



ALLIANCE

UNIVERSITY

Project Report

Bachelor Of Computer Applications
2nd Semester

Exploratory Data Analysis Project

Insurance Dataset Based on Real-World Statistics

By

SATHVIK B R

2411021240027

Githublink: <https://github.com/Sathvik0007/SDS-PROJECT-.git>

Department Of Computer Application
Alliance University

Chandrapura - Anekal Main Road, Anekal
Bengaluru – 56210

Introduction

The dataset used in this analysis is a sales dataset that contains various attributes related to product sales, including 'Units Sold', 'Unit Price', and other relevant features. The primary objective of this analysis is to explore and visualize the distribution of key variables, specifically 'Units Sold' and 'Unit Price'. By employing statistical visualizations such as histograms and boxplots, we aim to gain insights into the sales performance, identify trends, and detect any anomalies or outliers in the data. This understanding can inform business decisions, optimize pricing strategies, and enhance inventory management.

Objectives

1. **Analyze Sales Distribution:** To visualize and understand the distribution of 'Units Sold' and 'Unit Price' to identify patterns, trends, and central tendencies in the sales data.
2. **Identify Outliers:** To detect any outliers in the 'Units Sold' and 'Unit Price' data using boxplots, which can indicate unusual sales behavior or pricing strategies that may need further investigation.
3. **Understand Variability:** To assess the variability and spread of the data, helping to understand the range of sales performance and pricing strategies across different products.
4. **Support Data-Driven Decisions:** To provide insights that can inform business decisions related to inventory management, pricing strategies, and sales forecasting.
5. **Enhance Reporting:** To create visual representations of the data that can be used in reports and presentations, making it easier for stakeholders to grasp key insights quickly.

Libraries Used

1. **Pandas:** For data manipulation and analysis.
2. **Seaborn:** For creating visualizations like histograms and boxplots.
3. **Matplotlib:** For customizing and displaying plots.

These libraries facilitated effective analysis and visualization of the sales data.

