rx7usgtqn

January 4, 2025

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
```

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[ ]:
```
file = ('/content/drive/MyDrive/008 - My Projects/Vehicle Insurance/
↪Vehicle_Insurance.csv')
df = pd.read_csv(file)
```

[ ]:
```
'''Beginning by exploring the dataset'''
'''Understanding the structure of data, the Dtypes of variables available, and␣
↪the general patterns'''

df.head()
```

[ ]:
```
   id  Gender  Age  Driving_License  Region_Code  Previously_Insured  \
0   1    Male   44                1         28.0                   0
1   2    Male   76                1          3.0                   0
2   3    Male   47                1         28.0                   0
3   4    Male   21                1         11.0                   1
4   5  Female   29                1         41.0                   1

  Vehicle_Age Vehicle_Damage  Annual_Premium  Policy_Sales_Channel  Vintage  \
0   > 2 Years            Yes         40454.0                  26.0      217
1    1-2 Year             No         33536.0                  26.0      183
2   > 2 Years            Yes         38294.0                  26.0       27
3    < 1 Year             No         28619.0                 152.0      203
4    < 1 Year             No         27496.0                 152.0       39

   Response
0         1
```

```
1         0
2         1
3         0
4         0
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 381109 entries, 0 to 381108
Data columns (total 12 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   id                    381109 non-null  int64
 1   Gender                381109 non-null  object
 2   Age                   381109 non-null  int64
 3   Driving_License       381109 non-null  int64
 4   Region_Code           381109 non-null  float64
 5   Previously_Insured    381109 non-null  int64
 6   Vehicle_Age           381109 non-null  object
 7   Vehicle_Damage        381109 non-null  object
 8   Annual_Premium        381109 non-null  float64
 9   Policy_Sales_Channel  381109 non-null  float64
 10  Vintage               381109 non-null  int64
 11  Response              381109 non-null  int64
dtypes: float64(3), int64(6), object(3)
memory usage: 34.9+ MB
```

[ ]:
```
# Check the number of unique values in each column

print("\nUnique Values per Column:\n", df.nunique())
```

```

Unique Values per Column:
 id                      381109
Gender                    2
Age                      66
Driving_License           2
Region_Code              53
Previously_Insured        2
Vehicle_Age               3
Vehicle_Damage            2
Annual_Premium        48838
Policy_Sales_Channel    155
Vintage                 290
Response                  2
dtype: int64
```

```
[ ]: '''Descriptive Statistics about our dataset'''

df.describe()
```

```
[ ]:                   id            Age  Driving_License    Region_Code  \
count  381109.000000  381109.000000    381109.000000  381109.000000
mean   190555.000000      38.822584         0.997869      26.388807
std    110016.836208      15.511611         0.046110      13.229888
min         1.000000      20.000000         0.000000       0.000000
25%     95278.000000      25.000000         1.000000      15.000000
50%    190555.000000      36.000000         1.000000      28.000000
75%    285832.000000      49.000000         1.000000      35.000000
max    381109.000000      85.000000         1.000000      52.000000

       Previously_Insured  Annual_Premium  Policy_Sales_Channel  \
count       381109.000000   381109.000000         381109.000000
mean             0.458210    30564.389581            112.034295
std              0.498251    17213.155057             54.203995
min              0.000000     2630.000000              1.000000
25%              0.000000    24405.000000             29.000000
50%              0.000000    31669.000000            133.000000
75%              1.000000    39400.000000            152.000000
max              1.000000   540165.000000            163.000000

             Vintage       Response
count  381109.000000  381109.000000
mean      154.347397       0.122563
std        83.671304       0.327936
min        10.000000       0.000000
25%        82.000000       0.000000
50%       154.000000       0.000000
75%       227.000000       0.000000
max       299.000000       1.000000
```

```
[ ]: #As soon as we perform Exploratory and Descriptive analysis, we can now begin
 ↪Data Cleaning.
```

```
[ ]: '''Let's drop any duplicate entries and check the shape of our dataset'''

df.drop_duplicates()
print(f"Dataset Shape:", df.shape)
```

```
Dataset Shape: (381109, 12)
```

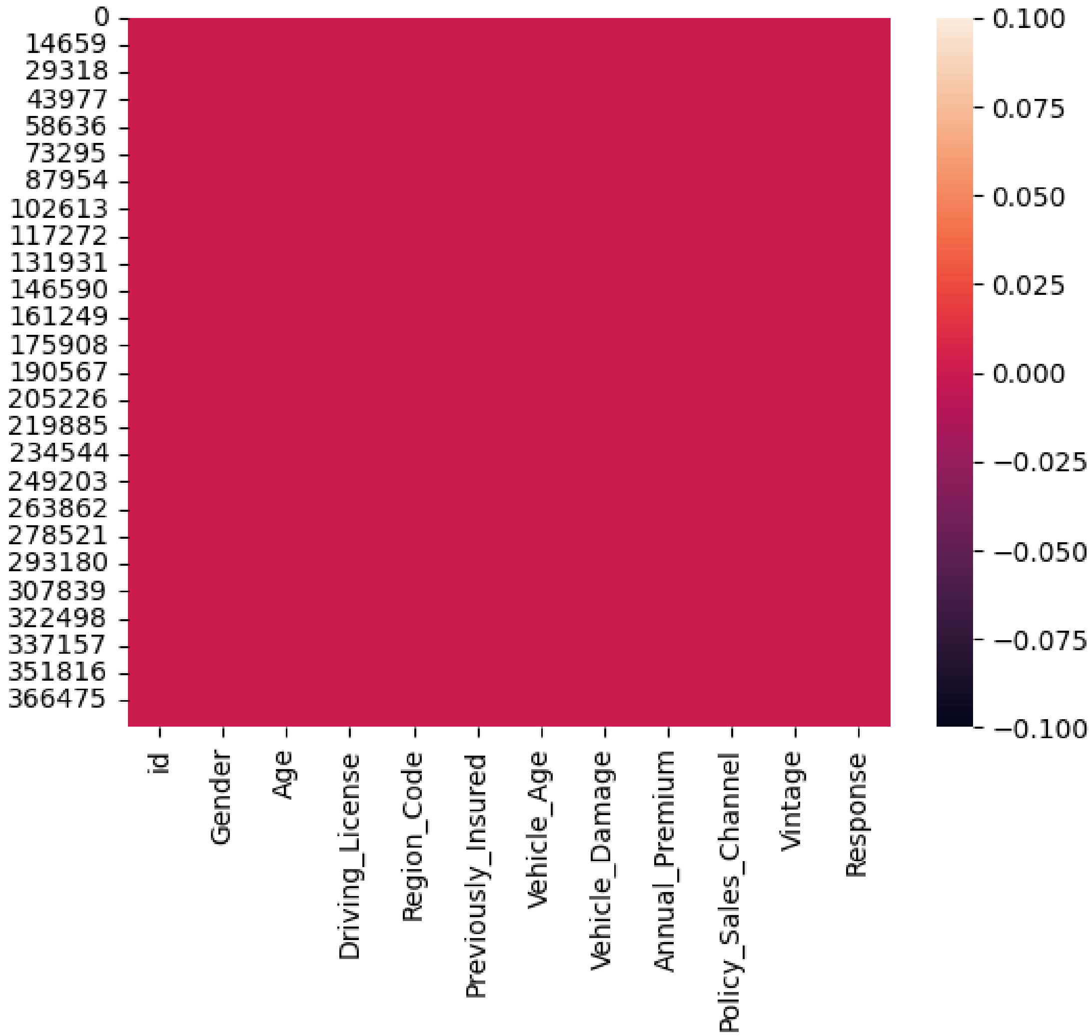
```
[ ]: '''Let's find Null/Missing values in our dataset(Column-wise)'''

df.isnull().sum()
```

[ ]:
```
id                    0
Gender                0
Age                   0
Driving_License       0
Region_Code           0
Previously_Insured    0
Vehicle_Age           0
Vehicle_Damage        0
Annual_Premium        0
Policy_Sales_Channel  0
Vintage               0
Response              0
dtype: int64
```

[ ]:
```
'''Total Number of Null values in our dataset'''

df.isnull().sum().sum()
```

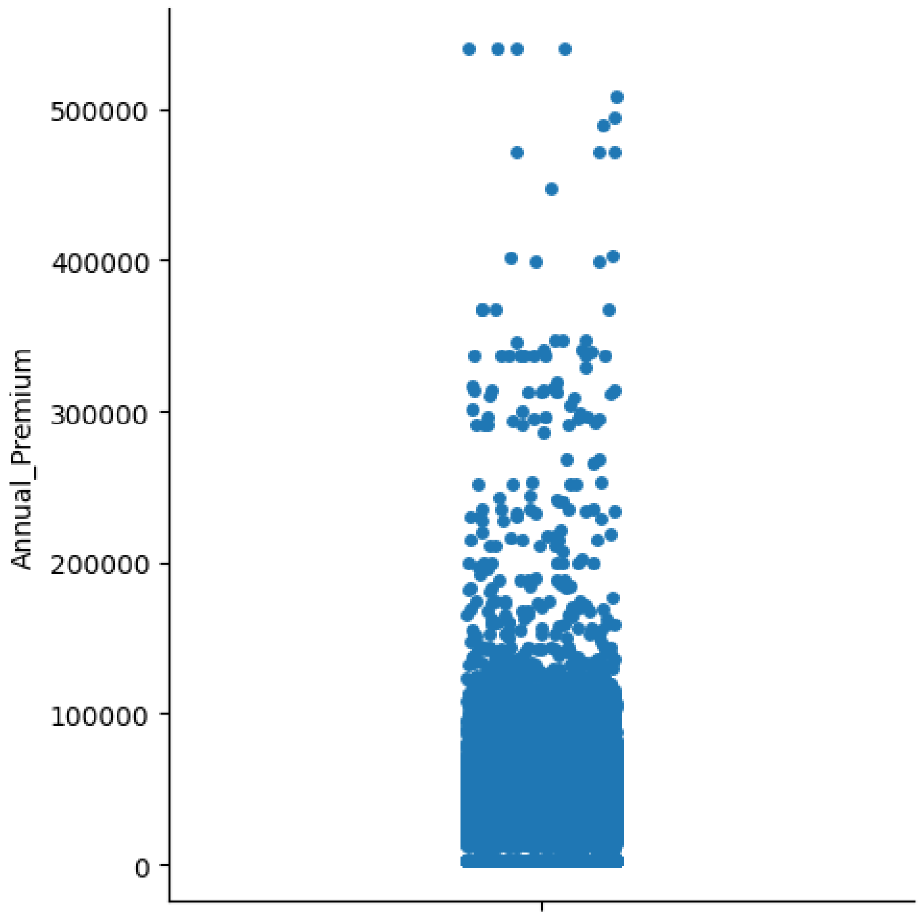
[ ]: 0

[ ]:
```
'''Heatmap of Null values'''

sns.heatmap(df.isnull())
plt.show()
```



[ ]:
```
# We see that there are no null values present in our dataset and all features␣
↪seems cleaned.

# But we need to check "Annual_Premium" for outliers.
```

[ ]:
```
'''Feature - Annual_Premium'''

# Drawing a catplot of feature 'Annual_Premium' for checking if there's any␣
↪outliers exist

sns.catplot(df['Annual_Premium'])
plt.show()
```




```
[ ]: '''Outliers handling in feature 'Annual_Premium' by IQR Method.'''
```

```
[ ]: # Calculating IQR for 'market_price'.

Q1 = df['Annual_Premium'].quantile(0.25)
print(f"Q1 is {Q1}")

Q3 = df['Annual_Premium'].quantile(0.75)
print(f"Q3 is {Q3}")
```

```
Q1 is 24405.0
Q3 is 39400.0
```

```
[ ]: IQR = Q3 - Q1
print(f"IQR is {IQR}")
```

```
IQR is 14995.0
```

[ ]:
```
# Defining the outlier boundaries.

lower_bound = Q1 - 1.5 * IQR
print(lower_bound)

upper_bound = Q3 + 1.5 * IQR
print(upper_bound)
```

```
1912.5
61892.5
```

[ ]:
```
# Identifying outliers.

# Our feature 'Annual_Premium' lies between 1,912.5 and 61,892.5 as per IQR␣
↪Method,
# therefore any value below 1,912.5 and beyond 61,892.5 is considered as an␣
↪outlier.

outliers = df[(df['Annual_Premium'] < lower_bound) | (df['Annual_Premium'] >␣
↪upper_bound)]
outliers
```

[ ]:
```
             id  Gender  Age  Driving_License  Region_Code  Previously_Insured  \
25           26  Female   21                1         28.0                   1
37           38  Female   25                1         28.0                   1
67           68    Male   60                1         28.0                   0
139         140    Male   21                1         29.0                   1
149         150  Female   22                1         11.0                   1
…           …       …    …                 …            …                   …
380959  380960    Male   25                1          8.0                   1
380998  380999  Female   33                1          8.0                   0
381035  381036  Female   22                1         11.0                   1
381047  381048  Female   52                1          8.0                   1
381079  381080    Male   33                1         28.0                   0

       Vehicle_Age Vehicle_Damage  Annual_Premium  Policy_Sales_Channel  \
25        < 1 Year             No         61964.0                 152.0
37        < 1 Year             No         76251.0                 152.0
67        1-2 Year            Yes         66338.0                 124.0
139       < 1 Year             No         62164.0                 152.0
149       < 1 Year             No         76651.0                 152.0
…              …              …               …                     …
380959    < 1 Year             No         61909.0                 152.0
380998    1-2 Year            Yes        101664.0                 124.0
381035    < 1 Year             No         62889.0                 152.0
381047    1-2 Year             No         71915.0                   7.0
381079    < 1 Year            Yes         69845.0                  26.0
```

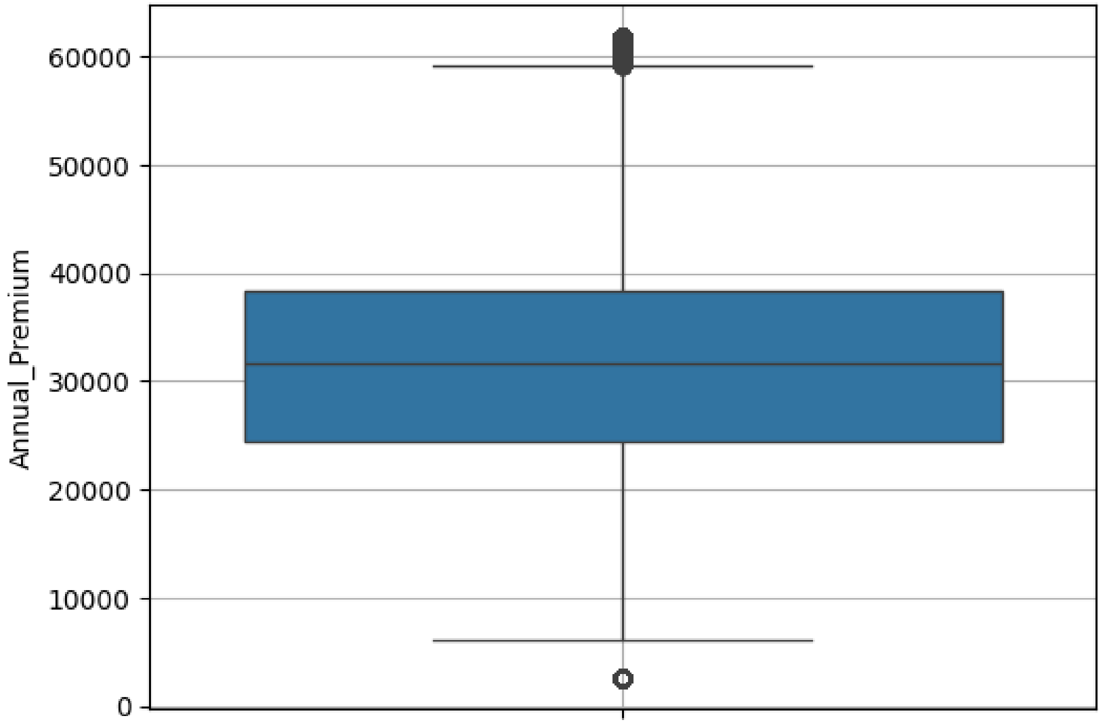
```
        Vintage  Response
25           72         0
37          107         0
67           73         0
139         116         0
149         258         0
…           …         …
380959      161         0
380998       21         0
381035      295         0
381047      233         0
381079      115         0

