Data Type
customer_id	Customer identifier	Character
customer_state	State of residence	Factor

highest_education	Highest level of education	Factor
employment_status	Employment status at time of claim	Factor
gender	Gender	Factor
income	Income (US Dollars)	Numeric
residence_type	Customer residence type	Factor
marital_status	Marital status	Factor
sales_channel	Customer acquisition method	Factor
coverage	Auto policy tier	Factor
policy	Auto policy type	Factor
vehicle_class	Vehicle type	Factor
vehicle_size	Vehicle size	Factor
monthly_premium	Customer monthly premium	Numeric
months_policy_active	Number of months policy has been active	Numeric
months_since_last_claim	Number of months since last claim	Numeric
current_claim_amount	Current claim amount	Numeric
total_claims	Total number of claims in customer history	Numeric
total_claims_amount	Total amount of all claims in customer history	Numeric
customer_lifetime_value	Customer lifetime value (total revenue - total claims cost)	Numeric

In [3]:

```
# Load necessary library
library(tidyverse)

# Specify the URL of the .rds file
claims_df <- readRDS(url("https://gmubusinessanalytics.netlify.app/data/claims_df.rds"))
```

In [4]:

```
# View data
claims_df
```

customer_id	customer_state	highest_education	employment_status	gender	income	residence_type	marital_statu
<chr>	<fct>	<fct>	<fct>	<fct>	<dbl>	<fct>	<fct
AA11235	Nevada	Bachelor	Medical Leave	Female	11167	Suburban	Marrie
AA16582	Washington	Bachelor	Medical Leave	Male	14072	Suburban	Divorce
AA34092	California	Associate	Employed	Male	33635	Suburban	Marrie
AA56476	Arizona	High School	Employed	Female	74454	Suburban	Sing
AA69265	Nevada	Bachelor	Employed	Female	60817	Suburban	Sing
AA71604	Arizona	Master	Employed	Female	87560	Suburban	Marrie
AA93585	California	Associate	Employed	Male	97024	Urban	Marrie
AB21519	California	Associate	Employed	Female	93272	Urban	Marrie

AB23825	California	Associate	Employed	Male	21509	Suburban	Sing
AB26022	Oregon	High School	Retired	Male	26487	Suburban	Sing
AB45325	Arizona	High School	Employed	Male	74215	Suburban	Marrie
AB60627	California	High School	Employed	Male	77517	Rural	Marrie
AB62982	Oregon	Doctoral	Employed	Female	77521	Suburban	Marrie
AB69140	California	Master	Employed	Male	36007	Suburban	Marrie
AB72731	California	Bachelor	Employed	Female	28358	Rural	Marrie
AB73565	California	Bachelor	Employed	Male	96748	Suburban	Marrie
AC22873	Arizona	High School	Medical Leave	Female	17120	Suburban	Marrie
AC24378	Arizona	High School	Employed	Female	48552	Urban	Marrie
AC40767	Washington	Bachelor	Employed	Male	68041	Urban	Sing
AC58002	California	Bachelor	Employed	Female	53907	Urban	Marrie
AC67315	Nevada	Bachelor	Employed	Female	96950	Suburban	Marrie
AC75391	Arizona	Associate	Employed	Female	35091	Suburban	Divorce
AC79024	Nevada	Bachelor	Employed	Male	23241	Suburban	Marrie
AD12500	California	High School	Employed	Female	42696	Suburban	Sing
AD38685	California	Associate	Employed	Male	62464	Urban	Marrie
AD56037	Arizona	High School	Employed	Male	87050	Suburban	Marrie
AD89594	California	Associate	Employed	Male	28651	Urban	Sing
AD95939	California	Bachelor	Employed	Male	28773	Suburban	Sing
AE23906	Arizona	Associate	Employed	Male	37256	Rural	Marrie
AE60813	Oregon	Associate	Employed	Female	75090	Rural	Marrie
⋮	⋮	⋮	⋮	⋮	⋮	⋮	
ZW51790	Arizona	Associate	Employed	Female	52342	Suburban	Marrie
ZW71731	California	Bachelor	Employed	Male	89284	Urban	Divorce
ZW76597	California	Bachelor	Retired	Female	13215	Suburban	Marrie
ZW79814	California	High School	Employed	Male	56980	Suburban	Marrie
ZW93288	California	Master	Employed	Female	22705	Suburban	Divorce

ZX35838	Oregon	Master	Employed	Female	70177	Rural	Marrie
ZX50209	California	Associate	Employed	Female	29815	Rural	Sing
ZX56541	California	Bachelor	Employed	Male	45329	Suburban	Marrie
ZX73673	Arizona	Bachelor	Employed	Male	74015	Suburban	Sing
ZX80668	Nevada	Bachelor	Employed	Male	43720	Suburban	Sing
ZX83542	California	Master	Disabled	Male	26585	Urban	Marrie
ZX86243	Arizona	Doctoral	Employed	Male	70247	Rural	Sing
ZX93551	Arizona	Bachelor	Retired	Female	23376	Suburban	Divorce
ZY33234	Nevada	High School	Employed	Female	66331	Suburban	Sing
ZY49833	California	Bachelor	Employed	Female	87020	Urban	Marrie
ZY57929	Arizona	Associate	Employed	Female	32799	Suburban	Divorce
ZY60545	California	Associate	Employed	Female	91535	Rural	Marrie
ZY90118	Washington	Associate	Medical Leave	Male	17161	Suburban	Marrie
ZY99878	California	High School	Employed	Male	90343	Urban	Sing
ZZ20738	California	High School	Employed	Female	28108	Suburban	Marrie
ZZ22047	Washington	Bachelor	Employed	Male	67798	Suburban	Divorce
ZZ22193	California	Master	Employed	Female	37675	Suburban	Sing
ZZ22858	Arizona	Bachelor	Employed	Female	70619	Rural	Marrie
ZZ41158	Washington	Associate	Employed	Male	28506	Suburban	Marrie
ZZ42291	California	Master	Employed	Female	77143	Rural	Marrie
ZZ43513	California	High School	Employed	Male	73597	Urban	Marrie
ZZ44902	Arizona	High School	Employed	Male	40117	Suburban	Marrie
ZZ49347	Oregon	High School	Employed	Male	72421	Suburban	Marrie
ZZ54454	Nevada	Master	Employed	Male	32510	Suburban	Sing
ZZ83340	Oregon	Doctoral	Employed	Female	96021	Urban	Marrie

Exploratory Data Analysis (80 Points)

Executives at this company have hired you as a data science consultant to evaluate their claims data and make recommendations on pricing, customer behavior, and car insurance policy adjustments.

You must think of **at least 8 relevant questions** that will provide evidence for your recommendations.

The goal of your analysis should be discovering which variables drive the differences between customers with large lifetime values and customers who cost the company more than they provide in revenue through monthly premiums.

Some of the many questions you can explore include:

- Are there types of customers, based on their policy or demographics, that are highly profitable?
- Do certain policies have a lower number of claims, leading to large profits?
- Are there "problem customers" which have a large number of claims?

You must answer each question and provide supporting data summaries with either a summary data frame (using `dplyr` / `tidyr`) or a plot (using `ggplot`) or both.

In total, you must have a minimum of 5 plots and 4 summary data frames for the exploratory data analysis section. Among the plots you produce, you must have at least 4 different types (ex. box plot, bar chart, histogram, heat map, etc...)

Each question must be answered with **supporting evidence** from your tables and plots.

See the example question below.

Sample Question

The sample below is from a previous semester where students analyzed a dataset, **employee_df**, with information on employees of a company and whether they decided to leave the company for another job.

The question, `R` code, and answer are examples of the correct style and language that you should use for your work.

Question

Is there a relationship between employees leaving the company and their current salary?

Answer: Yes, the data indicates that employees who leave the company tend to have lower salaries when compared to employees who do not. Among the 237 employees that left the company, the average salary was $76,625. This is over $20,000 less than the average salary of employees who did not leave the company.

Among the employees *who did not leave the company*, only 10% have a salary that is less than or equal to $60,000. When looking at employees who did leave the company, this increases to 34%.