Load the dataset

Dataset of students

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
df=pd.read_csv(r"/Users/sathvikbr/Documents/synthetic_insurance_data.csv")
df
```

	Age	Is_Senior	Marital_Status	Married_Premium_Discount	Prior_Insurance
\					
0	47	0	Married	86	1-5 years
1	37	0	Married	86	1-5 years
2	49	0	Married	86	1-5 years
3	62	1	Married	86	>5 years
4	36	0	Single	0	>5 years
...
9995	59	1	Single	0	1-5 years
9996	18	0	Married	86	1-5 years
9997	29	0	Married	86	<1 year
9998	47	0	Single	0	<1 year
9999	49	0	Divorced	0	1-5 years

	Prior_Insurance_Premium_Adjustment	Claims_Frequency	Claims_Severity	\
0	50	0	Low	
1	50	0	Low	
2	50	1	Low	
3	0	1	Low	
4	0	2	Low	
...	
9995	50	0	Low	
9996	50	0	Medium	
9997	100	0	Low	
9998	100	0	Medium	
9999	50	0	High	

	Claims_Adjustment	Policy_Type	...	Time_Since_First_Contact	\
0	0	Full Coverage	...	10	
1	0	Full Coverage	...	22	
2	50	Full Coverage	...	28	
3	50	Full Coverage	...	4	
4	100	Full Coverage	...	14	
...	
9995	0	Full Coverage	...	6	
9996	0	Full Coverage	...	3	
9997	0	Full Coverage	...	29	
9998	0	Liability-Only	...	8	
9999	0	Liability-Only	...	11	

Conversion_Status	Website_Visits	Inquiries	Quotes_Requested	\
-------------------	----------------	-----------	------------------	---

0	0	5	1	2
1	0	5	1	2
2	0	4	4	1
3	1	6	2	2
4	1	8	4	2
...
9995	1	4	3	2
9996	1	6	1	3
9997	1	3	4	3
9998	1	2	4	1
9999	1	5	0	2

	Time_to_Conversion	Credit_Score	Premium_Adjustment_Credit	Region \
0	99	704	-50	Suburban
1	99	726	-50	Urban
2	99	772	-50	Urban
3	2	809	-50	Urban
4	10	662	50	Suburban
...
9995	9	783	-50	Urban
9996	6	667	50	Urban
9997	3	637	50	Urban
9998	13	676	50	Suburban
9999	4	776	-50	Suburban

	Premium_Adjustment_Region
0	50
1	100
2	100
3	100
4	50
...	...
9995	100
9996	100
9997	100
9998	50
9999	50

[10000 rows x 27 columns]

df.head (20)

	Age	Is_Senior	Marital_Status	Married_Premium_Discount	Prior_Insurance
0	47	0	Married	86	1-5 years
1	37	0	Married	86	1-5 years
2	49	0	Married	86	1-5 years
3	62	1	Married	86	>5 years
4	36	0	Single	0	>5 years
5	36	0	Married	86	>5 years

6	63	1	Married	86	1-5 years
7	51	0	Single	0	<1 year
8	32	0	Married	86	>5 years
9	48	0	Single	0	>5 years
10	33	0	Single	0	>5 years
11	33	0	Married	86	<1 year
12	43	0	Single	0	1-5 years
13	18	0	Single	0	1-5 years
14	18	0	Married	86	1-5 years
15	31	0	Married	86	1-5 years
16	24	0	Single	0	1-5 years
17	44	0	Widowed	0	1-5 years
18	26	0	Single	0	<1 year
19	18	0	Married	86	1-5 years

	Prior_Insurance_Premium_Adjustment	Claims_Frequency	Claims_Severity	\
0	50	0	Low	
1	50	0	Low	
2	50	1	Low	
3	0	1	Low	
4	0	2	Low	
5	0	0	Medium	
6	50	0	Low	
7	100	0	Low	
8	0	0	Low	
9	0	1	High	
10	0	1	Low	
11	100	1	Low	
12	50	1	High	
13	50	1	Low	
14	50	1	Low	
15	50	0	Low	
16	50	0	Low	
17	50	1	Low	
18	100	0	Low	
19	50	0	Low	

	Claims_Adjustment	Policy_Type	...	Time_Since_First_Contact	\
0	0	Full Coverage	...	10	
1	0	Full Coverage	...	22	
2	50	Full Coverage	...	28	
3	50	Full Coverage	...	4	
4	100	Full Coverage	...	14	
5	0	Liability-Only	...	13	
6	0	Full Coverage	...	2	
7	0	Full Coverage	...	1	
8	0	Liability-Only	...	16	
9	200	Full Coverage	...	27	
10	50	Liability-Only	...	22	
11	50	Liability-Only	...	16	

12	200	Liability-Only	...	29
13	50	Liability-Only	...	22
14	50	Full Coverage	...	7
15	0	Full Coverage	...	23
16	0	Full Coverage	...	8
17	50	Full Coverage	...	4
18	0	Full Coverage	...	14
19	0	Liability-Only	...	11

	Conversion_Status	Website_Visits	Inquiries	Quotes_Requested	\
0	0	5	1	2	
1	0	5	1	2	
2	0	4	4	1	
3	1	6	2	2	
4	1	8	4	2	
5	1	4	1	1	
6	1	5	1	2	
7	0	3	0	2	
8	1	5	1	3	
9	0	5	3	2	
10	1	3	2	1	
11	1	3	1	3	
12	0	4	1	3	
13	1	7	0	3	
14	1	3	3	2	
15	0	3	3	2	
16	1	3	2	3	
17	1	3	1	3	
18	1	5	2	1	
19	1	3	2	1	

	Time_to_Conversion	Credit_Score	Premium_Adjustment_Credit	Region
0	99	704	-50	Suburban
1	99	726	-50	Urban
2	99	772	-50	Urban
3	2	809	-50	Urban
4	10	662	50	Suburban
5	7	729	-50	Rural
6	1	795	-50	Urban
7	99	639	50	Suburban
8	3	724	-50	Rural
9	99	710	-50	Urban
10	13	688	50	Suburban
11	6	659	50	Rural
12	99	745	-50	Urban
13	9	777	-50	Suburban
14	8	668	50	Suburban
15	99	775	-50	Urban
16	10	695	50	Suburban
17	7	739	-50	Urban

18	8	750	-50	Urban
19	11	625	50	Urban

	Premium_Adjustment_Region
0	50
1	100
2	100
3	100
4	50
5	0
6	100
7	50
8	0
9	100
10	50
11	0
12	100
13	50
14	50
15	100
16	50
17	100
18	100
19	100

[20 rows x 27 columns]

df.tail (20)

	Age	Is_Senior	Marital_Status	Married_Premium_Discount	Prior_Insurance
\					
9980	33	0	Single	0	>5 years
9981	32	0	Married	86	1-5 years
9982	47	0	Married	86	1-5 years
9983	43	0	Married	86	<1 year
9984	22	0	Single	0	1-5 years
9985	34	0	Divorced	0	1-5 years
9986	34	0	Single	0	1-5 years
9987	18	0	Married	86	1-5 years
9988	25	0	Married	86	<1 year
9989	28	0	Married	86	>5 years
9990	61	1	Married	86	<1 year
9991	42	0	Married	86	>5 years
9992	49	0	Widowed	0	1-5 years
9993	18	0	Single	0	1-5 years
9994	57	1	Single	0	<1 year
9995	59	1	Single	0	1-5 years
9996	18	0	Married	86	1-5 years
9997	29	0	Married	86	<1 year
9998	47	0	Single	0	<1 year

9999	49	0	Divorced	0	1-5 years
------	----	---	----------	---	-----------

	Prior_Insurance_Premium_Adjustment	Claims_Frequency	Claims_Severity	\
9980	0	0	Low	
9981	50	2	Low	
9982	50	0	Low	
9983	100	2	High	
9984	50	0	Low	
9985	50	0	Low	
9986	50	0	Low	
9987	50	0	High	
9988	100	0	Low	
9989	0	1	Low	
9990	100	1	Medium	
9991	0	0	Low	
9992	50	1	Low	
9993	50	0	Low	
9994	100	0	Low	
9995	50	0	Low	
9996	50	0	Medium	
9997	100	0	Low	
9998	100	0	Medium	
9999	50	0	High	

	Claims_Adjustment	Policy_Type	...	Time_Since_First_Contact	\
9980	0	Full Coverage	...	4	
9981	100	Liability-Only	...	26	
9982	0	Full Coverage	...	25	
9983	400	Full Coverage	...	3	
9984	0	Liability-Only	...	27	
9985	0	Full Coverage	...	8	
9986	0	Full Coverage	...	26	
9987	0	Liability-Only	...	7	
9988	0	Liability-Only	...	24	
9989	50	Full Coverage	...	25	
9990	100	Full Coverage	...	20	
9991	0	Full Coverage	...	16	
9992	50	Liability-Only	...	10	
9993	0	Liability-Only	...	5	
9994	0	Full Coverage	...	23	
9995	0	Full Coverage	...	6	
9996	0	Full Coverage	...	3	
9997	0	Full Coverage	...	29	
9998	0	Liability-Only	...	8	
9999	0	Liability-Only	...	11	

	Conversion_Status	Website_Visits	Inquiries	Quotes_Requested	\
9980	1	4	0	1	
9981	1	5	5	1	
9982	1	4	2	1	

9983	1	7	3	1
9984	1	5	0	2
9985	1	4	2	1
9986	1	4	2	3
9987	1	3	0	2
9988	1	7	3	2
9989	0	3	2	1
9990	1	4	3	3
9991	0	4	0	2
9992	1	4	0	3
9993	1	6	1	3
9994	1	3	3	1
9995	1	4	3	2
9996	1	6	1	3
9997	1	3	4	3
9998	1	2	4	1
9999	1	5	0	2

	Time_to_Conversion	Credit_Score	Premium_Adjustment_Credit	Region \
9980	5	817	-50	Suburban
9981	7	663	50	Urban
9982	5	729	-50	Rural
9983	2	714	-50	Urban
9984	9	626	50	Urban
9985	13	738	-50	Urban
9986	1	672	50	Urban
9987	2	710	-50	Rural
9988	12	691	50	Rural
9989	99	687	50	Urban
9990	6	646	50	Suburban
9991	99	662	50	Suburban
9992	10	828	-50	Suburban
9993	7	723	-50	Suburban
9994	5	709	-50	Urban
9995	9	783	-50	Urban
9996	6	667	50	Urban
9997	3	637	50	Urban
9998	13	676	50	Suburban
9999	4	776	-50	Suburban

	Premium_Adjustment_Region
9980	50
9981	100
9982	0
9983	100
9984	100
9985	100
9986	100
9987	0
9988	0