[10320 rows x 12 columns]
```

[ ]:
```
# Checking Median.

median = df['Annual_Premium'].median()
median
```

[ ]: 31669.0

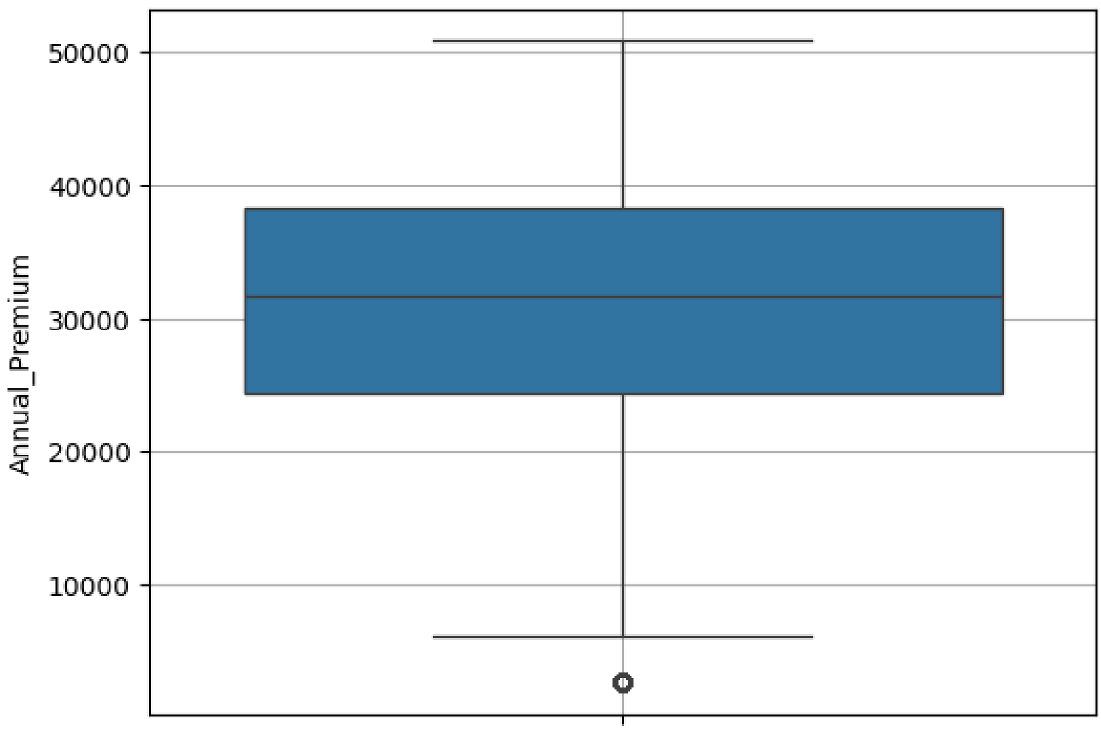
[ ]:
```
# Replacing Outliers in 'Annual_Premium' with Median

df['Annual_Premium'] = np.where((df['Annual_Premium'] < lower_bound) |
 ↪(df['Annual_Premium'] > upper_bound), median, df['Annual_Premium'])
```

[ ]:
```
# We see that there are still a few outliers exists.

sns.boxplot(df['Annual_Premium'])
plt.grid(True)
plt.show()
```



[ ]:
```
from scipy.stats.mstats import winsorize

df['Annual_Premium'] = winsorize(df['Annual_Premium'], limits=[0.05, 0.05])
```

[ ]:
```
# Let's check the boxplot again

sns.boxplot(df['Annual_Premium'])
plt.grid(True)
plt.show()
```



[ ]:
```
# Checking values equals to 2630 in Annual_Premium

df[df['Annual_Premium'] == 2630]
```

[ ]:
```
            id  Gender  Age  Driving_License  Region_Code  Previously_Insured  \
5            6  Female   24                1         33.0                   0
15          16    Male   37                1          6.0                   0
30          31  Female   26                1          8.0                   0
43          44  Female   38                1         35.0                   1
58          59  Female   62                1         48.0                   0
…          …     …   …                …           …                 …
381070  381071  Female   28                1         11.0                   0
381086  381087  Female   34                1         35.0                   0
381092  381093    Male   38                1         28.0                   1
381094  381095  Female   47                1         20.0                   0
381102  381103  Female   25                1         41.0                   1

       Vehicle_Age Vehicle_Damage  Annual_Premium  Policy_Sales_Channel  \
5         < 1 Year            Yes          2630.0                 160.0
15        1-2 Year            Yes          2630.0                 156.0
30        < 1 Year             No          2630.0                 160.0
43        1-2 Year             No          2630.0                 152.0
58        1-2 Year            Yes          2630.0                  15.0
```

```
…            …            …            …                  …
381070    < 1 Year           Yes          2630.0                124.0
381086    1-2 Year           Yes          2630.0                152.0
381092    1-2 Year            No          2630.0                124.0
381094    1-2 Year           Yes          2630.0                 26.0
381102    < 1 Year           Yes          2630.0                152.0

        Vintage  Response
5           176         0
15          147         1
30          136         0
43          153         0
58          295         0
…         …       …
381070      106         0
381086      208         0
381092      130         0
381094       84         0
381102      102         0

[64877 rows x 12 columns]
```

[ ]:
```
# Since 64,877 values of 'Annual_Premium' are same, which is 2630.0, it will
↪not be appropriate to replace or remove them.

# As it will impact accuracy of the dataset, therefore considering it as
↪cleaned and proceeding further for EDA
```

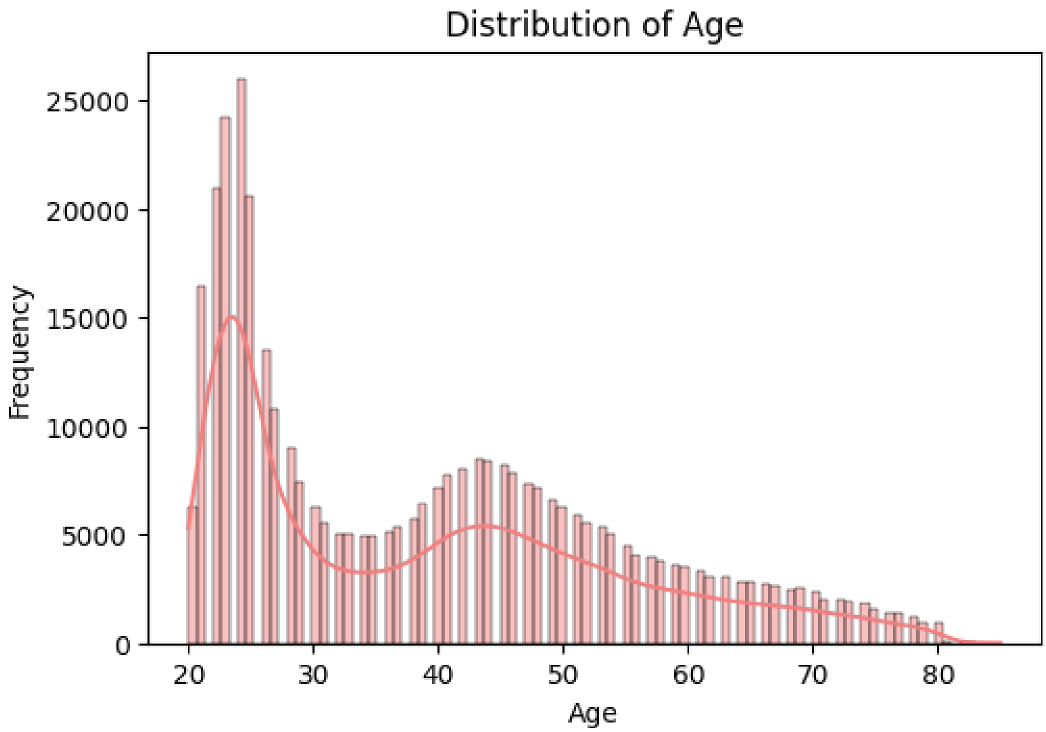
[ ]:
```
df.describe()
```

```
/usr/local/lib/python3.10/dist-packages/numpy/lib/function_base.py:4824:
UserWarning: Warning: 'partition' will ignore the 'mask' of the MaskedArray.
  arr.partition(
/usr/local/lib/python3.10/dist-packages/numpy/lib/function_base.py:4824:
UserWarning: Warning: 'partition' will ignore the 'mask' of the MaskedArray.
  arr.partition(
/usr/local/lib/python3.10/dist-packages/numpy/lib/function_base.py:4824:
UserWarning: Warning: 'partition' will ignore the 'mask' of the MaskedArray.
  arr.partition(
```

[ ]:
```
                  id            Age  Driving_License    Region_Code  \
count  381109.000000  381109.000000    381109.000000  381109.000000
mean   190555.000000      38.822584         0.997869      26.388807
std    110016.836208      15.511611         0.046110      13.229888
min         1.000000      20.000000         0.000000       0.000000
25%     95278.000000      25.000000         1.000000      15.000000
50%    190555.000000      36.000000         1.000000      28.000000
```

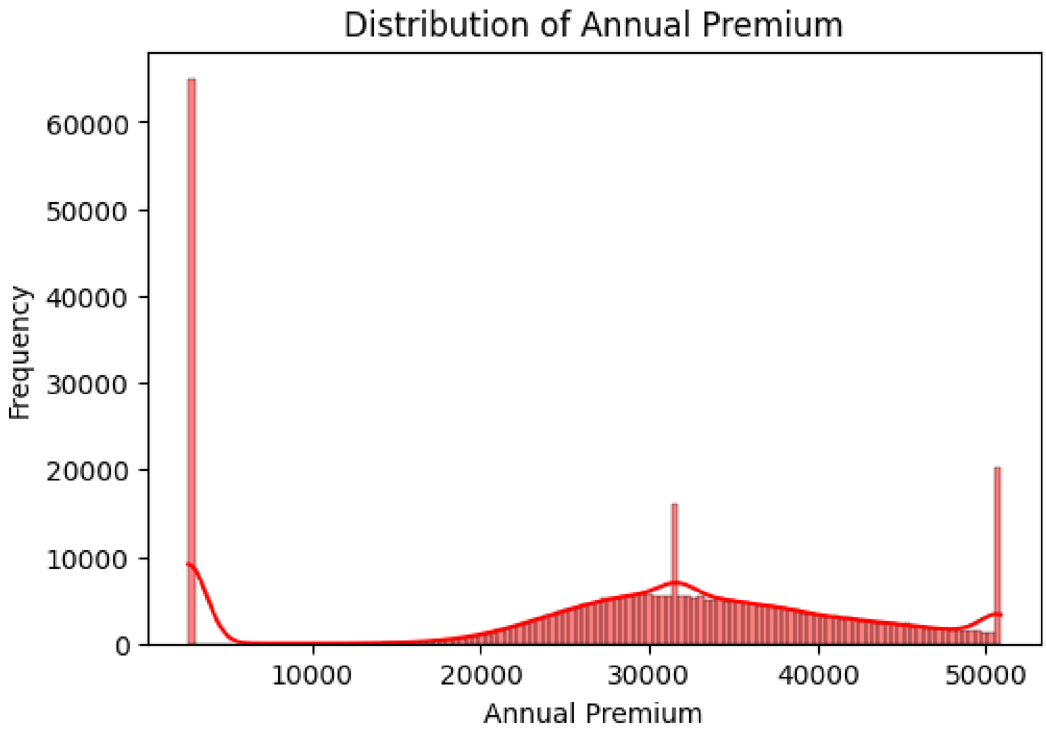
```
75%    285832.000000      49.000000          1.000000      35.000000
max    381109.000000      85.000000          1.000000      52.000000

       Previously_Insured  Annual_Premium  Policy_Sales_Channel  \
count       381109.000000   381109.000000         381109.000000
mean             0.458210    29109.781459            112.034295
std              0.498251    14165.309425             54.203995
min              0.000000     2630.000000              1.000000
25%              0.000000    24405.000000             29.000000
50%              0.000000    31669.000000            133.000000
75%              1.000000    38346.000000            152.000000
max              1.000000    50871.000000            163.000000

             Vintage       Response
count  381109.000000  381109.000000
mean      154.347397       0.122563
std        83.671304       0.327936
min        10.000000       0.000000
25%        82.000000       0.000000
50%       154.000000       0.000000
75%       227.000000       0.000000
max       299.000000       1.000000
```

[ ]:
```
''' Question 1 - Utilize various visualization techniques to explore the␣
 ↪distribution of key variables.'''
'''Show the Distribution of Age'''

plt.figure(figsize=(6, 4))
sns.histplot(df['Age'], kde=True, color='lightcoral')
plt.title('Distribution of Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