Supporting Table and Visualization

Note - the sample code and output below is an image, not code cells

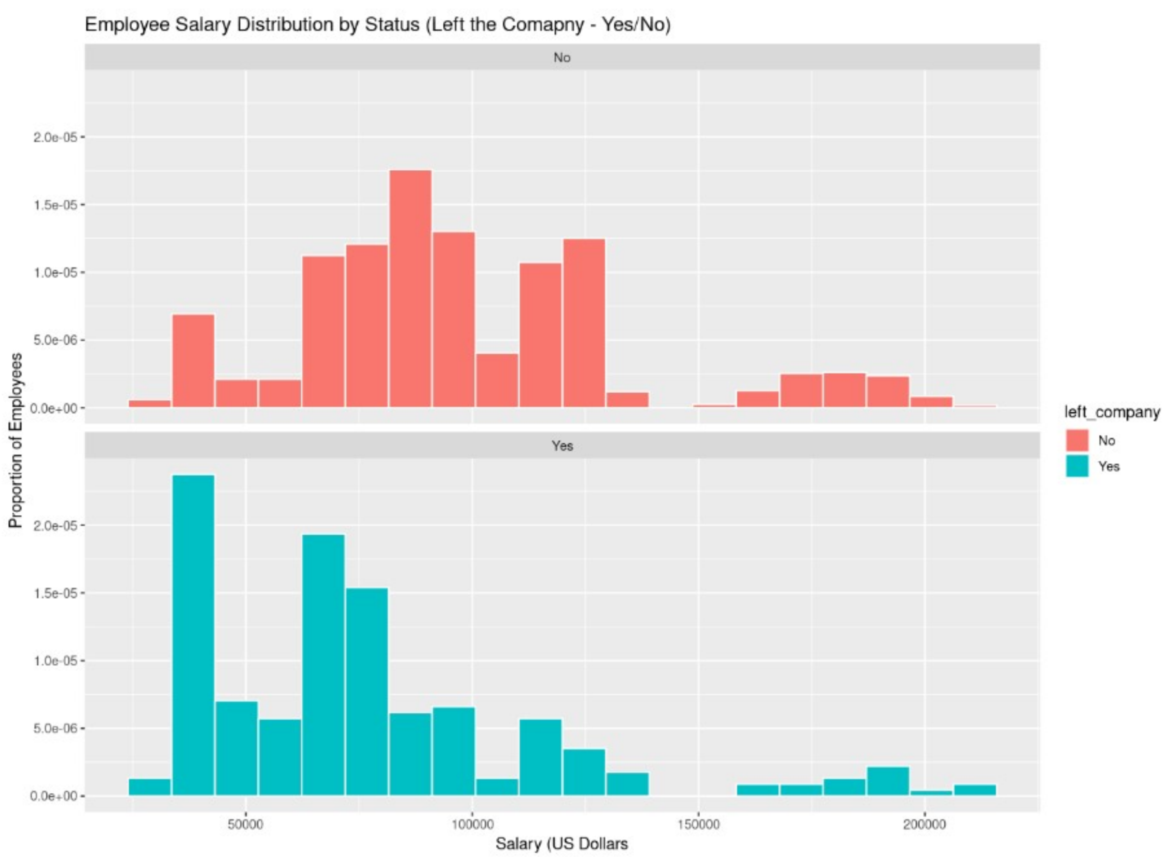
```
employee_data %>%
  group_by(left_company) %>%
  summarise(n_employees = n(),
            min_salary = min(salary),
            avg_salary = mean(salary),
            max_salary = max(salary),
            sd_salary = sd(salary),
            pct_less_60k = mean(salary <= 60000))
```

[13]

	left_company	n_employees	min_salary	avg_salary	max_salary	sd_salary	pct_less_60k
1	No	1233	29848.5566	97430.5201	212134.7005	36470.1844	0.0973
2	Yes	237	30488.1497	76625.5606	211621.0276	38567.4614	0.3418

```
ggplot(data = employee_data, aes(x = salary, fill = left_company)) +
   geom_histogram(aes(y = after_stat(density)), color = "white", bins = 20) +
   facet_wrap(~ left_company, nrow = 2) +
   labs(title = "Employee Salary Distribution by Status (Left the Comapny - Yes/No)",
           x = "Salary (US Dollars", y = "Proportion of Employees")
```

[14]



Question 1

Question: What are the demographic characteristics (age, gender, location) of our most profitable customers?

Answer: Yes, there are demographic characteristics that distinguish our most profitable customers.

Gender: Among the most profitable customers, 59.09% are Female, and 40.90% are Male, indicating a higher proportion of females in the most profitable customer segment.

Location: The distribution of the most profitable customers by state shows that California (35.46%), Oregon (28.23%), and Arizona (18.694%) have the highest proportions, suggesting that location is a relevant factor in profitability.

Supporting Analysis

In [32]:

```
# This code adjusts the figure output size in the notebook
options(repr.plot.width=11, repr.plot.height=8)
```

In [37]:

```
library(ggplot2)
library(dplyr)


# Calculate the overall percentage of profitable customers by gender
gender_distribution <- profitable_customers %>%
  group_by(gender) %>%
  summarise(count = n()) %>%
  mutate(percentage = count / sum(count) * 100)

# Calculate the distribution of profitable customers by state
state_distribution <- profitable_customers %>%
  group_by(customer_state) %>%
  summarise(count = n()) %>%
  mutate(percentage = count / sum(count) * 100)

# gender distribution
gender_distribution

# state distribution
state_distribution


# Summary data frames
profitable_customers <- claims_df %>% filter(customer_lifetime_value > quantile(customer
summary_q1 <- profitable_customers %>% count(customer_state, gender)
summary_q1

# Bar chart
ggplot(summary_q1, aes(x = customer_state, y = n, fill = gender)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(title = 'Distribution of Profitable Customers by State and Gender',
       x = 'State',
       y = 'Number of Profitable Customers')
```

A tibble: 2 × 3

gender	count	percentage
<fct>	<int>	<dbl>
Female	923	59.09091
Male	639	40.90909

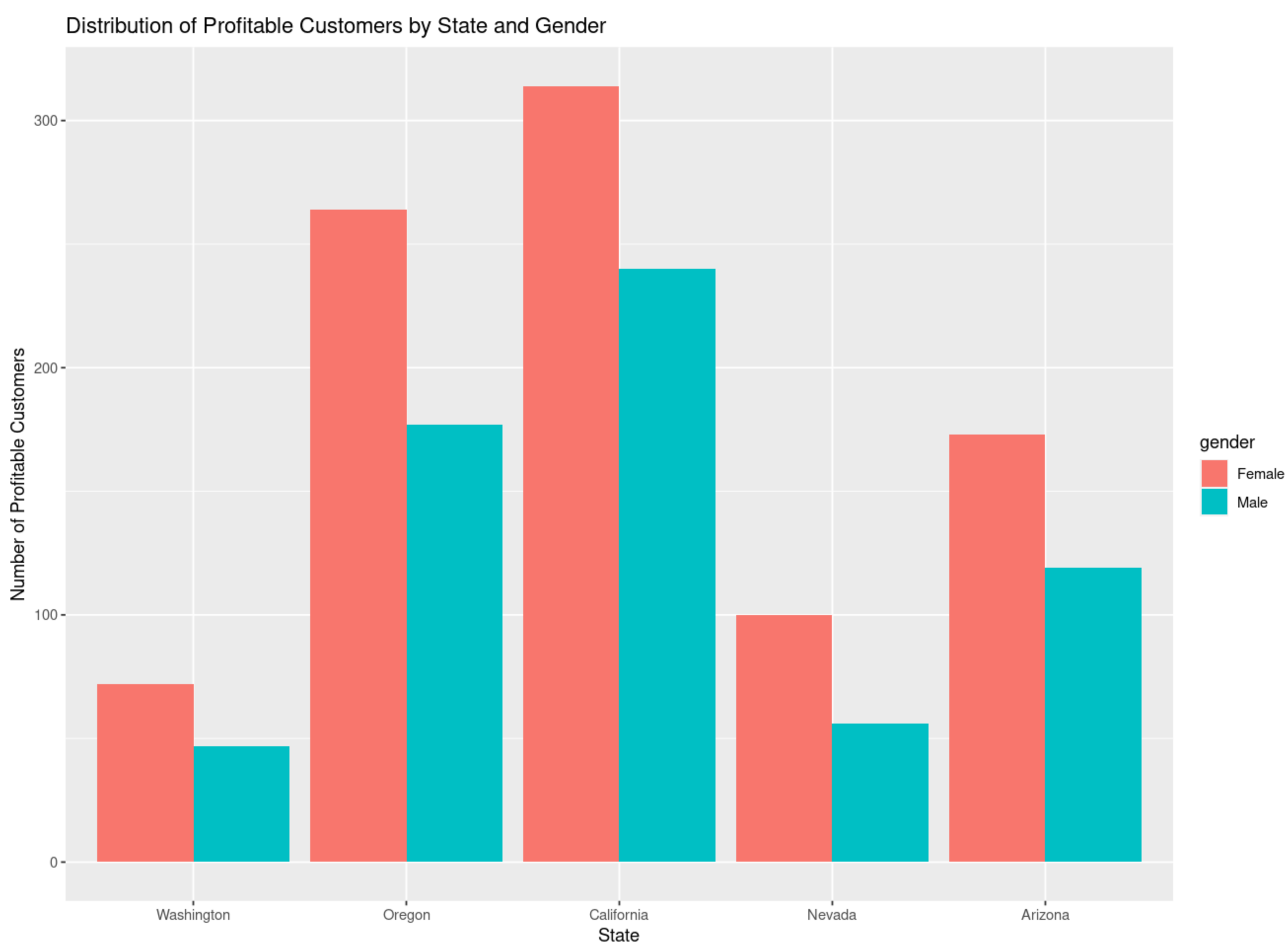
A tibble: 5 × 3

customer_state	count	percentage
<fct>	<int>	<dbl>
Washington	119	7.618438

Oregon	441	28.233035
California	554	35.467350
Nevada	156	9.987196
Arizona	292	18.693982

A tibble: 10 × 3

customer_state	gender	n
<fct>	<fct>	<int>
Washington	Female	72
Washington	Male	47
Oregon	Female	264
Oregon	Male	177
California	Female	314
California	Male	240
Nevada	Female	100
Nevada	Male	56
Arizona	Female	173
Arizona	Male	119



Question 2

Question: Is there a relation between the frequency and amount of claims to customer lifetime value?