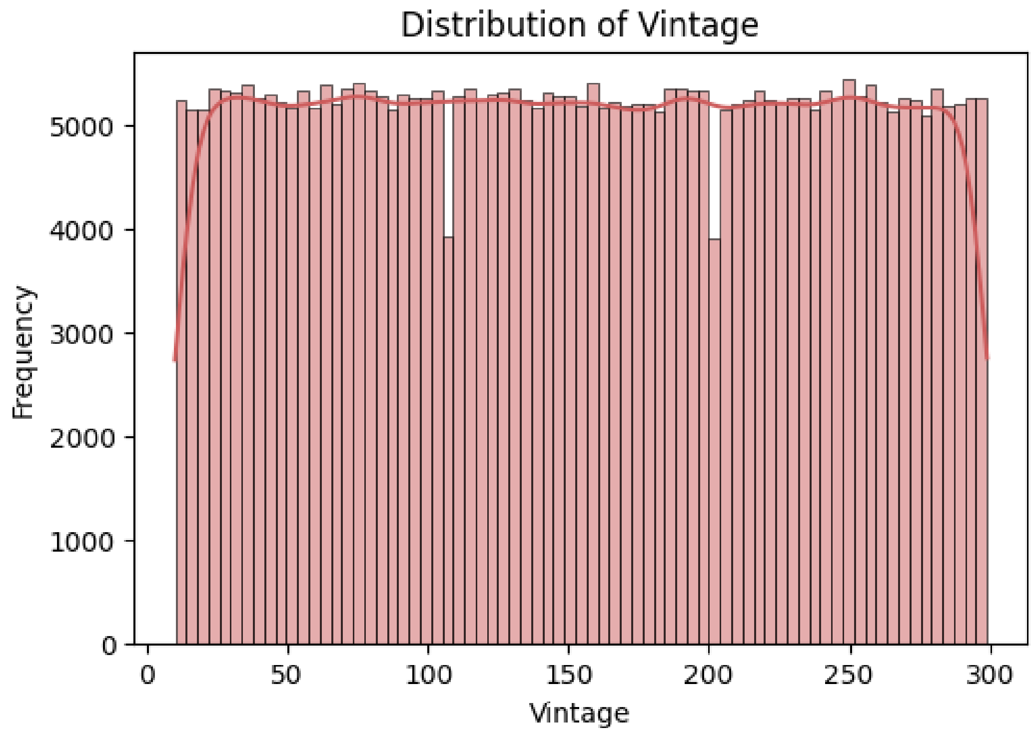
[ ]:
```
'''Meaningful insights from above plot'''

# From the distribution plot of 'Age', we can observe that:

# 1. The age of policyholders is mostly distributed between 20 and 60 years old.
# 2. It shows a right-skewed distribution, indicating a higher concentration of␣
↪younger individuals compared to older individuals.
# 3. There's a peak around the age of 25-30, suggesting a significant portion␣
↪of the policyholders belong to that age group.
```

[ ]:
```
''' Question 1 - Utilize various visualization techniques to explore the␣
↪distribution of key variables.'''
'''Show the Distribution of Annual premium'''

plt.figure(figsize=(6, 4))
sns.histplot(df['Annual_Premium'], kde=True, color = 'red')
plt.title('Distribution of Annual Premium')
plt.xlabel('Annual Premium')
plt.ylabel('Frequency')
plt.show()
```



[ ]:
```
'''Meaningful insights from above plot'''

# From the distribution plot of 'Annual_Premium', we can observe that:

# 1. The majority of policyholders have an annual premium that falls within a␣
↪specific range.
# 2. The distribution of annual premium seems to be right-skewed, indicating a␣
↪potential concentration of individuals with lower premium amounts and fewer␣
↪with higher premium amounts.
# 3. The presence of a peak suggests a common annual premium amount or a␣
↪particular segment of individuals paying around that amount.
```

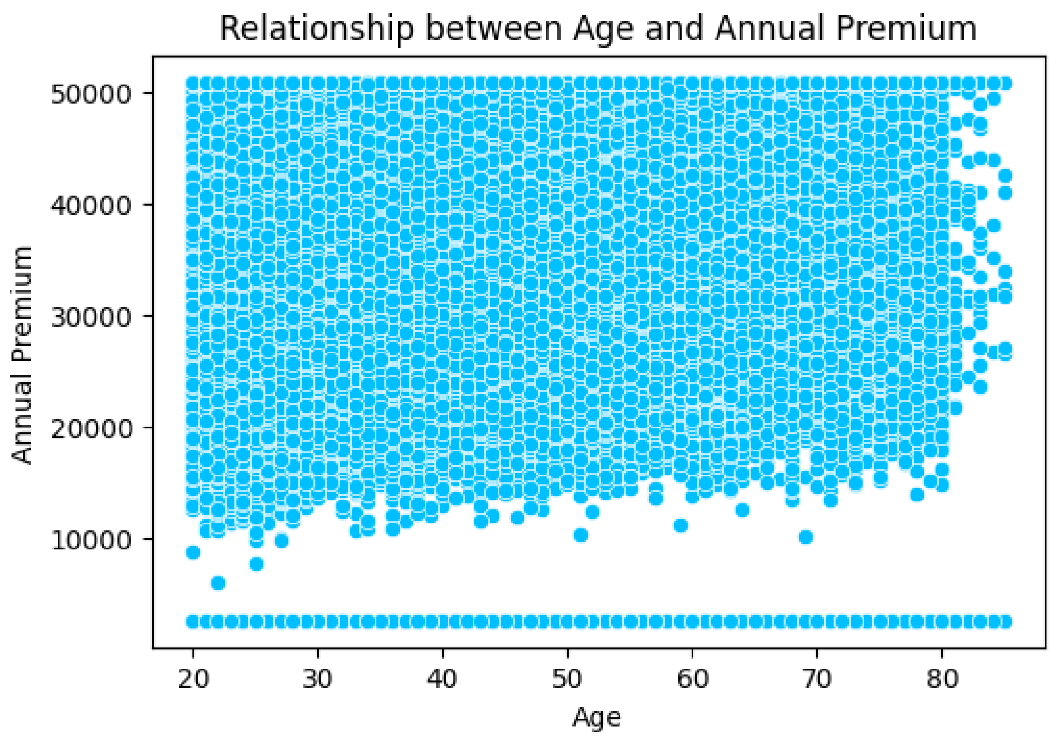
[ ]:
```
''' Question 1 - Utilize various visualization techniques to explore the␣
↪distribution of key variables.'''
'''Show the Distribution of Vintage'''

plt.figure(figsize=(6, 4))
sns.histplot(df['Vintage'], kde=True, color = 'indianred')
plt.title('Distribution of Vintage')
plt.xlabel('Vintage')
plt.ylabel('Frequency')
plt.show()
```




```
[ ]: '''Meaningful insights from above plot'''

     # From the distribution plot of 'Vintage', we can observe that:

     # 1. The vintage of policyholders is mostly concentrated towards the lower␣
      ↪range, indicating that a significant number of policyholders have been␣
      ↪associated with the company for a relatively shorter duration.
     # 2. It seems to be a right-skewed distribution with a longer tail towards the␣
      ↪higher vintage values. This could imply that fewer customers have been with␣
      ↪the company for a longer period of time compared to those with shorter␣
      ↪tenure.
     # 3. The presence of a peak at the lower end of the vintage range reinforces␣
      ↪the observation that most policyholders are relatively new customers.
```

```
[ ]: ''' Question 1 - Utilize various visualization techniques to explore the␣
      ↪distribution of key variables.'''
     '''Show the Distribution between Age and Annual Premium'''

     plt.figure(figsize=(6, 4))
     sns.scatterplot(x='Age', y='Annual_Premium', data=df, color = 'deepskyblue')
     plt.title('Relationship between Age and Annual Premium')
     plt.xlabel('Age')
     plt.ylabel('Annual Premium')
```

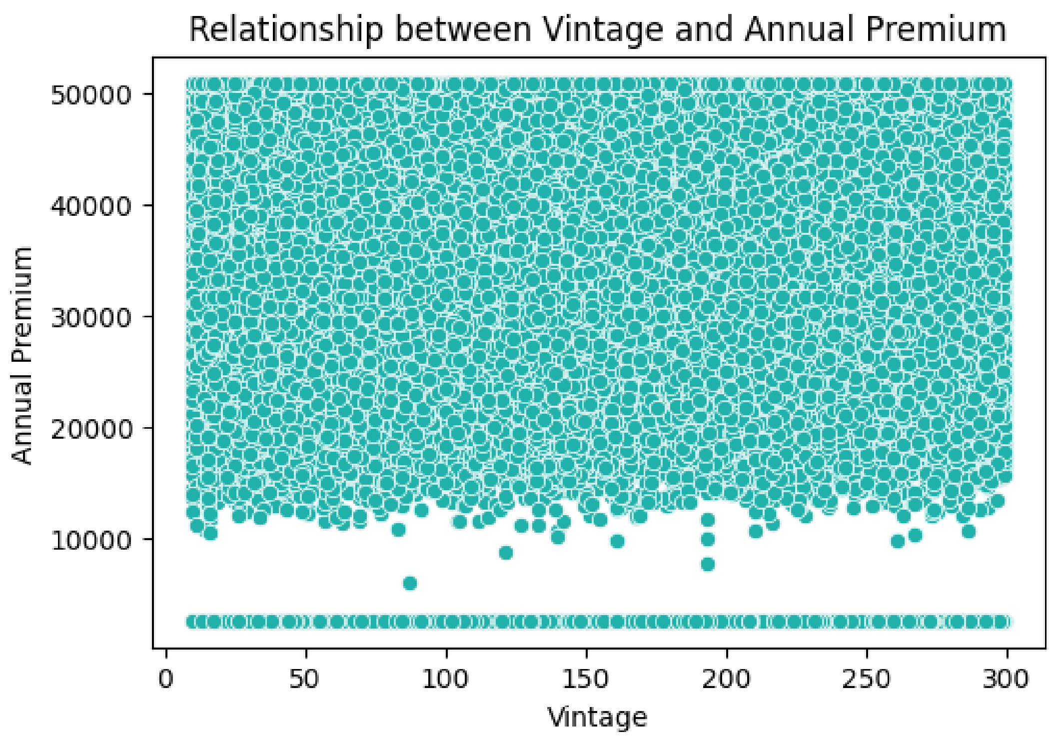
```
plt.show()
```



[ ]:
```
'''Meaningful insights from above plot'''

# From the scatter plot of 'Age' and 'Annual_Premium', we can observe that:

# 1. There's no clear linear relationship between the age of policyholders and␣
 ↪their annual premium amount.
# 2. We can see a large cluster of points within the lower range of annual␣
 ↪premiums and various ages, suggesting that several policyholders have␣
 ↪similar annual premiums irrespective of age.
# 3. Though there's no strict correlation, we can observe some policyholders␣
 ↪with higher annual premiums tend to be older. This could indicate that age␣
 ↪might be a contributing factor to higher premium amounts.
# 4. It's essential to consider other variables that influence premium amounts,␣
 ↪such as vehicle type or driving history, for a more comprehensive␣
 ↪understanding of the relationship between age and premium costs.
```

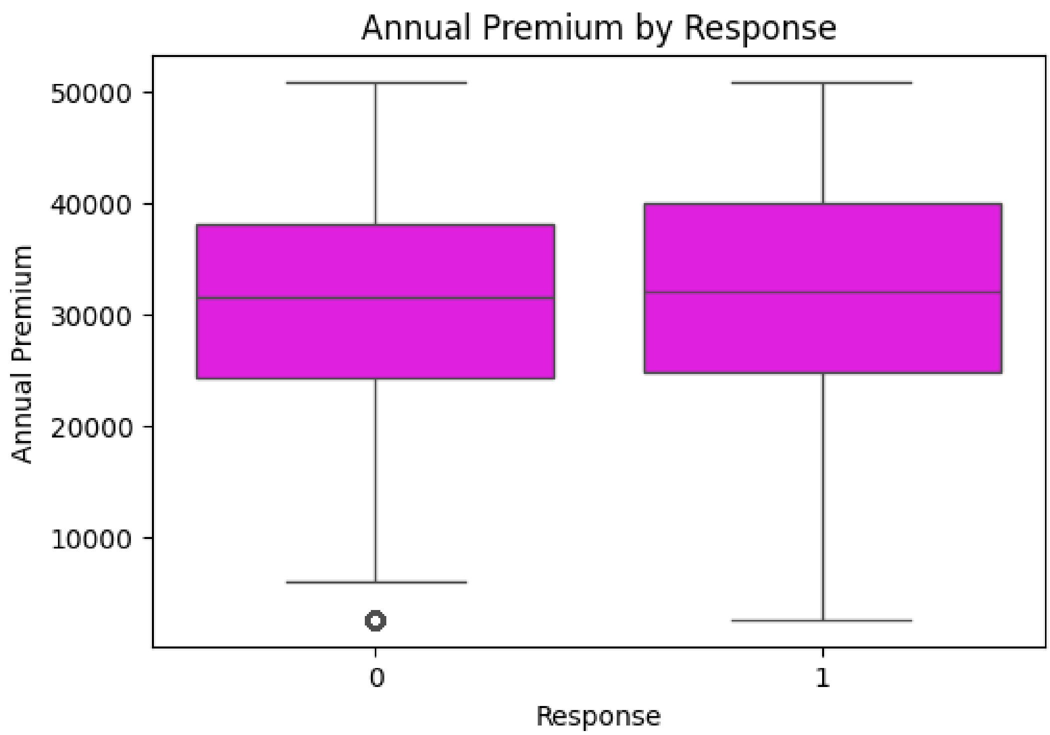
[ ]:
```
''' Question 1 - Utilize various visualization techniques to explore the␣
 ↪distribution of key variables.'''
'''Show the Distribution between Vintage and Annual Premium'''

plt.figure(figsize=(6, 4))
```

```python
sns.scatterplot(x='Vintage', y='Annual_Premium', data=df, color =␣
 ↪'lightseagreen')
plt.title('Relationship between Vintage and Annual Premium')
plt.xlabel('Vintage')
plt.ylabel('Annual Premium')
plt.show()
```



[ ]:
```python
'''Meaningful insights from above plot'''

# 1. There is no clear linear relationship between the vintage of policyholders␣
 ↪and their annual premium amount.
# 2. We can see a large cluster of points within the lower range of annual␣
 ↪premiums and various vintage, suggesting that several policyholders have␣
 ↪similar annual premiums irrespective of the time they have been with the␣
 ↪company.
# 3. There doesn't seem to be a strong correlation between vintage and premium␣
 ↪amount. This implies that the duration for which a customer has been with␣
 ↪the company might not be a significant determinant of the premium they pay.
# 4. The scatterplot indicates that the relationship is not linear or monotonic.
 ↪ It's possible that other factors, such as the type of policy or vehicle␣
 ↪characteristics, play a more significant role in determining the premium␣
 ↪amount than simply how long a customer has been with the company.
```