Answer: Yes, there is a relation between the frequency and amount of claims to customer lifetime value.

The correlation between total claims and customer lifetime value is -0.28, indicating a slight negative relationship; as the number of claims increases, customer lifetime value tends to decrease. The correlation between total claims amount and customer lifetime value is -0.38, showing a moderate negative relationship; as the total claims amount increases, customer lifetime value tends to decrease more significantly.

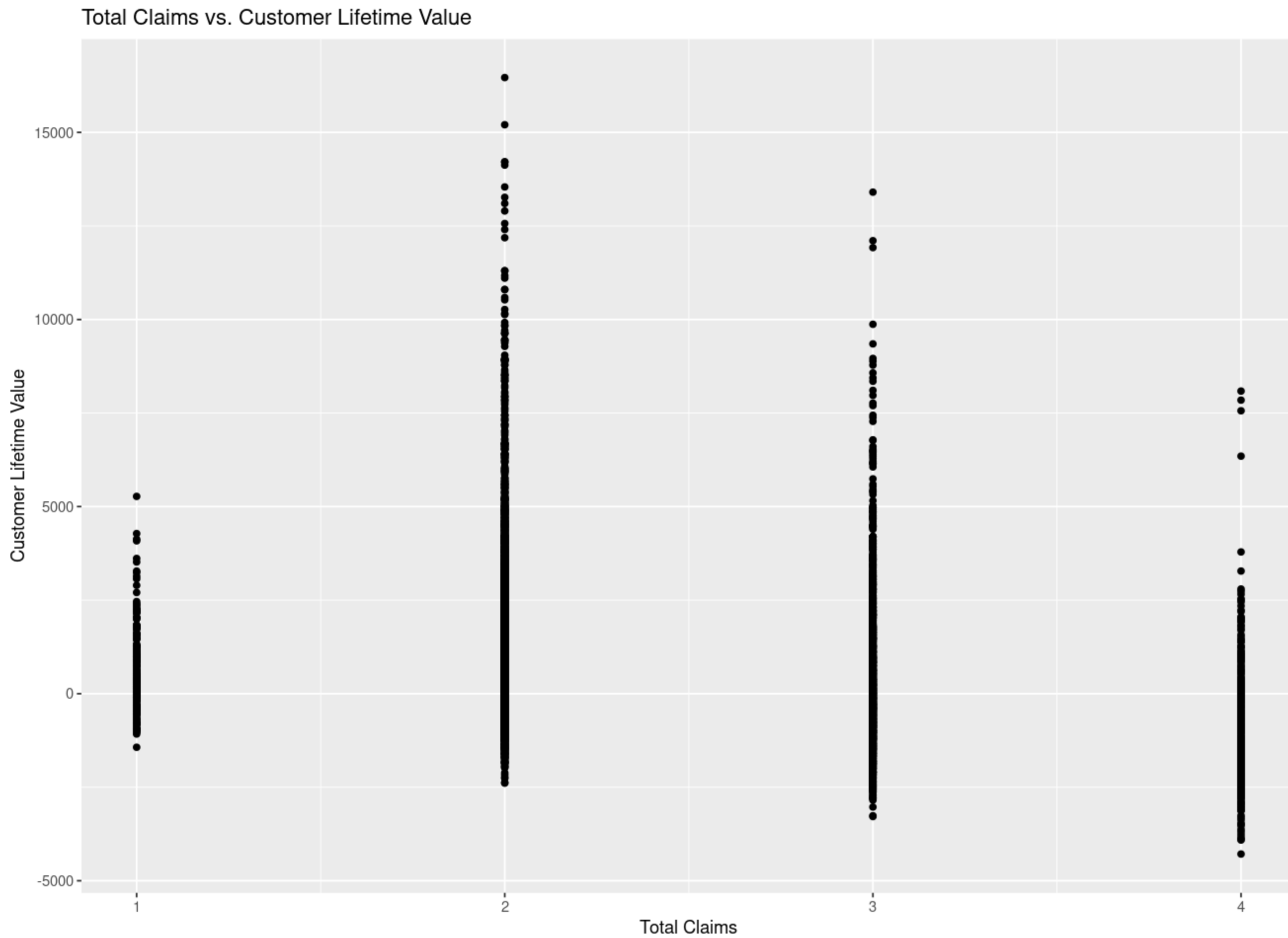
Supporting Analysis

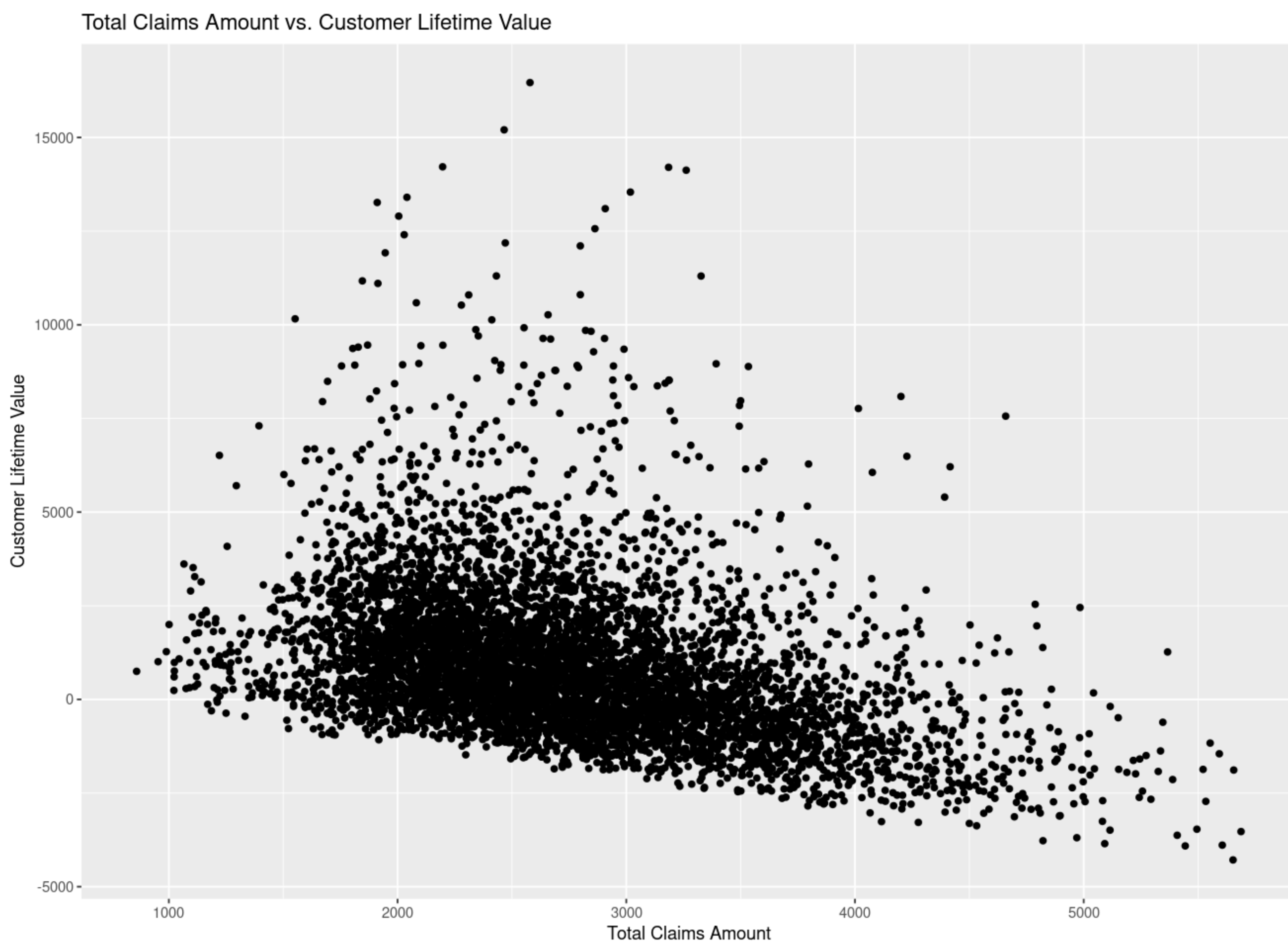
In [7]:

```
# Summary dataframe with correlation coefficients
summary_q2 <- claims_df %>% select(total_claims, total_claims_amount, customer_lifetime_
  cor()
summary_q2

# Scatter plot for total_claims vs. customer_lifetime_value
ggplot(claims_df, aes(x = total_claims, y = customer_lifetime_value)) +
  geom_point() +
  labs(title = 'Total Claims vs. Customer Lifetime Value',
       x = 'Total Claims',
       y = 'Customer Lifetime Value')

# Scatter plot for total_claims_amount vs. customer_lifetime_value
ggplot(claims_df, aes(x = total_claims_amount, y = customer_lifetime_value)) +
  geom_point() +
  labs(title = 'Total Claims Amount vs. Customer Lifetime Value',
       x = 'Total Claims Amount',
       y = 'Customer Lifetime Value')
```

A matrix: 3 × 3 of type dbl

	total_claims	total_claims_amount	customer_lifetime_value
total_claims	1.0000000	0.7362366	-0.2863264
total_claims_amount	0.7362366	1.0000000	-0.3861211
customer_lifetime_value	-0.2863264	-0.3861211	1.0000000


Total Claims vs. Customer Lifetime Value
Customer Lifetime Value
15000
10000
5000
0
-5000
1
2
3
4
Total Claims


Total Claims Amount vs. Customer Lifetime Value
Customer Lifetime Value
15000
10000
5000
0
-5000
1000
2000
3000
4000
5000
Total Claims Amount

Question 3

Question: Are there significant differences in lifetime values between customers with different policy types?

Answer: Yes, there are significant differences in lifetime values between customers with different policy types.

Corporate policy holders have an average customer lifetime value of 951.32, Personal policy holders have an average of 923.66, Special policy holders have a lower average of 745.95, indicating that policy type is a determinant in customer lifetime value.

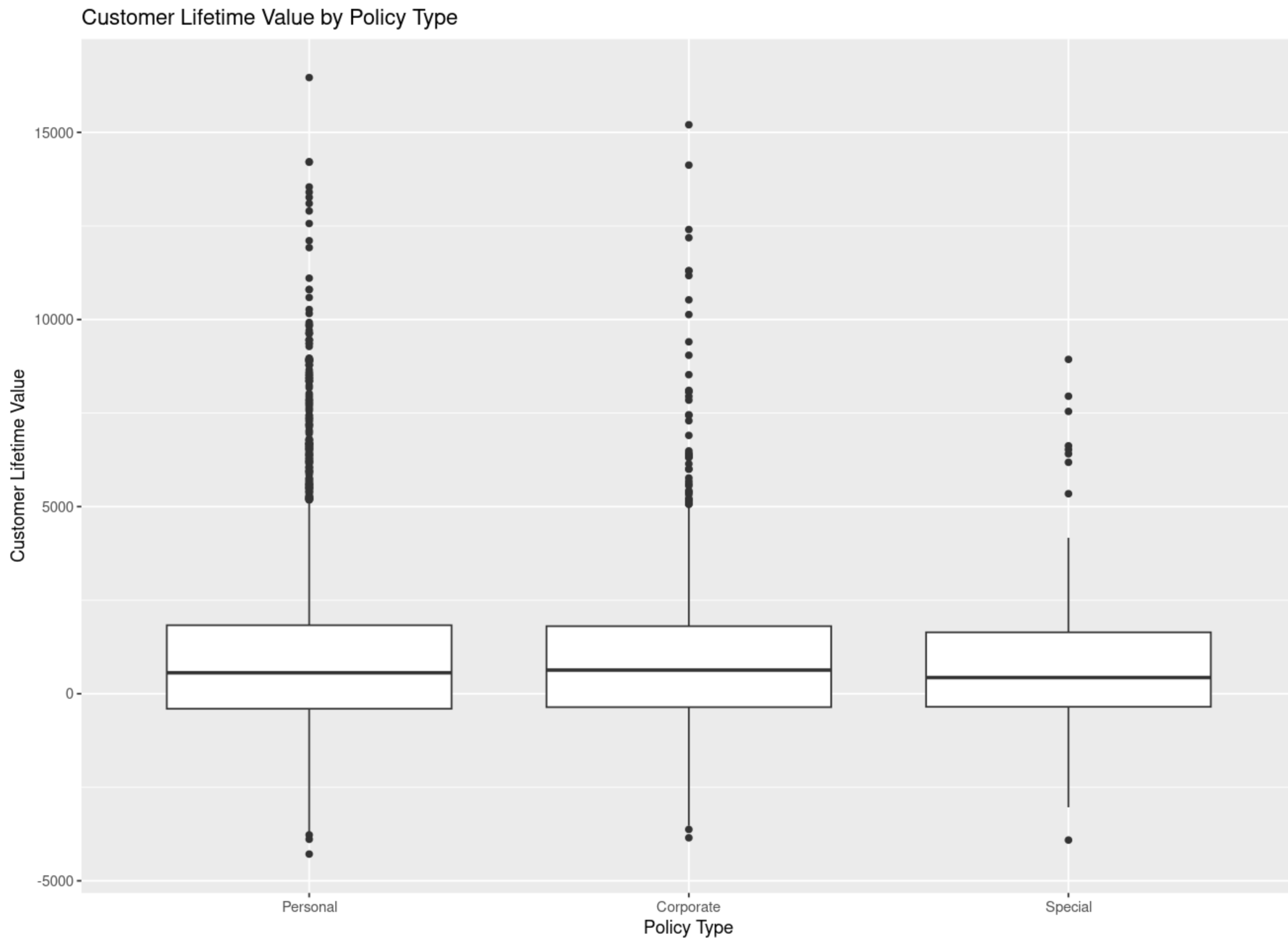
Supporting Analysis

In [14]:

```
# Summary dataframe with average customer lifetime value by policy type
summary_q3 <- claims_df %>% group_by(policy) %>%
  summarise(avg_customer_lifetime_value = mean(customer_lifetime_value))
summary_q3

# Box plot
ggplot(claims_df, aes(x = policy, y = customer_lifetime_value)) +
  geom_boxplot() +
  labs(title = 'Customer Lifetime Value by Policy Type',
       x = 'Policy Type',
       y = 'Customer Lifetime Value')
```

A tibble: 3 × 2

policy	avg_customer_lifetime_value
<fct>	<dbl>
Personal	923.6647
Corporate	951.3238
Special	745.9582



Question 4

Question: Which customer behaviors or attributes are correlated with higher lifetime values?

Answer: Yes, customer behaviors or attributes are correlated with higher lifetime values.

The correlation between monthly premium and customer lifetime value is 0.7368, indicating a strong positive relationship; as the monthly premium increases, customer lifetime value also tends to increase significantly.