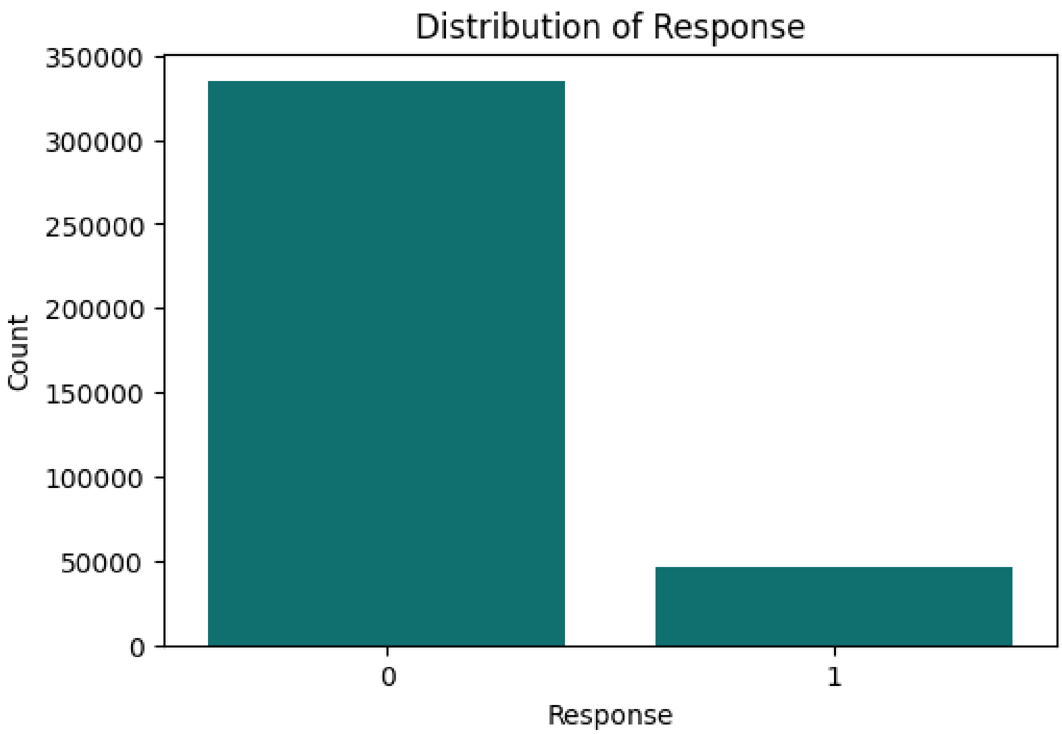
[ ]:
```
''' Question 1 - Utilize various visualization techniques to explore the␣
↪distribution of key variables.'''
'''Show the Distribution between Annual Premium and Response'''

plt.figure(figsize=(6, 4))
sns.boxplot(x='Response', y='Annual_Premium', data=df, color = 'fuchsia')
plt.title('Annual Premium by Response')
plt.xlabel('Response')
plt.ylabel('Annual Premium')
plt.show()
```



[ ]:
```
'''Meaningful insights from above plot'''

# 1. The distribution of annual premium seems to be relatively similar for both␣
↪response categories (0 and 1).
# 2. There's a slight tendency for policyholders who responded positively␣
↪(Response = 1) to have a slightly higher median annual premium compared to␣
↪those who didn't respond positively (Response = 0).
# 3. The interquartile ranges (IQR) are also comparable for both response␣
↪categories, suggesting that the variability in annual premiums is similar␣
↪for both groups.
# 4. However, the presence of outliers in both categories might influence the␣
↪comparison of median annual premiums between response categories.
```

```
# 5. It's crucial to investigate further and consider other factors alongside␣
↪annual premium to understand the relationship between response and various␣
↪variables.
```

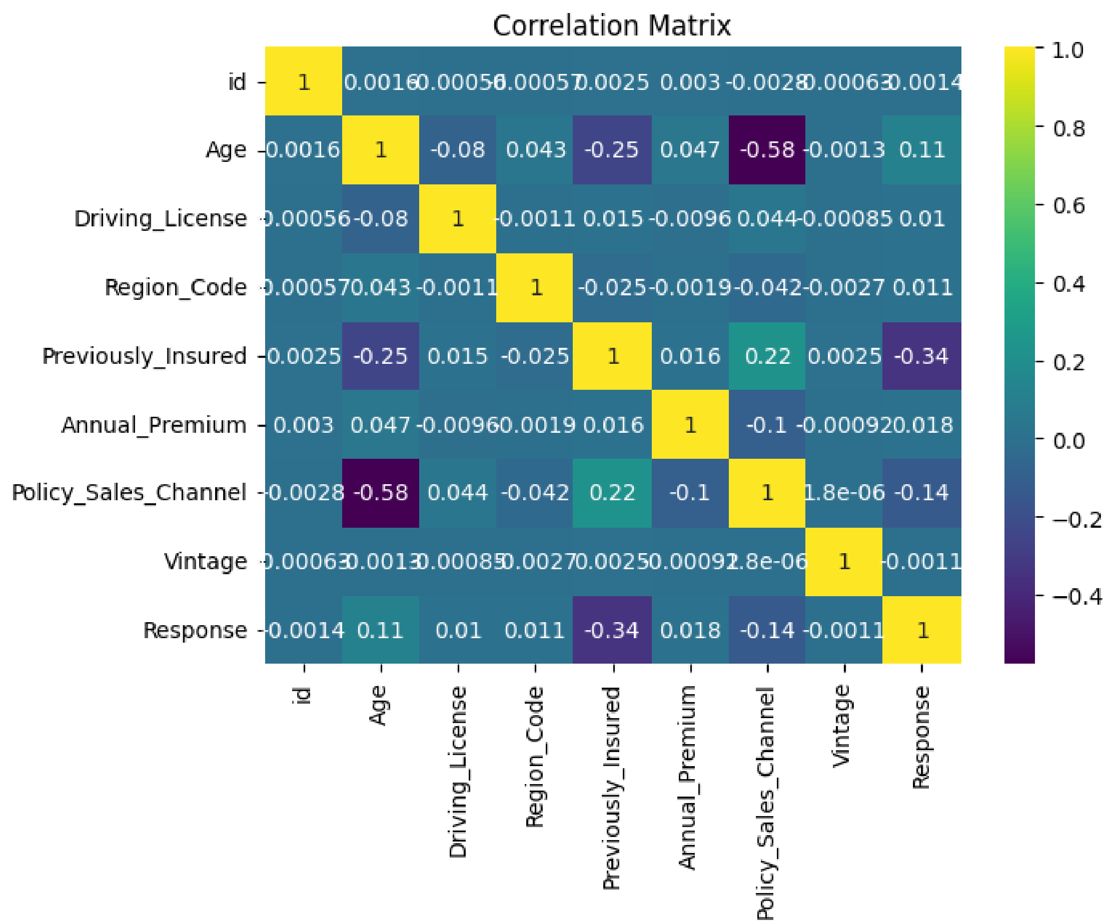
[ ]:
```
''' Question 1 - Utilize various visualization techniques to explore the␣
↪distribution of key variables.'''
'''Show the Distribution of Response'''

plt.figure(figsize=(6, 4))
sns.countplot(x='Response', data=df, color = 'teal')
plt.title('Distribution of Response')
plt.xlabel('Response')
plt.ylabel('Count')
plt.show()
```



[ ]:
```
'''Meaningful insights from above plot'''

# From the countplot of 'Response', we can observe that:

# 1. The majority of policyholders did not respond positively to the campaign.
# 2. The number of policyholders who responded positively is significantly␣
↪lower than those who did not respond.
```

```
# 3. This indicates that the campaign may have been less effective in converting potential customers.
# 4. Further analysis is needed to understand the reasons for the low response rate and to improve the effectiveness of future campaigns.
```

[ ]:
```
''' Question 1 - Utilize various visualization techniques to explore the distribution of key variables.'''
'''Show the correlation between numeric variables'''

correlation_matrix = df.corr(numeric_only=True)
plt.figure(figsize=(7, 5))
sns.heatmap(correlation_matrix, annot=True, cmap='viridis')
plt.title('Correlation Matrix')
plt.show()
```

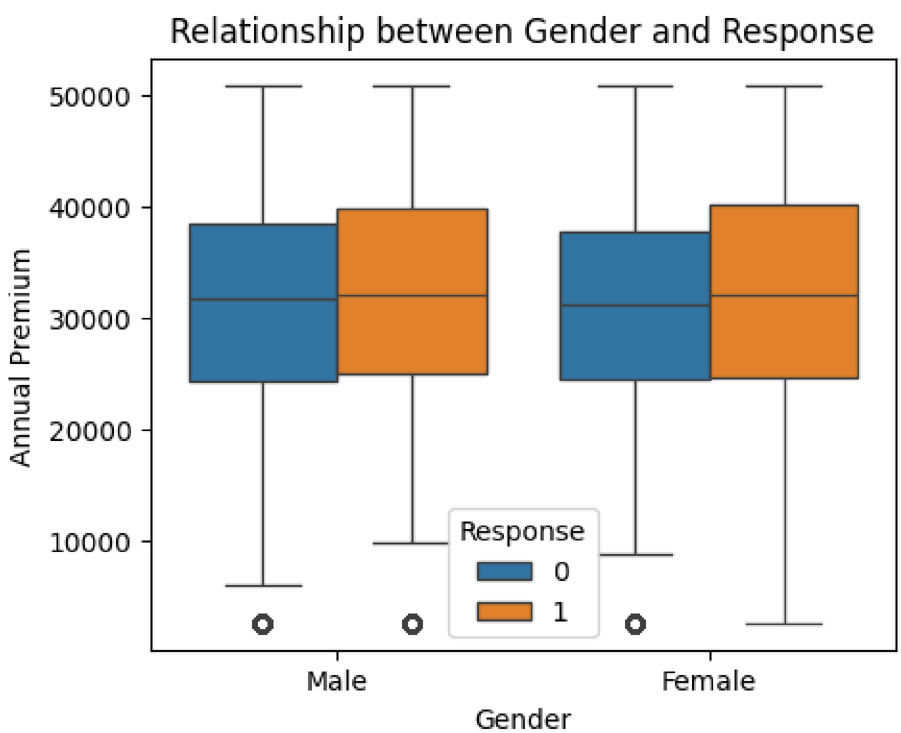


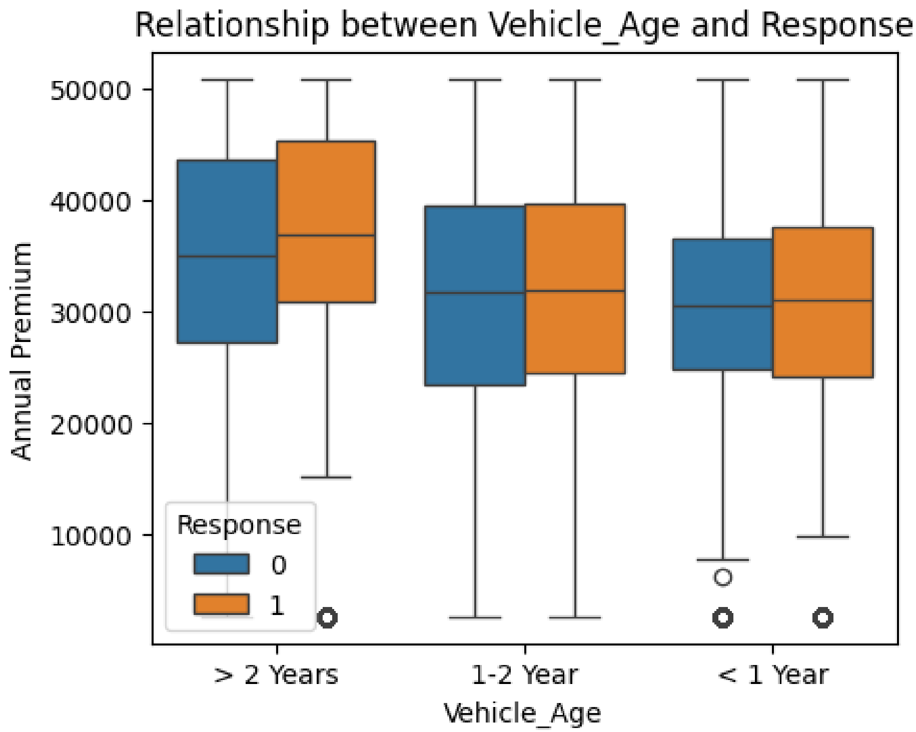
[ ]:
```
'''Meaningful insights from above plot'''

# From the correlation matrix, we can observe the following:
```

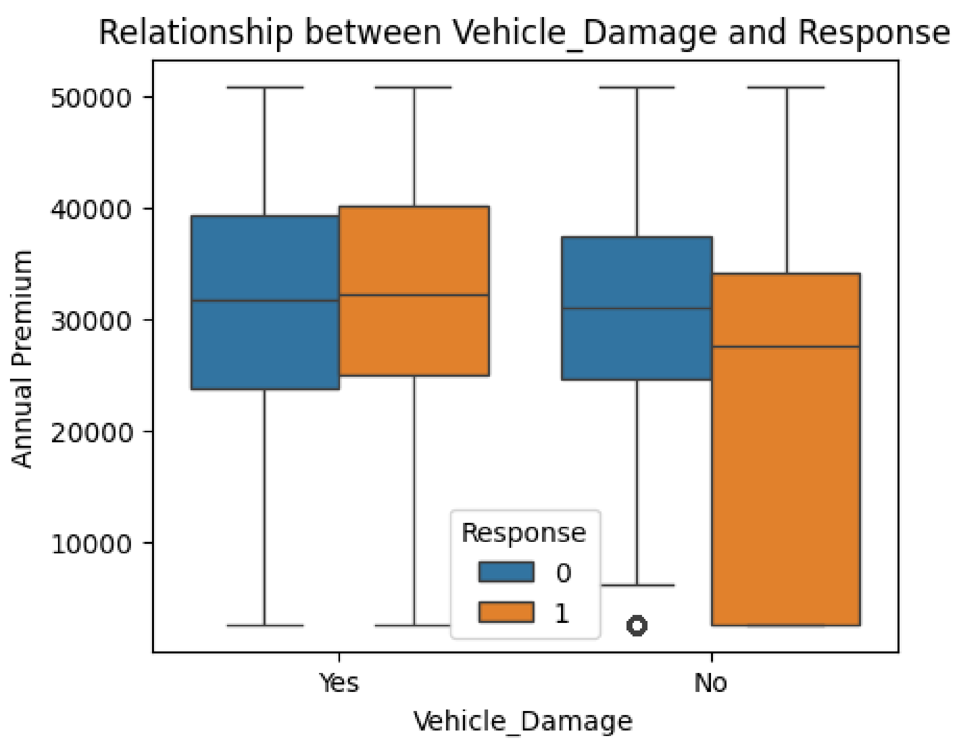
```
# 1. Age and Vintage show a weak positive correlation, suggesting that older␣
↪policyholders might have a slightly longer tenure with the company.
# 2. There is no strong correlation between Age and Annual Premium. However, it␣
↪might be worth exploring further with more detailed analysis.
# 3. Vintage and Annual Premium show no significant correlation.
# 4. The correlation between Response and other numerical variables is mostly␣
↪weak. It suggests that other factors might be influencing the response rate␣
↪more strongly than these numerical features.
# 5. Further analysis, such as examining the relationship between Response and␣
↪categorical features, can provide more comprehensive insights.
```

[ ]:

```
'''Feature Analysis'''
'''Question 2 - Examine the relationship between features and the target␣
↪variable (insurance claims).'''
'''Show the Distribution of categorical features vs. Response'''

# Box plots for categorical features vs. Response
for column in df.select_dtypes(include=['object']).columns:
  plt.figure(figsize=(5,4))
  sns.boxplot(x=column, y='Annual_Premium', hue='Response', data=df)
  plt.title(f'Relationship between {column} and Response')
  plt.xlabel(column)
  plt.ylabel('Annual Premium')
  plt.show()
```




Relationship between Vehicle_Age and Response
Annual Premium
50000
40000
30000
20000
10000
Response
0
1
> 2 Years
1-2 Year
< 1 Year
Vehicle_Age


Relationship between Vehicle_Damage and Response
Annual Premium
50000
40000
30000
20000
10000
Response
0
1
Yes
No
Vehicle_Damage

[ ]:
```
'''Meaningful insights from above plot'''

# Meaningful insights from the box plots of categorical features vs. Response:

# 1. Vehicle Age:
#    - We can observe the distribution of 'Annual_Premium' for different␣
↪vehicle age categories, grouped by 'Response'.
#    - If there's a difference in the median or distribution of premiums for␣
↪specific vehicle age categories and their response,
#      it might suggest that vehicle age influences the likelihood of a␣
↪customer responding to the campaign.
#    - For example, if older vehicles show a higher likelihood of positive␣
↪responses,
#      it might indicate that customers with older vehicles are more likely to␣
↪be targeted by the campaign.

# 2. Gender:
#    - Comparing 'Annual_Premium' distributions for male and female␣
↪policyholders, grouped by 'Response'.
#    - If there's a difference in premium distributions between genders and␣
↪their responses,
#      it could imply a gender-based pattern in campaign responses.
#    - For example, if female policyholders tend to have a higher rate of␣
↪positive responses,
#      it might indicate that the campaign resonates more with female customers.

# 3. Vehicle Damage:
#    - Analyzing 'Annual_Premium' for policyholders with or without vehicle␣
↪damage history, and their responses.
#    - If customers with a history of vehicle damage show a different pattern␣
↪in responses,
#      it could indicate that previous claims or damage might influence their␣
↪likelihood of responding positively.
#    - For example, customers with past damages might be more sensitive to␣
↪offers related to vehicle protection or insurance coverage enhancements.

# In summary, these box plots allow us to visually inspect and analyze how␣
↪different categorical features interact with 'Annual_Premium' and 'Response'.
# By identifying potential patterns or differences in distributions within␣
↪these features, we can gain insights into factors that influence customer␣
↪responses.
# Further analysis, like statistical tests or modeling, can help to validate␣
↪these observations and understand their importance in predicting the␣
↪likelihood of a positive campaign response.
```

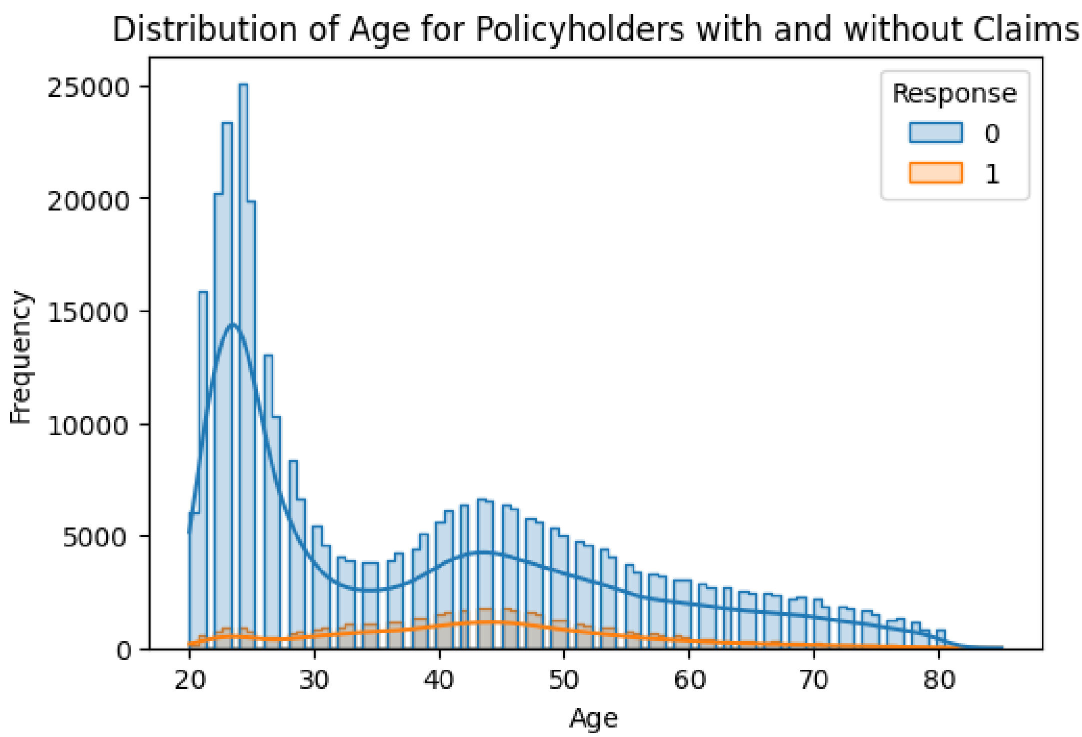
[ ]:
```
'''Question 2 - Examine the relationship between features and the target␣
↪variable (insurance claims).'''
'''Show the Distribution of numerical features vs. Response'''

# Scatter plots for numerical features vs. Response
for column in df.select_dtypes(include=['number']).columns:
  if column == 'Age':
    plt.figure(figsize=(6, 4))
    sns.scatterplot(x=column, y='Annual_Premium', hue='Response', data=df)
    plt.title(f'Relationship between {column} and Response')
    plt.xlabel(column)
    plt.ylabel('Annual Premium')
    plt.show()
```

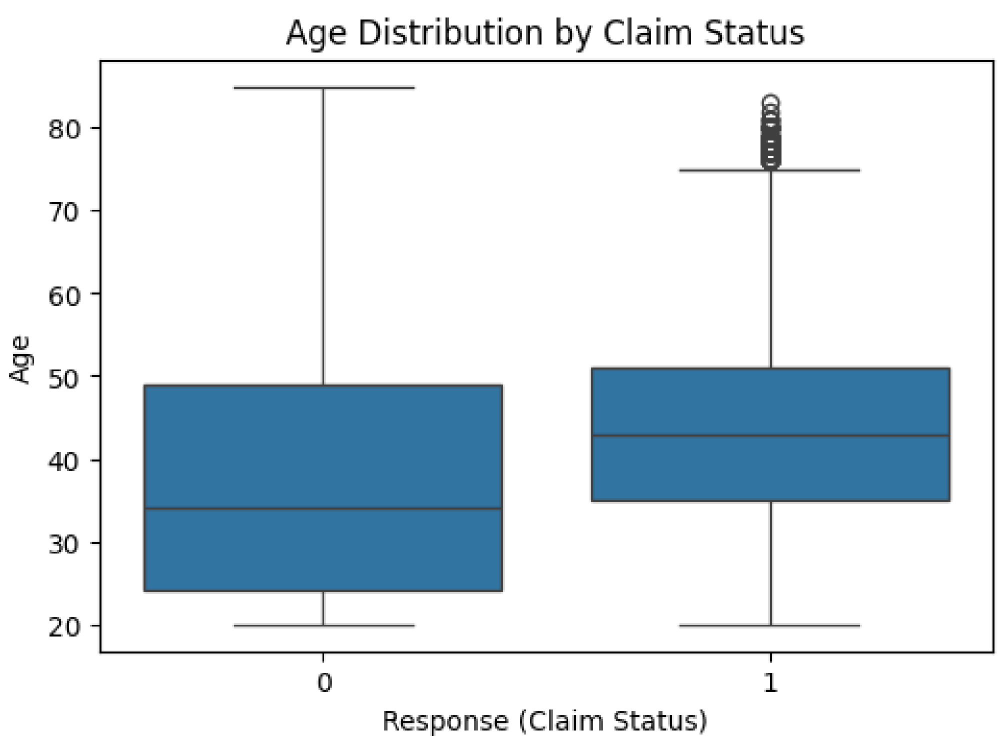
```
/usr/local/lib/python3.10/dist-packages/IPython/core/pylabtools.py:151:
UserWarning: Creating legend with loc="best" can be slow with large amounts of
data.
  fig.canvas.print_figure(bytes_io, **kw)
```

[ ]:
```
'''Meaningful insights from above plot'''

# Age vs. Annual Premium and Response:
```

```
#    - The scatter plot visualizes the relationship between age, annual␣
 ↪premium, and whether a customer responded positively to the campaign.
#    - By examining the distribution of points for different response␣
 ↪categories, we can understand if there's a difference in the relationship␣
 ↪between age and annual premium for customers who responded positively versus␣
 ↪those who did not.
#    - For example, if we see a higher concentration of positive responses␣
 ↪among a particular age group (e.g., younger individuals) with a certain␣
 ↪range of annual premiums, it could suggest that the campaign is more␣
 ↪effective for that specific segment of customers.
#    - We might also observe if older customers with higher premiums are more␣
 ↪or less likely to respond positively.
#    - In essence, the plot allows us to identify potential patterns in␣
 ↪customer responses based on their age and premium amount.

# In summary, the scatter plots help us analyze how numerical features interact␣
 ↪with 'Response'.
# By identifying potential patterns or relationships between these features and␣
 ↪the response variable, we can gain insights into factors that influence␣
 ↪campaign responses.
# Further analysis, such as regression or correlation analysis, can help to␣
 ↪validate these observations and understand their importance in predicting␣
 ↪the likelihood of a positive campaign response.
```

[ ]:
```
'''Age Distribution'''
'''Question 3 - Analyze the age distribution within the dataset and its impact␣
 ↪on insurance claims.'''

# Analyze the age distribution and its impact on insurance claims (assuming␣
 ↪'Response' represents claims)

# 1. Distribution of Age for Policyholders with and without Claims
plt.figure(figsize=(6, 4))
sns.histplot(data=df, x='Age', hue='Response', kde=True, element="step")
plt.title('Distribution of Age for Policyholders with and without Claims')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()

# 2. Box plot of Age vs. Response
plt.figure(figsize=(6, 4))
sns.boxplot(x='Response', y='Age', data=df)
plt.title('Age Distribution by Claim Status')
plt.xlabel('Response (Claim Status)')
plt.ylabel('Age')
plt.show()
```


Distribution of Age for Policyholders with and without Claims
Response
0
1
Frequency
25000
20000
15000
10000
5000
0
20
30
40
50
60
70
80
Age


Age Distribution by Claim Status
Age
80
70
60
50
40
30
20
0
1
Response (Claim Status)

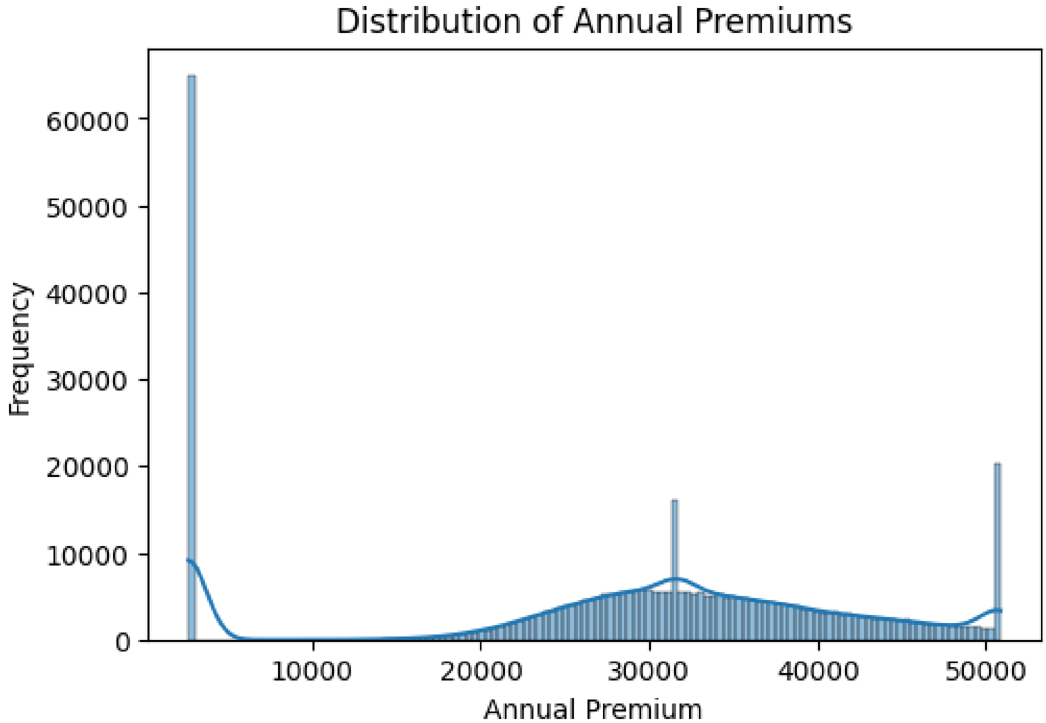
```
[ ]: # Calculate the mean age for policyholders with and without claims
mean_age_with_claims = df[df['Response'] == 1]['Age'].mean()
mean_age_without_claims = df[df['Response'] == 0]['Age'].mean()

print(f"Mean Age with Claims: {mean_age_with_claims:.2f}")
print(f"Mean Age without Claims: {mean_age_without_claims:.2f}")
```