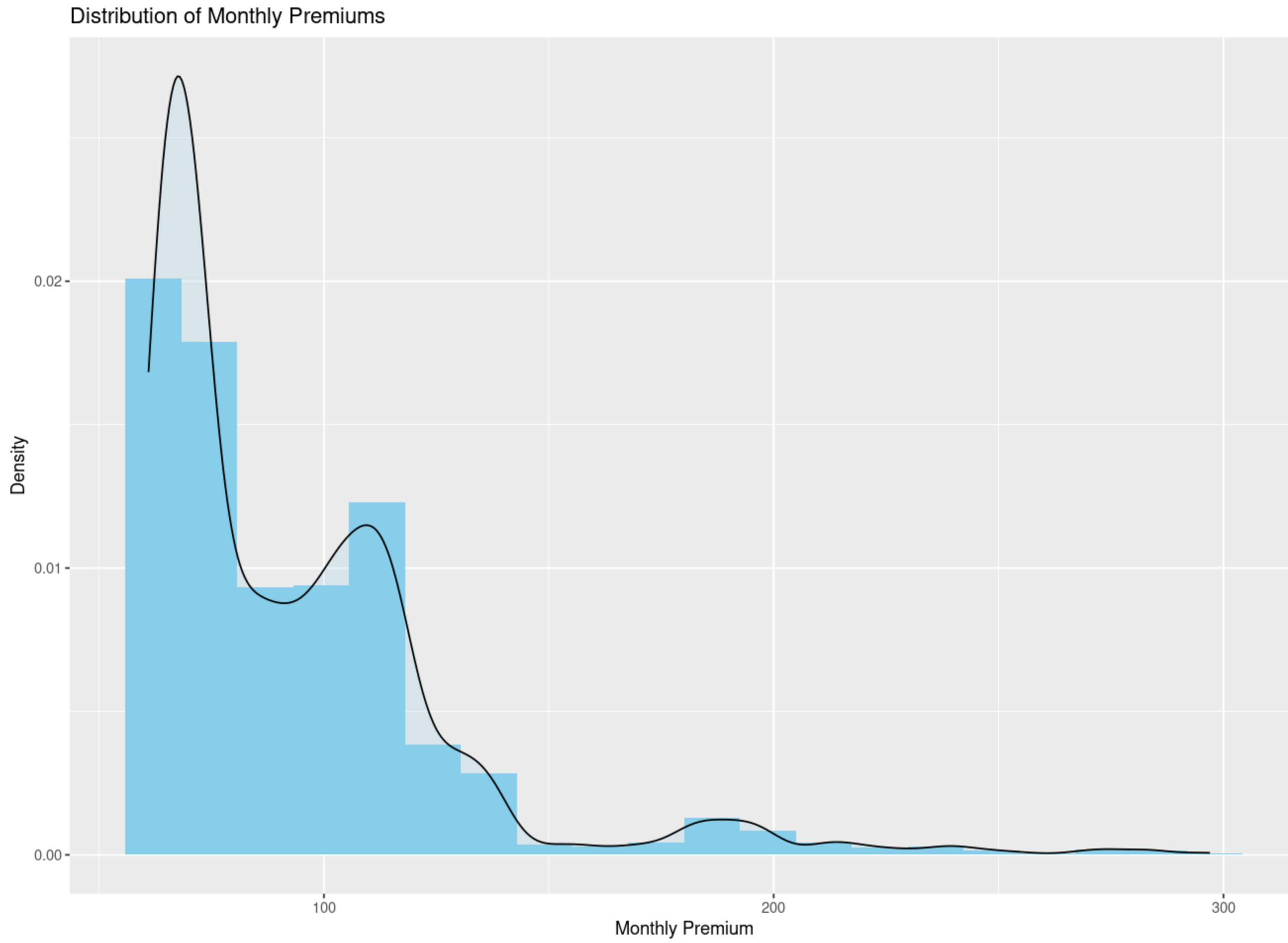
Supporting Analysis

In [15]:
```
# Summary dataframe with correlation coefficient
summary_q4 <- claims_df %>% select(monthly_premium, customer_lifetime_value) %>%
  cor()
summary_q4

# Histogram
ggplot(claims_df, aes(x = monthly_premium)) +
  geom_histogram(aes(y = ..density..), bins = 20, fill = "skyblue") +
  geom_density(alpha = .2, fill = "skyblue") +
  labs(title = 'Distribution of Monthly Premiums',
       x = 'Monthly Premium',
       y = 'Density')
```

A matrix: 2 × 2 of type dbl

	monthly_premium	customer_lifetime_value
monthly_premium	1.0000000	0.7368989

customer_lifetime_value	0.7368989	1.0000000



Question 5

Question: Do certain car models or years have a higher frequency of claims?

Answer: No, there does not appear to be a significant difference in the frequency of claims among different vehicle classes. The average number of claims is fairly consistent across vehicle classes, with slight variations but no clear trend indicating that certain car models or types have a markedly higher frequency of claims.

Supporting Analysis

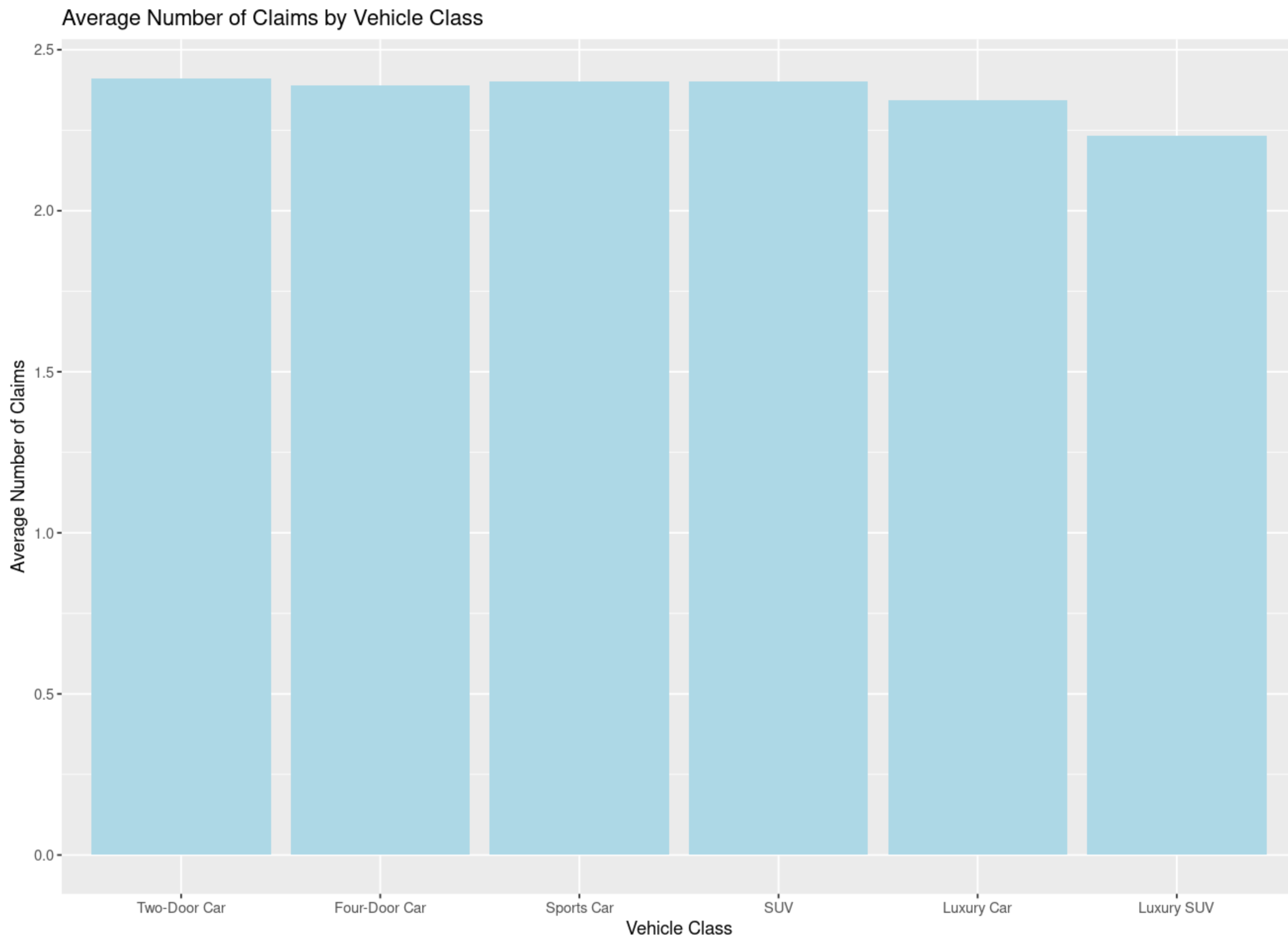
In [26]:

```
# Summary dataframe with the average number of claims by vehicle class
summary_q5 <- claims_df %>% group_by(vehicle_class) %>%
  summarise(avg_total_claims = mean(total_claims))
summary_q5

# Bar chart
ggplot(summary_q5, aes(x = vehicle_class, y = avg_total_claims)) +
  geom_col(fill = "lightblue") +
  labs(title = 'Average Number of Claims by Vehicle Class',
       x = 'Vehicle Class',
       y = 'Average Number of Claims')
```

A tibble: 6 × 2

vehicle_class	avg_total_claims
<fct>	<dbl>
Two-Door Car	2.411765

Four-Door Car	2.387644
Sports Car	2.400000
SUV	2.400482
Luxury Car	2.344538
Luxury SUV	2.233083



Question 6

Question: What is the impact of deductibles on the number of claims and overall profitability?

Answer: Yes, the type of coverage, which can serve as a proxy for deductible levels, has an impact on both the number of claims and overall profitability.

Customers with Basic coverage have a higher average number of claims (2.53) compared to those with Extended (2.166) and Premium (2.154) coverages, indicating that higher deductibles (associated with more comprehensive coverages) may lead to fewer claims. Regarding profitability, customers with Premium coverage have the highest average customer lifetime value (2879.41), followed by Extended (1538.96) and Basic (326), suggesting that higher coverage levels (and possibly higher deductibles) are associated with greater profitability.