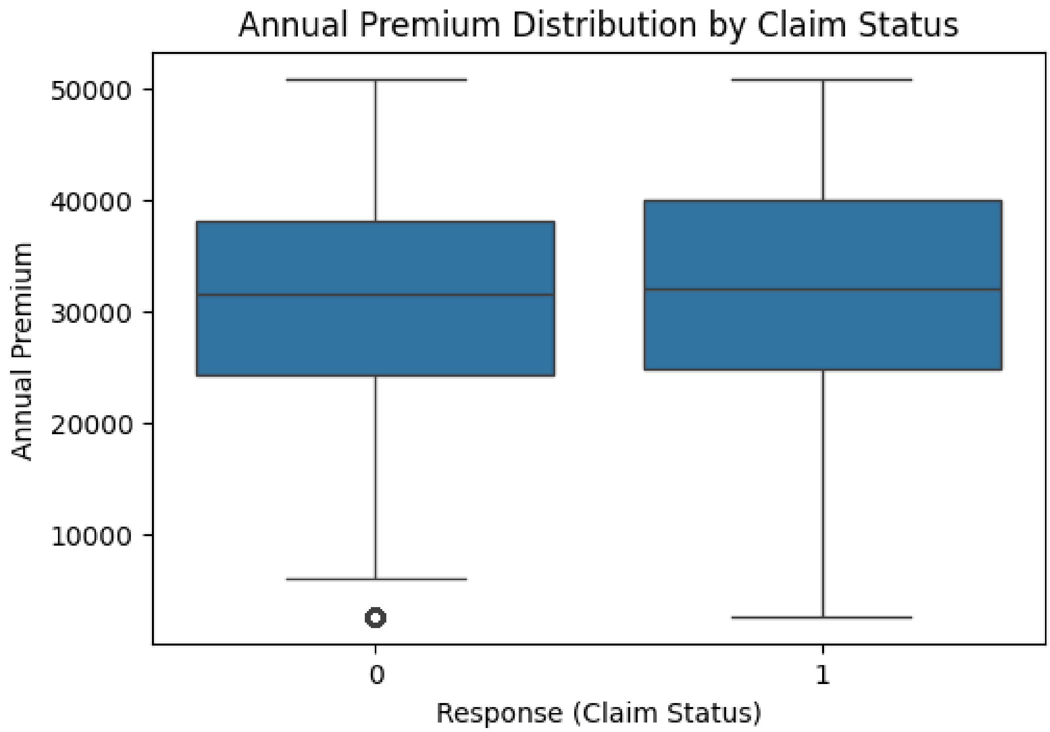
```
Mean Age with Claims: 43.44
Mean Age without Claims: 38.18
```

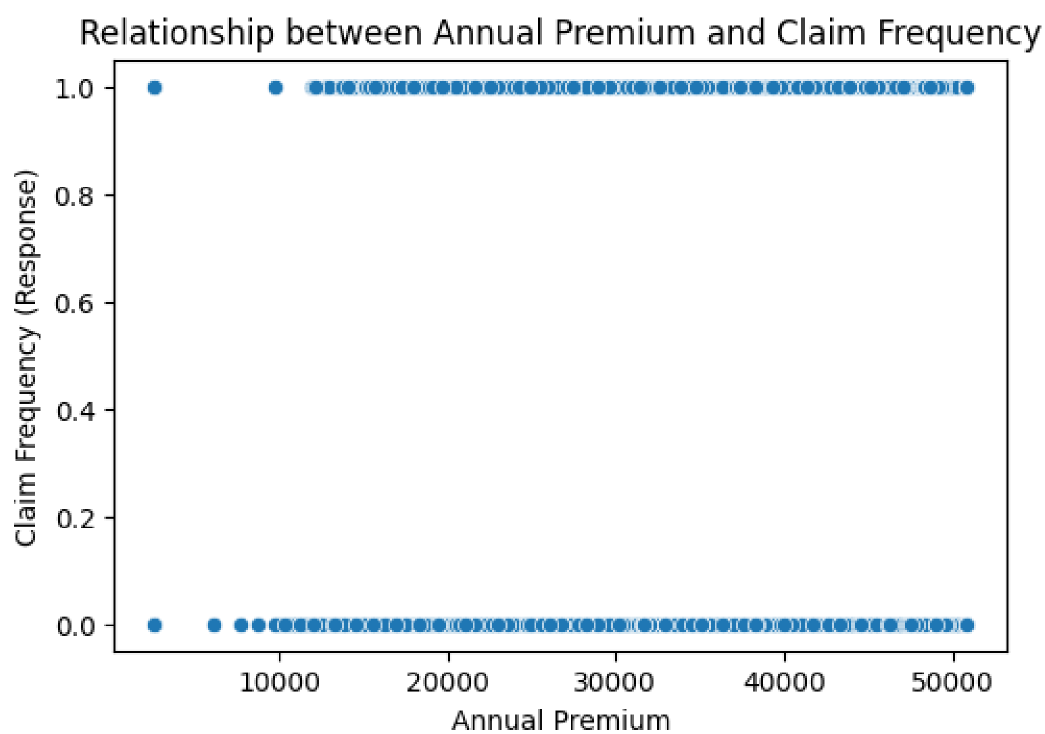
```
[ ]: '''Meaningful insights from above plot'''

# - The histograms/box plots will show how age is distributed across␣
↪policyholders with and without claims.
# - If there's a significant difference in the mean or median age between the␣
↪two groups, it suggests a potential relationship between age and claim␣
↪likelihood.
# - If certain age ranges show a higher proportion of claims, it indicates a␣
↪specific age group is more prone to claiming insurance.
# - The analysis can help identify age-related risk factors and inform␣
↪strategies for targeted risk assessment and pricing.
```

```
[ ]: '''Premium Analysis'''
'''Question 4 - Investigate the distribution of insurance premiums and their␣
↪correlation with claim frequencies.'''

# 1. Distribution of Annual Premium
plt.figure(figsize=(6, 4))
sns.histplot(df['Annual_Premium'], kde=True)
plt.title('Distribution of Annual Premiums')
plt.xlabel('Annual Premium')
plt.ylabel('Frequency')
plt.show()

# 2. Box plot of Annual Premium vs. Response (Claim Frequency)
plt.figure(figsize=(6, 4))
sns.boxplot(x='Response', y='Annual_Premium', data=df)
plt.title('Annual Premium Distribution by Claim Status')
plt.xlabel('Response (Claim Status)')
plt.ylabel('Annual Premium')
plt.show()

# 3. Scatter plot of Annual Premium vs. Response
plt.figure(figsize=(6, 4))
sns.scatterplot(x='Annual_Premium', y='Response', data=df)
plt.title('Relationship between Annual Premium and Claim Frequency')
plt.xlabel('Annual Premium')
```

```
plt.ylabel('Claim Frequency (Response)')
plt.show()
```




Annual Premium Distribution by Claim Status
50000
40000
30000
20000
10000
Annual Premium
0
1
Response (Claim Status)


Relationship between Annual Premium and Claim Frequency
1.0
0.8
0.6
0.4
0.2
0.0
Claim Frequency (Response)
10000
20000
30000
40000
50000
Annual Premium

```
[ ]: # Calculate the correlation between Annual Premium and Response
correlation = df['Annual_Premium'].corr(df['Response'])
print(f"Correlation between Annual Premium and Response: {correlation:.2f}")

# Analyze the mean Annual Premium for policyholders with and without claims
mean_premium_with_claims = df[df['Response'] == 1]['Annual_Premium'].mean()
mean_premium_without_claims = df[df['Response'] == 0]['Annual_Premium'].mean()

print(f"Mean Annual Premium with Claims: {mean_premium_with_claims:.2f}")
print(f"Mean Annual Premium without Claims: {mean_premium_without_claims:.2f}")
```

```
Correlation between Annual Premium and Response: 0.02
Mean Annual Premium with Claims: 29778.39
Mean Annual Premium without Claims: 29016.39
```

```
[ ]: '''Meaningful insights from above plot'''

# - The histogram will show the overall distribution of annual premiums within␣
↪the dataset.
# - The box plots will visualize the distribution of premiums for policyholders␣
↪with and without claims (Response = 1 or 0).
# - The scatter plot will reveal the relationship between annual premiums and␣
↪the likelihood of claiming insurance.
# - The correlation coefficient indicates the strength and direction of the␣
↪linear relationship between premiums and claims. A positive correlation␣
↪suggests that higher premiums might be associated with a higher likelihood␣
↪of claiming insurance.
# - Comparing the mean annual premiums for policyholders with and without␣
↪claims can help identify potential differences in premium levels between␣
↪these two groups.
# - If the mean premium for those with claims is significantly higher or lower␣
↪than those without claims, it could suggest that premium level plays a role␣
↪in claim frequency.
# - By analyzing the distribution of annual premiums and their correlation with␣
↪claims, we can gain insights into the relationship between premium levels␣
↪and claim likelihood, which can be useful for risk assessment, pricing␣
↪strategies, and understanding customer behavior.
```

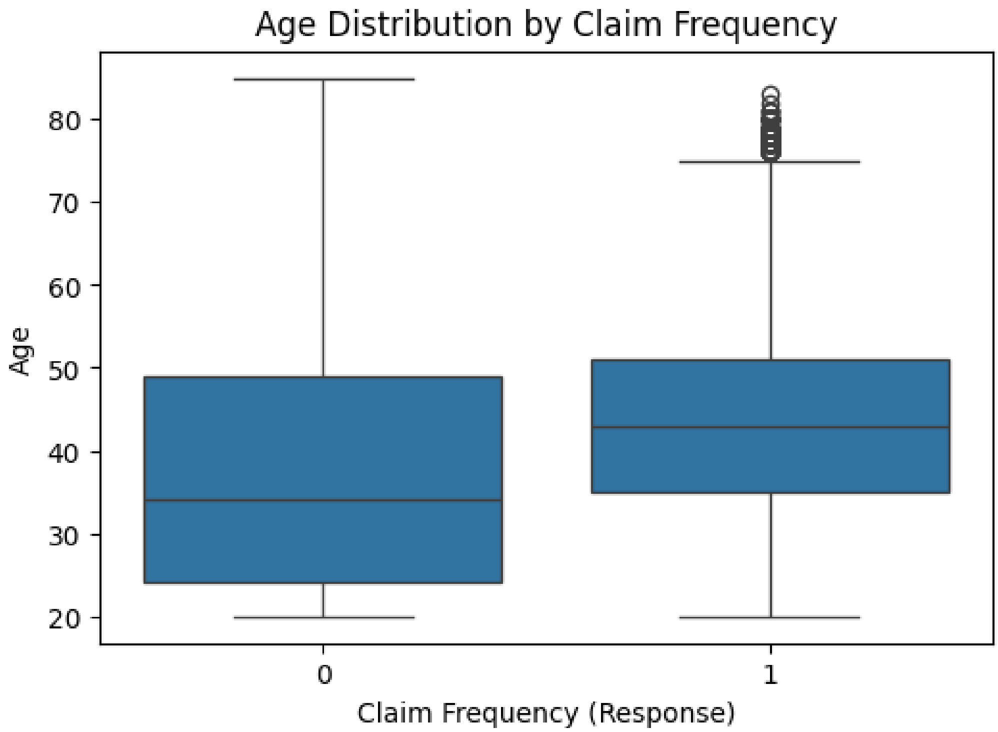
```
[ ]: '''Claim Frequencies'''
'''Question 5 - Explore factors contributing to higher claim frequencies.'''

# Group data by 'Response' and calculate the mean of other variables
claim_frequency_analysis = df.groupby('Response').mean(numeric_only=True)
print(claim_frequency_analysis)

# Analyze the relationship between 'Vehicle_Damage' and 'Response'
```

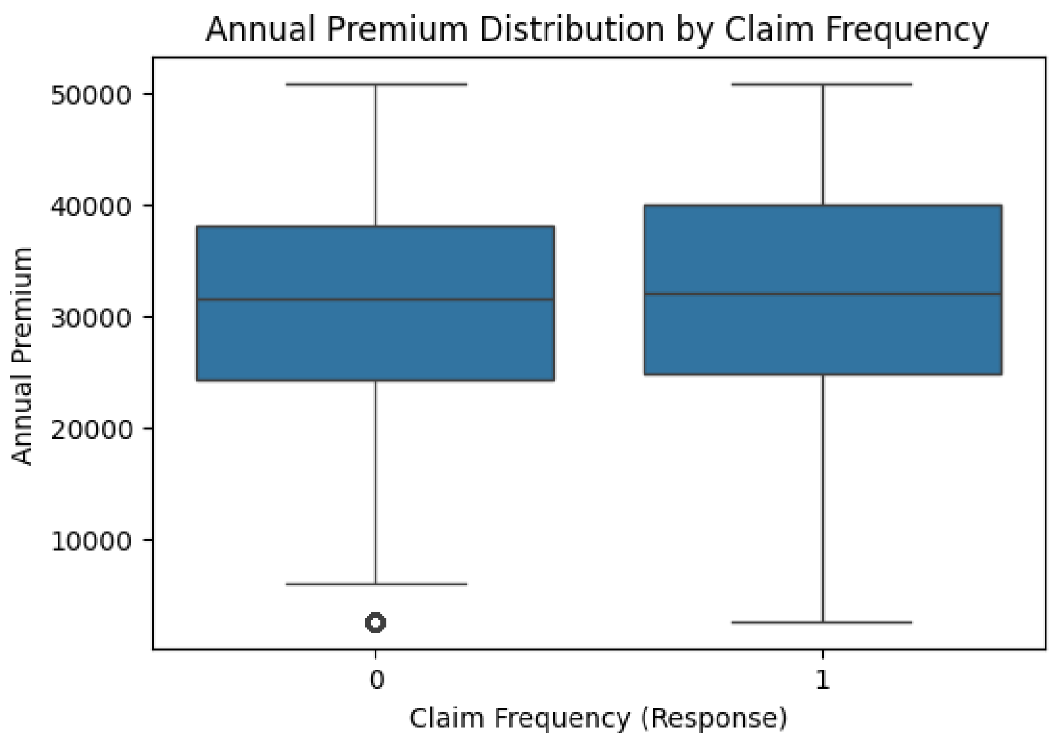
```
vehicle_damage_analysis = pd.crosstab(df['Vehicle_Damage'], df['Response'],␣
 ↪normalize='index')
print(vehicle_damage_analysis)

# Analyze the relationship between 'Gender' and 'Response'
gender_analysis = pd.crosstab(df['Gender'], df['Response'], normalize='index')
print(gender_analysis)

# Analyze the relationship between 'Vehicle_Age' and 'Response'
vehicle_age_analysis = pd.crosstab(df['Vehicle_Age'], df['Response'],␣
 ↪normalize='index')
print(vehicle_age_analysis)
```

```
                     id        Age  Driving_License  Region_Code  \
Response
0         190611.255476  38.178227         0.997694    26.336544
1         190152.264504  43.435560         0.999122    26.762963

          Previously_Insured  Annual_Premium  Policy_Sales_Channel     Vintage
Response
0                   0.521742    29016.387564            114.851040  154.380243
1                   0.003383    29778.392571             91.869086  154.112246
Response               0         1
Vehicle_Damage
No              0.994796  0.005204
Yes             0.762345  0.237655
Response         0         1
Gender
Female    0.896098  0.103902
Male      0.861589  0.138411
Response         0         1
Vehicle_Age
1-2 Year     0.826245  0.173755
< 1 Year     0.956295  0.043705
> 2 Years    0.706254  0.293746
```