Supporting Analysis

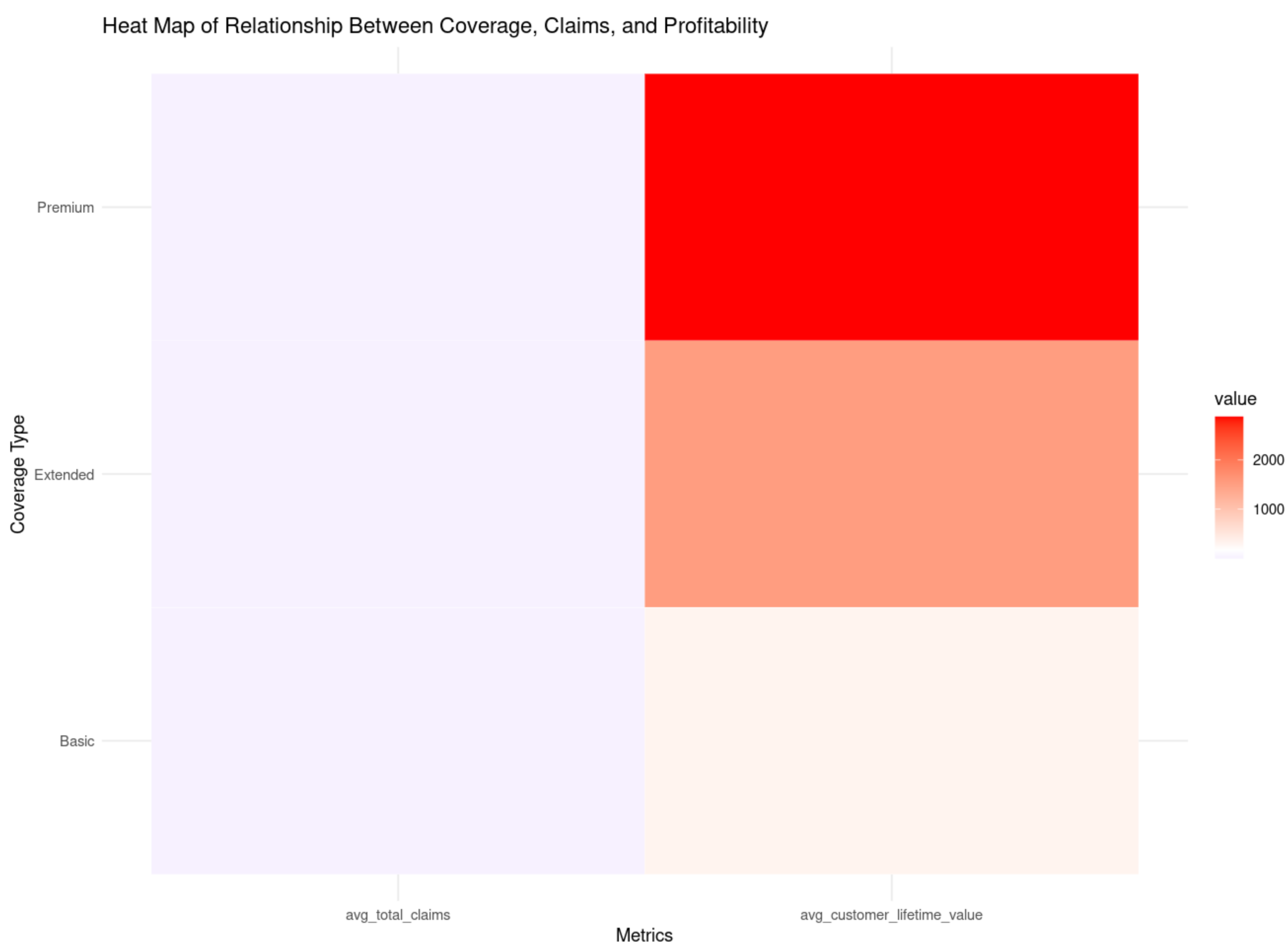
In [38]:

```
library(ggplot2)
library(dplyr)
library(reshape2)
```

```
# Assuming 'data' is your dataframe name
coverage_summary <- claims_df %>%
  group_by(coverage) %>%
  summarise(avg_total_claims = mean(total_claims),
            avg_customer_lifetime_value = mean(customer_lifetime_value))

# Melt the data for use in ggplot
coverage_melted <- melt(coverage_summary, id.vars = 'coverage')

# Create the heat map using the melted data
ggplot(coverage_melted, aes(x = variable, y = coverage, fill = value)) +
  geom_tile(color = "white") +
  scale_fill_gradient2(low = "blue", high = "red", mid = "white", midpoint = median(cove
  labs(title = "Heat Map of Relationship Between Coverage, Claims, and Profitability", x
  theme_minimal()

# Print the summary dataframe
coverage_summary
```

A tibble: 3 × 3

coverage	avg_total_claims	avg_customer_lifetime_value
<fct>	<dbl>	<dbl>
Basic	2.537090	326.0904
Extended	2.166846	1538.9661
Premium	2.154514	2879.4115



Question 7

Question: Are there geographic areas where claims are more frequent or more costly?

Answer: No, there do not appear to be significant geographic differences in the frequency of claims across states. The average number of claims is relatively consistent among the states. However, when it comes to the costliness of claims:

There are slight variations in the average claims amount by state, with Washington (2760.73), California (2775.01), and Nevada (2753.5) having slightly higher average claim amounts compared to Arizona (2707.75) and Oregon (2725.01). These differences suggest that while claim frequencies are similar, the costliness of claims can vary by geographic area, albeit with a modest difference.

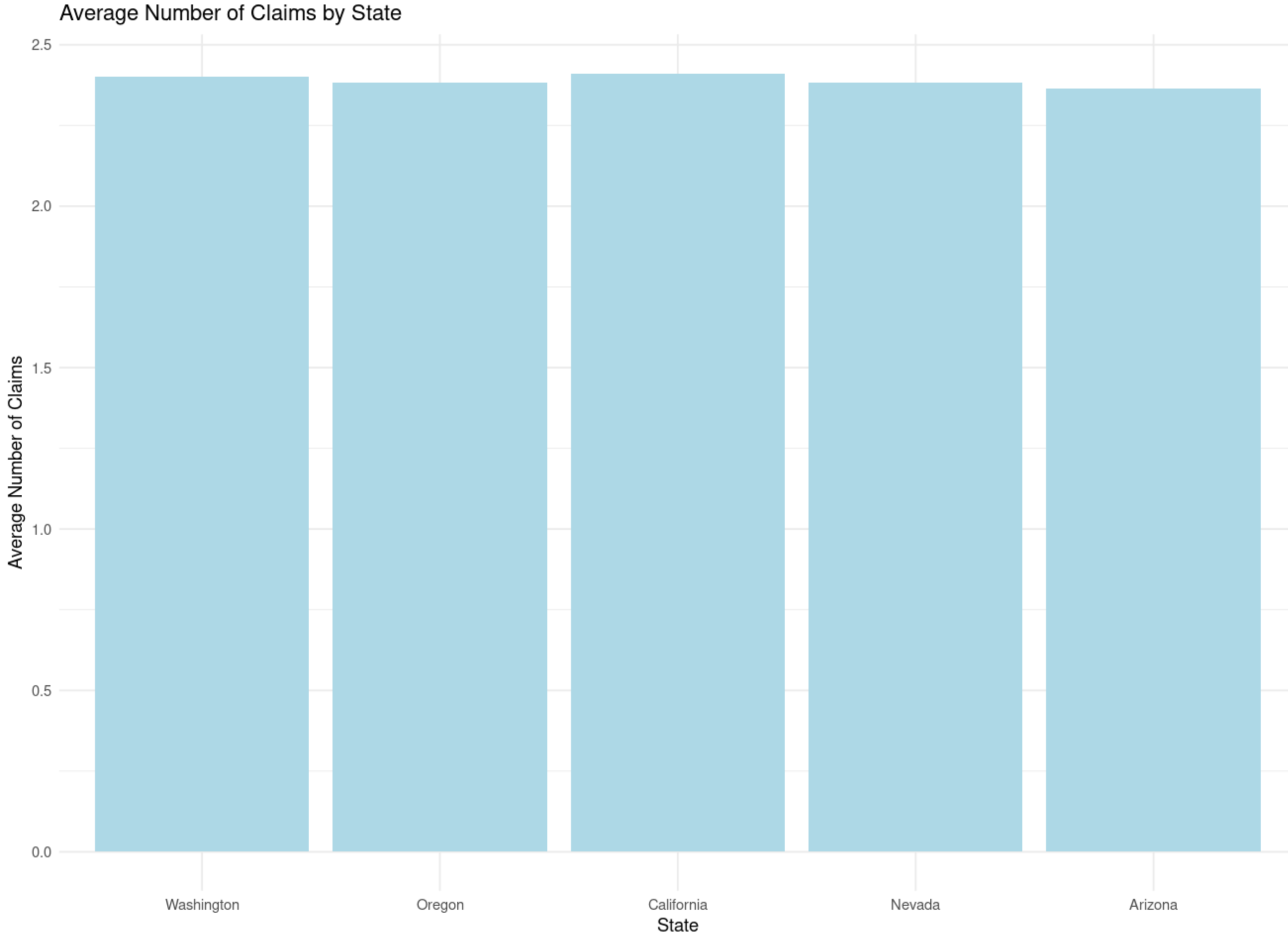
Supporting Analysis

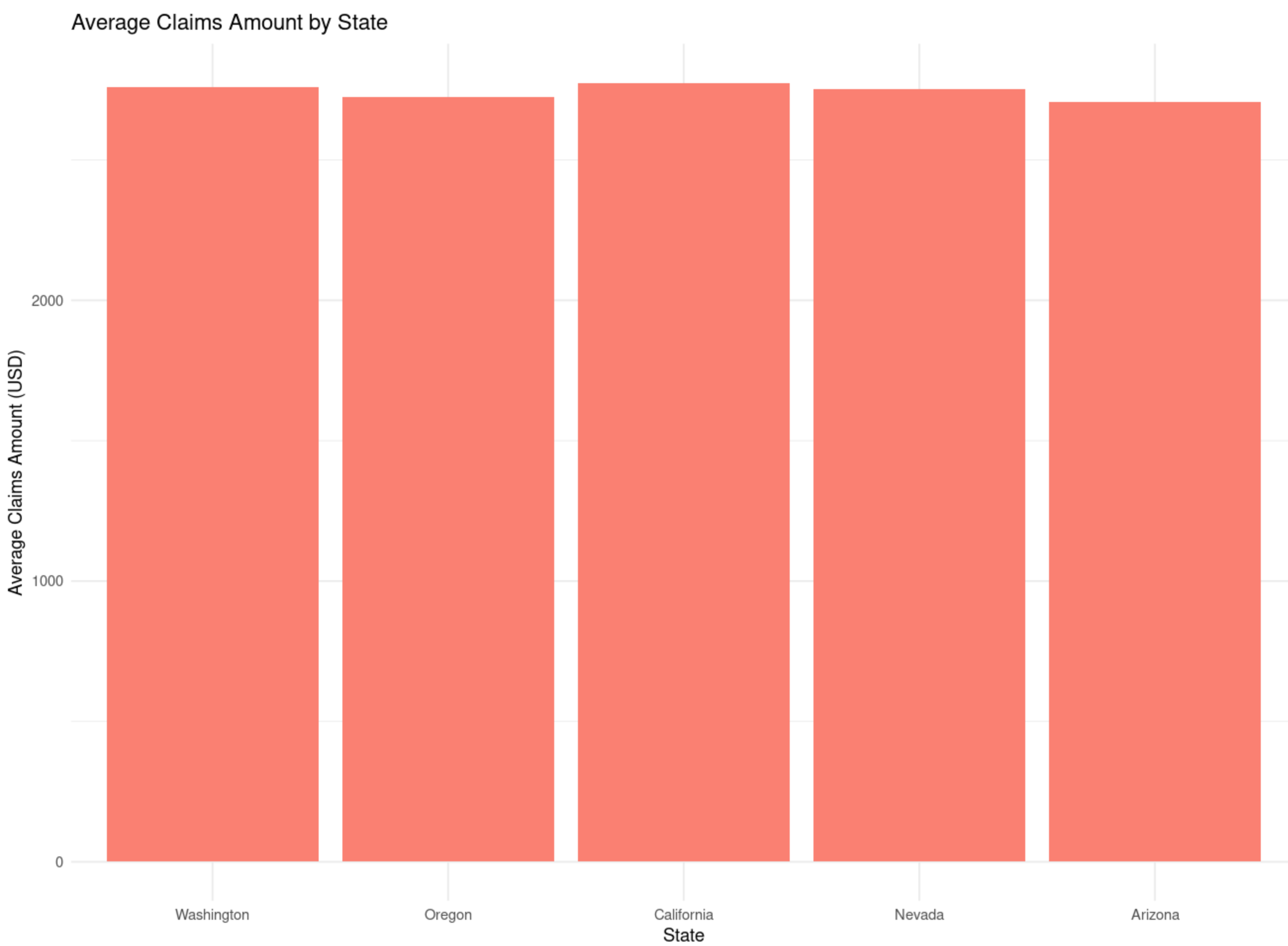
In [23]:

```
# Summary dataframe for average number and amount of claims by state
summary_q7 <- claims_df %>%
  group_by(customer_state) %>%
  summarise(avg_total_claims = mean(total_claims), avg_total_claims_amount = mean(total_

summary_q7

# Bar chart for average number of claims by state
ggplot(claims_df, aes(x = customer_state, y = total_claims)) +
  geom_bar(stat = "summary", fun = "mean", fill = "lightblue") +
  theme_minimal() +
  labs(title = "Average Number of Claims by State", x = "State", y = "Average Number of

# Bar chart for average claims amount by state
ggplot(claims_df, aes(x = customer_state, y = total_claims_amount)) +
  geom_bar(stat = "summary", fun = "mean", fill = "salmon") +
  theme_minimal() +
  labs(title = "Average Claims Amount by State", x = "State", y = "Average Claims Amount
```

A tibble: 5 × 3

customer_state	avg_total_claims	avg_total_claims_amount
<fct>	<dbl>	<dbl>
Washington	2.402527	2760.731
Oregon	2.384005	2725.011
California	2.411628	2775.018
Nevada	2.384359	2753.501
Arizona	2.365792	2707.752


Average Number of Claims by State
2.5
2.0
1.5
1.0
0.5
0.0
Average Number of Claims
Washington
Oregon
California
Nevada
Arizona
State


Average Claims Amount by State
2000
1000
0
Average Claims Amount (USD)
Washington
Oregon
California
Nevada
Arizona
State

Question 8

Question: How do claim amounts and frequencies compare across different customer segments and policy types?

Answer: No, there do not appear to be significant differences in the frequency of claims across different policy types, with the numbers being quite close: Corporate (2.39), Personal (2.389), and Special (2.43). However, when looking at the claim amounts:

The average claims amount is slightly higher for Special policy holders (2792.55) compared to Corporate (2747.89) and Personal (2741.30), indicating that while claim frequencies are similar, the costliness of claims can vary slightly by policy type, suggesting a modest impact on profitability.