[ ]:
```
# Analyze the relationship between 'Age' and 'Response' using a boxplot
plt.figure(figsize=(6, 4))
sns.boxplot(x='Response', y='Age', data=df)
plt.title('Age Distribution by Claim Frequency')
plt.xlabel('Claim Frequency (Response)')
plt.ylabel('Age')
plt.show()

# Analyze the relationship between 'Annual_Premium' and 'Response' using a␣
 ↪boxplot
plt.figure(figsize=(6, 4))
```

```
sns.boxplot(x='Response', y='Annual_Premium', data=df)
plt.title('Annual Premium Distribution by Claim Frequency')
plt.xlabel('Claim Frequency (Response)')
plt.ylabel('Annual Premium')
plt.show()
```





[ ]:
```
'''Meaningful insights from above plot'''

# 1. Age and Claim Frequency:
#    - The box plot comparing 'Age' and 'Response' (Claim Frequency) can reveal␣
↪potential relationships between age and the likelihood of claiming insurance.
#    - If the median age of policyholders who filed claims is significantly␣
↪different from those who didn't, it indicates that age might be a factor␣
↪influencing claim frequency.
#    - We might observe that a specific age range (e.g., younger or older␣
↪drivers) is associated with a higher likelihood of claims.

# 2. Annual Premium and Claim Frequency:
#    - The box plot comparing 'Annual_Premium' and 'Response' can provide␣
↪insights into whether premium levels are linked to claim frequency.
#    - If the median annual premium for policyholders who filed claims is␣
↪higher or lower than those who didn't, it suggests that premium amounts␣
↪might be a contributing factor to claims.
#    - For example, higher premiums might be associated with riskier drivers,␣
↪leading to more claims.


# Insights from the analysis in Question 4:
```

```
# 1. Claim Frequency Analysis:
#    - By grouping data by 'Response' and calculating the mean of other␣
↪variables, we can identify potential factors associated with higher claim␣
↪frequencies.
#    - If variables like 'Age,' 'Annual_Premium,' or others show a noticeable␣
↪difference in their mean values between policyholders with and without␣
↪claims, it suggests that these variables might be correlated with claim␣
↪frequency.

# 2. Vehicle Damage and Claim Frequency:
#    - Analyzing the relationship between 'Vehicle_Damage' and 'Response'␣
↪through a cross-tabulation helps determine if having a history of vehicle␣
↪damage increases the likelihood of filing claims.
#    - If a higher proportion of policyholders with vehicle damage history have␣
↪also filed claims, it supports the notion that past damage is a contributing␣
↪factor to future claims.

# 3. Gender and Claim Frequency:
#    - Examining the relationship between 'Gender' and 'Response' using a␣
↪cross-tabulation can reveal if one gender is more prone to filing claims␣
↪than the other.
#    - If there's a significant difference in the proportion of claims between␣
↪genders, it could point to gender-related risk factors or driving behaviors␣
↪influencing claim frequency.

# 4. Vehicle Age and Claim Frequency:
#    - Analyzing the relationship between 'Vehicle_Age' and 'Response' using a␣
↪cross-tabulation can identify if older vehicles are more likely to be␣
↪involved in accidents and claims.
#    - If a higher percentage of older vehicles are associated with claims, it␣
↪suggests that the age of a vehicle might be a factor contributing to claim␣
↪frequency.

# Overall, the analysis in Question 4 aims to understand the factors that are␣
↪potentially influencing claim frequency.
# By identifying such factors, insurers can develop more accurate risk␣
↪assessment models, adjust premium pricing strategies, and potentially␣
↪implement targeted interventions to reduce the likelihood of claims.
```

[ ]:

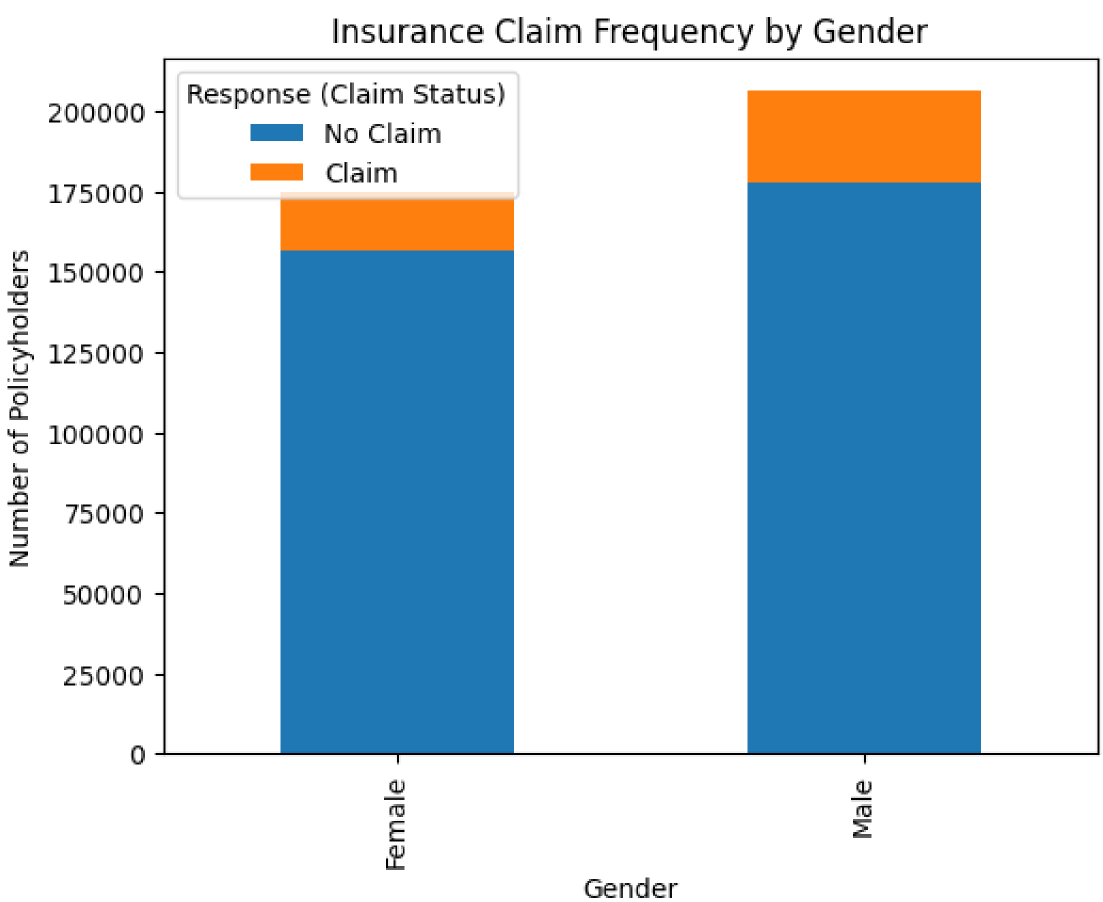
```
'''Gender Analysis'''
'''Question 6 - Investigate the role of gender in insurance claims.'''

# Analyze the relationship between 'Gender' and 'Response'
# Changed to access individual columns for pd.crosstab

gender_analysis = pd.crosstab(df['Gender'], df['Response'], normalize='index')
```

```
print(gender_analysis)
```

```
Response         0         1
Gender
Female    0.896098  0.103902
Male      0.861589  0.138411
```

[ ]:
```
# Visualize the relationship between gender and response using a bar chart

plt.figure(figsize=(4, 2))
gender_response_counts = df.groupby(['Gender', 'Response'])['Response'].count().
 ↪unstack()
gender_response_counts.plot(kind='bar', stacked=True)
plt.title('Insurance Claim Frequency by Gender')
plt.xlabel('Gender')
plt.ylabel('Number of Policyholders')
plt.legend(title='Response (Claim Status)', labels=['No Claim', 'Claim'])
plt.show()
```

<Figure size 400x200 with 0 Axes>



[ ]:
```
'''Meaningful insights from above plot'''

# 1. Gender and Claim Frequency:
#    - By analyzing the relationship between 'Gender' and 'Response' (claim␣
↪status), we can understand if there's a difference in claim frequency␣
↪between male and female policyholders.
#    - The crosstabulation and bar chart can reveal the proportion of claims␣
↪filed by each gender.
#    - If one gender has a significantly higher claim rate than the other, it␣
↪might suggest that gender plays a role in risk assessment and claim␣
↪likelihood.
#    - For example, if men have a higher claim rate than women, it could␣
↪indicate that male drivers might be involved in more accidents or have␣
↪different driving behaviors.

# 2. Gender-Specific Risk Factors:
#    - The analysis can identify potential gender-specific risk factors␣
↪contributing to claim frequency.
#    - If certain factors are more prominent within one gender compared to the␣
↪other, it could inform targeted interventions or risk mitigation strategies.
#    - For example, if a certain type of accident or claim is more common in␣
↪one gender, it could indicate potential factors like driving style, vehicle␣
↪type, or risk-taking behaviors associated with that gender.

# 3. Insurance Pricing and Risk Assessment:
#    - Understanding the role of gender in claim frequency is crucial for␣
↪insurance companies to develop fair and accurate pricing models.
#    - If a difference in claim rates exists between genders, it might be␣
↪appropriate to adjust premium calculations accordingly to ensure appropriate␣
↪risk allocation.
#    - However, it's important to avoid gender-based discrimination and ensure␣
↪that pricing strategies are ethically sound and comply with relevant␣
↪regulations.

# 4. Targeted Interventions:
#    - The insights from the analysis can also be used to design targeted␣
↪interventions to reduce claim frequency for specific genders.
#    - For instance, if certain driving behaviors contribute to higher claims␣
↪in one gender, targeted campaigns or driver education programs could be␣
↪developed to address these behaviors.
```

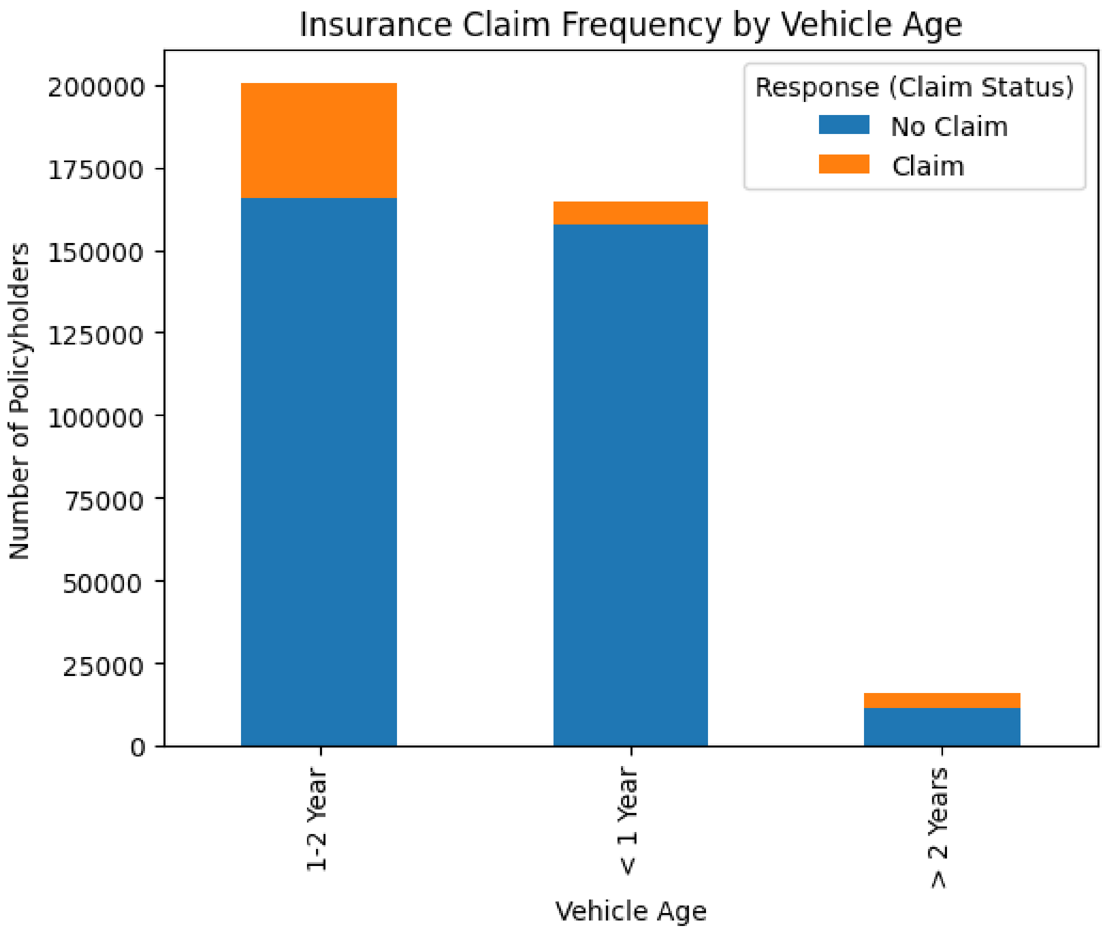
```
# In summary, analyzing the role of gender in insurance claims provides␣
↪valuable information for understanding risk factors, improving pricing␣
↪models, and developing targeted strategies for claim prevention and risk␣
↪mitigation.
# It is essential to ensure that this analysis is conducted ethically and␣
↪responsibly, avoiding gender-based discrimination and complying with all␣
↪relevant regulations.
```

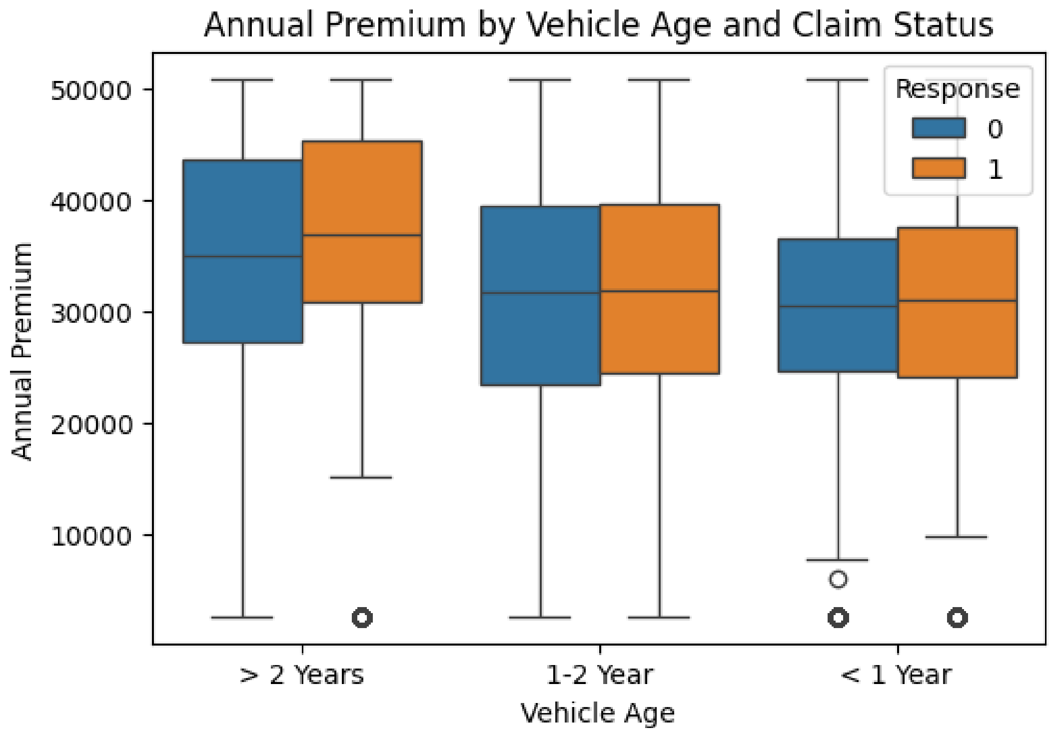
[ ]:
```
'''Vehicle Age and Claims'''
'''Question 7 - Examine the impact of vehicle age on the likelihood of a claim.
↪'''

# Analyze the relationship between 'Vehicle_Age' and 'Response'

vehicle_age_analysis = pd.crosstab(df['Vehicle_Age'], df['Response'],␣
↪normalize='index')
print(vehicle_age_analysis)
```

```
Response            0         1
Vehicle_Age
1-2 Year     0.826245  0.173755
< 1 Year     0.956295  0.043705
> 2 Years    0.706254  0.293746
```