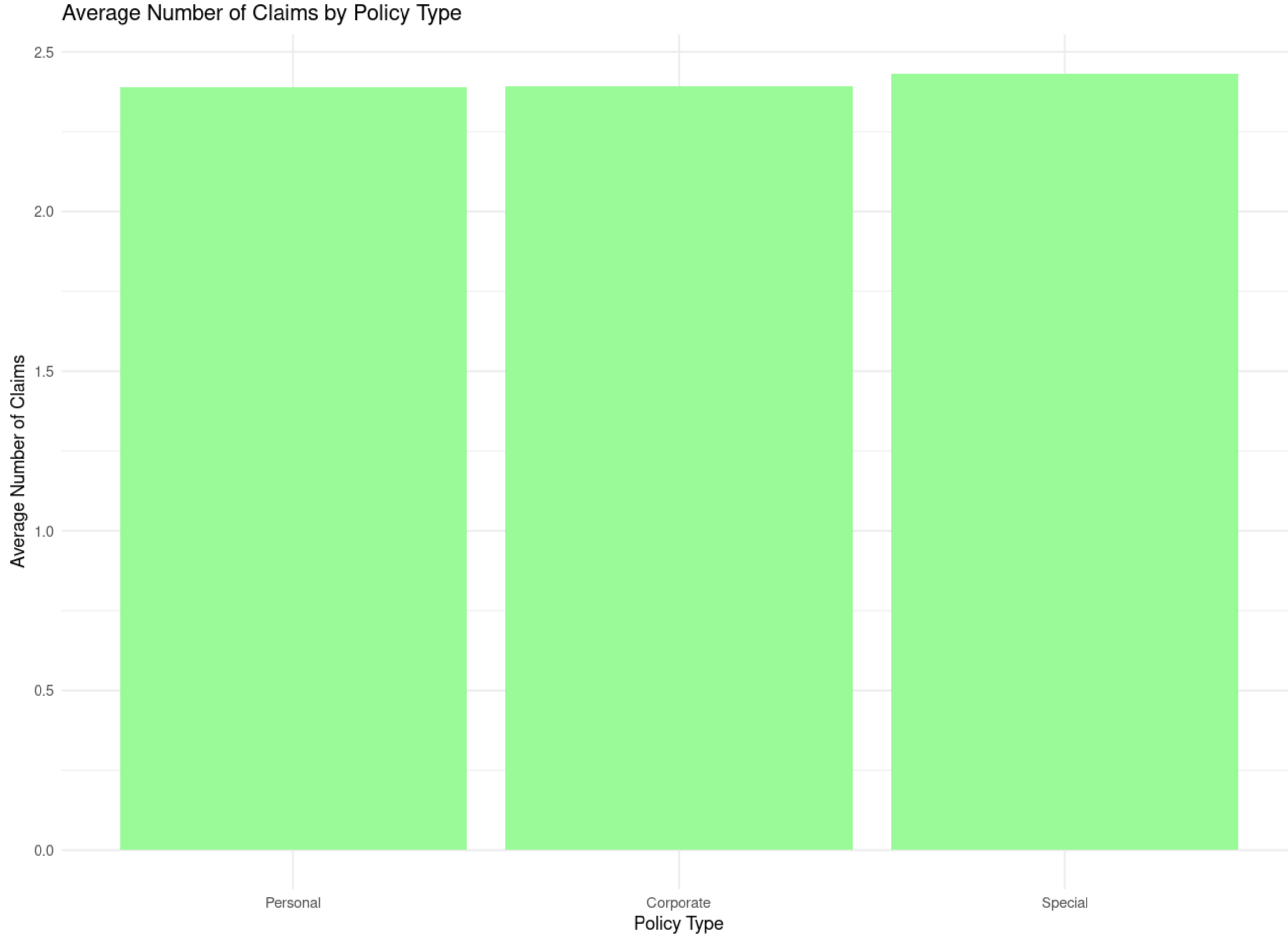
Supporting Analysis

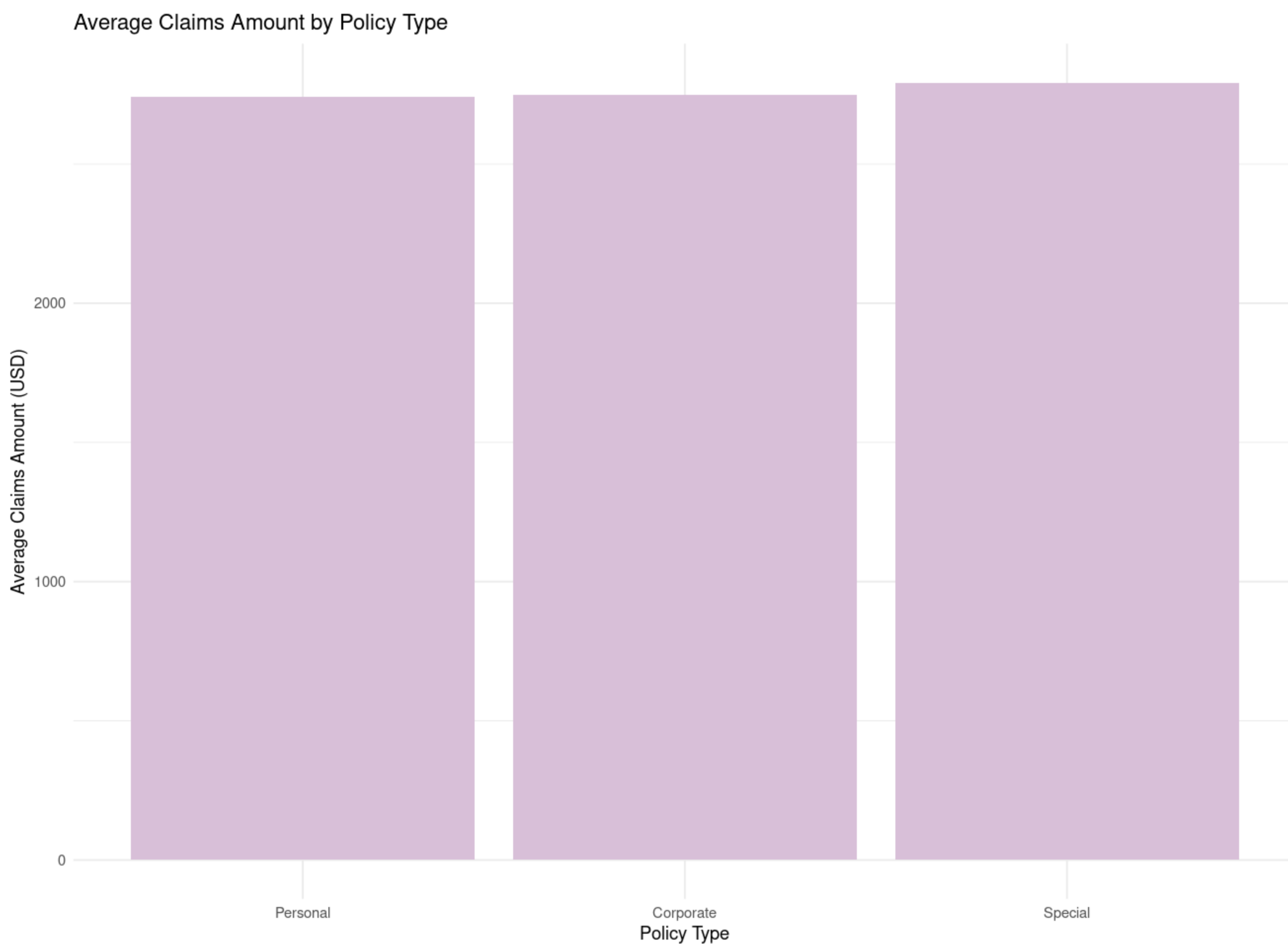
In [22]:

```
# Summary dataframe for average number and amount of claims by policy type
summary_q8 <- claims_df %>%
  group_by(policy) %>%
  summarise(avg_total_claims = mean(total_claims), avg_total_claims_amount = mean(total_

summary_q8

# Bar chart for average number of claims by policy type
ggplot(claims_df, aes(x = policy, y = total_claims)) +
  geom_bar(stat = "summary", fun = "mean", fill = "palegreen") +
  theme_minimal() +
  labs(title = "Average Number of Claims by Policy Type", x = "Policy Type", y = "Averag

# Bar chart for average claims amount by policy type
ggplot(claims_df, aes(x = policy, y = total_claims_amount)) +
  geom_bar(stat = "summary", fun = "mean", fill = "thistle") +
  theme_minimal() +
  labs(title = "Average Claims Amount by Policy Type", x = "Policy Type", y = "Average C
```

A tibble: 3 × 3

policy	avg_total_claims	avg_total_claims_amount
<fct>	<dbl>	<dbl>
Personal	2.389652	2741.304
Corporate	2.390813	2747.892
Special	2.433460	2792.551





Executive Summary (20 Points)

Write an executive summary of your overall findings and recommendations to the executives at this company. Think of this section as your closing remarks of a presentation, where you summarize your key findings and make recommendations to improve pricing, company operations, and car insurance policy adjustments.

Your executive summary must be written in a professional tone, with minimal grammatical errors, and should include the following sections:

1. An introduction where you explain the business problem and goals of your data analysis

- What problem(s) is this company trying to solve? Why are they important to their future success?
- What was the goal of your analysis? What questions were you trying to answer and why do they matter?

1. Highlights and key findings from your Exploratory Data Analysis section

- What were the interesting findings from your analysis and **why are they important for the business**?
    - Note: **Do not list all your questions and answers from the exploratory analysis section**. You should summarize the findings and list them in order by their potential business impact
- This section is meant to **establish the need for your recommendations** in the following section

1. Your recommendations to the company

- Each recommendation must be supported by your data analysis results
- You must clearly explain **why** you are making each recommendation and which results from your data analysis support this recommendation
- You must also describe the potential business impact of your recommendation:
    - Why is this a good recommendation?
    - What benefits will the business achieve?

Please add you executive summary in the text block below.

Introduction

... In the dynamic arena of car insurance, companies are on a constant quest to refine their pricing mechanisms, boost operational efficiencies, and tailor their policy offerings to maximize profitability. The core business problem for this company involves pinpointing the determinants of customer lifetime value and integrating these insights with effective cost control measures. Achieving sustained success necessitates a deep dive into the relationship between customer demographics, policy specifics, and claims information to fine-tune pricing and policy frameworks. The goal of this analysis was to identify critical factors that distinguish the most valuable customers from those who are less financially beneficial to the company. Through a series of thoughtfully designed questions, our goal was to shed light on actionable insights that would facilitate informed strategic decisions.

Key Findings

...

- Demographic Insights for Profitability: Our analysis indicated a predominant share of profitable customers are female and predominantly located in regions like California and Oregon. This insight is pivotal for crafting targeted marketing initiatives and adapting regional pricing strategies to attract and retain these high-value segments.
- Claims Analysis and Customer Value: We observed a notable negative correlation between the frequency and aggregate amount of claims and customer lifetime value. This underscores the importance of sophisticated risk management and claims handling to mitigate potential erosion of value.
- Analysis of Policy Types: Our findings revealed noticeable disparities in lifetime values among different policy categories, with 'Special' policies not performing as well as 'Corporate' and 'Personal' policies. This signals a clear opportunity for policy review and adjustment to improve profitability.
- The Link Between Premiums and Value: A significant positive correlation was found between monthly premium amounts and customer lifetime value, suggesting that customers paying higher premiums tend to be more lucrative over time.

These insights are crucial for identifying strategic leverage points where targeted adjustments could significantly boost profitability and enhance customer satisfaction.

Recommendations

... Based on our analysis, the following recommendations are proposed:

- Focused Customer Acquisition: Intensify marketing campaigns towards demographics proven to be highly profitable, especially targeting females and customers in high-value regions like California and Oregon. This strategy aims to enrich the customer base with individuals of higher lifetime value.
- Advanced Claims Management: Deploy sophisticated analytics to forecast claim frequencies and severities accurately. Proactive risk management, coupled with encouraging preventive behaviors among customers, can substantially reduce claim expenditures and preserve customer value.
- Policy Optimization: Conduct a thorough review of 'Special' policy offerings with an eye towards restructuring or adjusting pricing to boost their profitability. Modifications could include altering coverage parameters or offering incentives to customers with low claim histories.
- Refined Premium Pricing Strategy: Craft a dynamic pricing model that reflects the strong association between premium levels and customer lifetime value. This model should factor in diverse risk elements and customer behaviors to achieve more precise and profitable premium settings.

Implementing these recommendations is expected to fortify the company’s financial performance and secure a competitive advantage in the market.