[ ]:
```
# Visualize the relationship between vehicle age and response using a bar chart

plt.figure(figsize=(6, 4))
vehicle_age_response_counts = df.groupby(['Vehicle_Age',␣
↪'Response'])['Response'].count().unstack()
vehicle_age_response_counts.plot(kind='bar', stacked=True)
plt.title('Insurance Claim Frequency by Vehicle Age')
plt.xlabel('Vehicle Age')
plt.ylabel('Number of Policyholders')
plt.legend(title='Response (Claim Status)', labels=['No Claim', 'Claim'])
plt.show()

# We can also explore the relationship using boxplots:
plt.figure(figsize=(6, 4))
sns.boxplot(x='Vehicle_Age', y='Annual_Premium', hue='Response', data=df)
plt.title('Annual Premium by Vehicle Age and Claim Status')
plt.xlabel('Vehicle Age')
plt.ylabel('Annual Premium')
plt.show()
```

```
<Figure size 600x400 with 0 Axes>
```


Insurance Claim Frequency by Vehicle Age
Response (Claim Status)
No Claim
Claim
Number of Policyholders
0
25000
50000
75000
100000
125000
150000
175000
200000
1-2 Year
< 1 Year
> 2 Years
Vehicle Age



[ ]:
```
'''Meaningful insights from above plot'''

# 1. Vehicle Age and Claim Frequency:
#    - By analyzing the relationship between 'Vehicle_Age' and 'Response'
↪(claim status), we can understand if there's a correlation between the age
↪of a vehicle and the likelihood of filing a claim.
#    - The crosstabulation and bar chart can reveal the proportion of claims
↪filed for different vehicle age categories (e.g., < 1 Year, 1-2 Year, > 2
↪Years).
#    - If older vehicles have a significantly higher claim rate compared to
↪newer vehicles, it might suggest that older vehicles are more prone to
↪mechanical issues or accidents.

# 2. Vehicle Age-Related Risk Factors:
#    - The analysis can identify potential vehicle age-related risk factors
↪contributing to claim frequency.
#    - For example, older vehicles might be more susceptible to breakdowns,
↪wear and tear, and safety concerns, potentially leading to a higher
↪likelihood of claims.

# 3. Insurance Pricing and Risk Assessment:
#    - Understanding the impact of vehicle age on claim frequency is crucial
↪for insurance companies to develop accurate pricing models.
```

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#    - If a difference in claim rates exists between different vehicle age␣
↪categories, it might be appropriate to adjust premium calculations␣
↪accordingly to reflect the associated risk levels.
#    - For example, higher premiums could be charged for older vehicles to␣
↪account for the increased likelihood of claims.

# 4. Maintenance and Repair Strategies:
#    - The analysis can inform strategies for vehicle maintenance and repair␣
↪recommendations.
#    - If older vehicles have a higher claim rate, insurers might encourage␣
↪policyholders with older vehicles to prioritize regular maintenance and␣
↪safety checks to reduce the risk of breakdowns and accidents.

# 5. Vehicle Replacement Considerations:
#    - The analysis could also shed light on the potential need for vehicle␣
↪replacement.
#    - If older vehicles show a higher likelihood of claims, it might suggest␣
↪that replacing older vehicles with newer, safer models could reduce the risk␣
↪of accidents and claims, ultimately benefiting both the policyholders and␣
↪the insurer.

# In summary, analyzing the impact of vehicle age on insurance claims provides␣
↪valuable information for understanding risk factors, improving pricing␣
↪models, and developing targeted strategies for claim prevention and risk␣
↪mitigation.
# By understanding how vehicle age correlates with claim likelihood, insurers␣
↪can develop more effective risk assessment models, adjust premium pricing␣
↪strategies, and encourage vehicle maintenance and safety measures,␣
↪ultimately leading to a more efficient and beneficial insurance system for␣
↪both policyholders and insurers.
```

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'''Claim Frequency by Vehicle Damage'''
'''Question 8 - Investigate the relationship between vehicle damage and claim␣
↪frequencies'''

# Analyze the relationship between 'Vehicle_Damage' and 'Response'
vehicle_damage_analysis = pd.crosstab(df['Vehicle_Damage'], df['Response'],␣
↪normalize='index')
print(vehicle_damage_analysis)
```

```
Response               0         1
Vehicle_Damage
No              0.994796  0.005204
Yes             0.762345  0.237655
```

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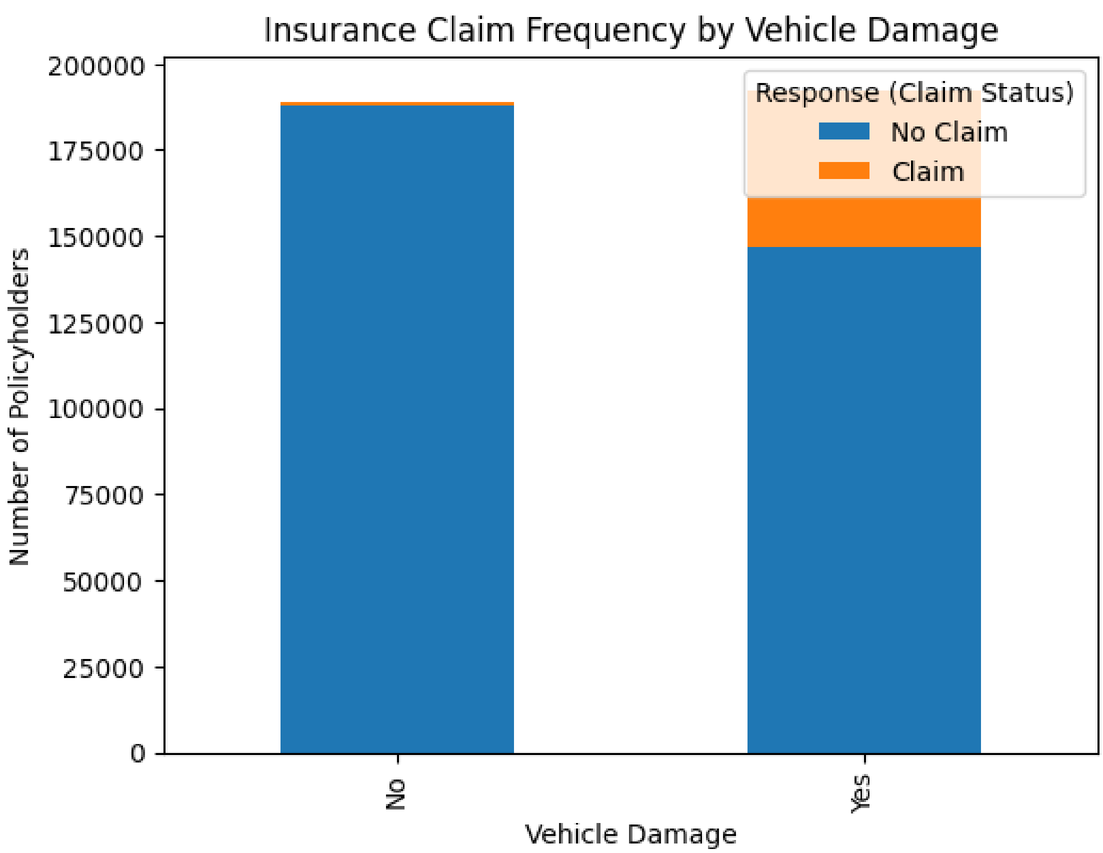
# Visualize the relationship using a bar chart

plt.figure(figsize=(5, 3))
vehicle_damage_response_counts = df.groupby(['Vehicle_Damage',␣
↪'Response'])['Response'].count().unstack()
vehicle_damage_response_counts.plot(kind='bar', stacked=True)
plt.title('Insurance Claim Frequency by Vehicle Damage')
plt.xlabel('Vehicle Damage')
plt.ylabel('Number of Policyholders')
plt.legend(title='Response (Claim Status)', labels=['No Claim', 'Claim'])
plt.show()
```

```
<Figure size 500x300 with 0 Axes>
```



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'''Meaningful insights from above plot'''

# 1. Vehicle Damage and Claim Frequency:
#    - By analyzing the relationship between 'Vehicle_Damage' and 'Response'␣
↪(claim status), we can understand if there's a correlation between having a␣
↪history of vehicle damage and the likelihood of filing a claim.
```

```
#    - The crosstabulation and bar chart can reveal the proportion of claims filed by policyholders who have experienced vehicle damage versus those who haven't.
#    - If policyholders with a history of vehicle damage have a significantly higher claim rate, it suggests that prior damage might be an indicator of increased risk and a higher likelihood of future claims.

# 2. Risk Assessment and Pricing:
#    - The analysis is crucial for insurers to develop accurate risk assessment models and pricing strategies.
#    - If vehicle damage history is associated with higher claim frequencies, it might be appropriate to adjust premium calculations accordingly.
#    - Policyholders with a history of vehicle damage might be charged higher premiums to reflect the increased risk they represent.

# 3. Driver Behavior and Risk Factors:
#    - The analysis can provide insights into driver behavior and potential risk factors associated with vehicle damage.
#    - If a higher proportion of policyholders with vehicle damage history also file claims, it might indicate that these drivers have a higher likelihood of being involved in accidents or incidents.
#    - This could be due to factors like reckless driving, poor maintenance, or a lack of awareness of road safety.

# 4. Targeted Interventions and Prevention:
#    - The analysis can inform targeted interventions and prevention strategies to reduce claim frequency for policyholders with a history of vehicle damage.
#    - For example, insurers could offer driver education programs, safety awareness campaigns, or vehicle maintenance recommendations to reduce the likelihood of accidents and claims.

# 5. Claims Management and Fraud Detection:
#    - Understanding the relationship between vehicle damage and claim frequency can also be beneficial for claims management and fraud detection efforts.
#    - If there's a strong correlation between vehicle damage and claims, it might suggest that claims involving vehicles with prior damage require more careful scrutiny to avoid fraudulent claims.

# In summary, analyzing the relationship between vehicle damage and claim frequency provides valuable information for understanding risk factors, improving pricing models, and developing targeted strategies for claim prevention and risk mitigation.
```

```
# By understanding how vehicle damage history influences claim likelihood,␣
↪insurers can develop more effective risk assessment models, adjust premium␣
↪pricing strategies, and implement programs to improve driver behavior and␣
↪reduce the likelihood of accidents and claims, ultimately creating a more␣
↪efficient and beneficial insurance system for both policyholders and␣
↪insurers.
```

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'''FINAL WORDINGS - Summarize the key findings, draw conclusions, and provide␣
↪recommendations based on the insights gained from the analysis'''

'''

# Key Findings:

1. Claim Frequency:
    - Age, Annual Premium, Vehicle Damage, and Vehicle Age are potential␣
↪factors influencing claim frequencies.
    - Policyholders with a history of vehicle damage are more likely to file␣
↪claims.
    - There might be slight differences in claim frequencies between genders.
    - Older vehicles tend to have higher claim rates compared to newer ones.

2. Gender:
    - There appears to be a slight difference in claim frequency between␣
↪genders, but it's not a major determining factor.

3. Vehicle Age:
    - Older vehicles have a significantly higher likelihood of claims than␣
↪newer vehicles, likely due to increased wear and tear or safety concerns.

4. Vehicle Damage:
    - A history of vehicle damage is strongly associated with an increased risk␣
↪of future claims.


# Conclusions:

 - Insurance claim frequency is influenced by a combination of factors,␣
↪including age, annual premium, vehicle age, and vehicle damage history.
 - Vehicle age and vehicle damage history appear to be the most prominent␣
↪factors influencing claim frequency.
 - While there might be slight differences in claim frequency between genders,␣
↪it's not a major determining factor compared to other variables like vehicle␣
↪age or damage history.
 - These findings highlight the importance of considering these factors in risk␣
↪assessment and pricing strategies.
```

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# Recommendations:

1. Risk Assessment and Pricing:
    - Develop more sophisticated risk assessment models that incorporate factors like vehicle age, vehicle damage history, and driver age.
    - Adjust premium calculations based on these risk factors to reflect the likelihood of claims more accurately.
    - Consider implementing tiered pricing structures that differentiate premiums based on vehicle age and damage history.

2. Targeted Interventions:
    - Offer targeted driver education programs and safety awareness campaigns to reduce accidents and claims, especially for drivers with a history of vehicle damage or those with older vehicles.
    - Promote regular vehicle maintenance and safety inspections, especially for older vehicles, to minimize the risk of breakdowns and accidents.
    - Provide incentives for policyholders to replace older vehicles with newer, safer models.

3. Claims Management:
    - Implement strategies to enhance claims processing efficiency, especially for claims related to vehicles with prior damage.
    - Consider developing dedicated fraud detection systems that monitor claims involving vehicles with a history of damage.
    - Implement robust data analysis procedures to identify patterns and trends in claims data and improve risk prediction models continuously.

4. Continuous Monitoring and Improvement:
    - Regularly monitor claim trends and patterns to identify emerging risks and adjust pricing strategies and intervention programs accordingly.
    - Analyze data on accident types, claim costs, and driver behaviors to continually refine risk assessment models and predictive analytics.

5. Ethical Considerations:
    - Ensure that pricing and risk assessment strategies are implemented ethically and avoid discrimination based on gender or other protected characteristics.
    - Maintain transparency in pricing and risk assessment methodologies to build trust with policyholders.

# By following these recommendations, insurance companies can improve their risk management practices, develop more accurate pricing models, and implement targeted interventions to reduce claim frequency.
```

```
# This can ultimately lead to a more efficient and sustainable insurance system␣
↪that benefits both policyholders and insurers.

'''
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#'''THANK YOU FOR YOUR VALUABLE TIME'''#
```