```

9989          100
9990          50
9991          50
9992          50
9993          50
9994         100
9995         100
9996         100
9997         100
9998          50
9999          50

```

[20 rows x 27 columns]

```
df.describe()
```

	Age	Is_Senior	Married_Premium_Discount \
count	10000.000000	10000.000000	10000.000000
mean	39.991700	0.159300	42.131400
std	14.050358	0.365974	42.993376
min	18.000000	0.000000	0.000000
25%	29.000000	0.000000	0.000000
50%	39.000000	0.000000	0.000000
75%	50.000000	0.000000	86.000000
max	90.000000	1.000000	86.000000

	Prior_Insurance_Premium_Adjustment	Claims_Frequency \
count	10000.000000	10000.000000
mean	47.625000	0.497200
std	34.354438	0.716131
min	0.000000	0.000000
25%	0.000000	0.000000
50%	50.000000	0.000000
75%	50.000000	1.000000
max	100.000000	5.000000

	Claims_Adjustment	Policy_Adjustment	Premium_Amount \
count	10000.000000	10000.000000	10000.000000
mean	36.780000	-79.860000	2219.571400
std	65.910288	97.955806	148.521132
min	0.000000	-200.000000	1800.000000
25%	0.000000	-200.000000	2100.000000
50%	0.000000	0.000000	2236.000000
75%	50.000000	0.000000	2336.000000
max	800.000000	0.000000	2936.000000

	Safe_Driver_Discount	Multi_Policy_Discount	... Total_Discounts \
count	10000.000000	10000.000000	10000.000000
mean	0.199900	0.305100	30.110000
std	0.399945	0.460473	33.689782

min	0.000000	0.000000	...	0.000000
25%	0.000000	0.000000	...	0.000000
50%	0.000000	0.000000	...	50.000000
75%	0.000000	1.000000	...	50.000000
max	1.000000	1.000000	...	150.000000

	Time_Since_First_Contact	Conversion_Status	Website_Visits	\
count	10000.000000	10000.000000	10000.000000	
mean	15.478000	0.576700	5.022900	
std	8.677975	0.494107	2.238231	
min	1.000000	0.000000	0.000000	
25%	8.000000	0.000000	3.000000	
50%	16.000000	1.000000	5.000000	
75%	23.000000	1.000000	6.000000	
max	30.000000	1.000000	16.000000	

	Inquiries	Quotes_Requested	Time_to_Conversion	Credit_Score	\
count	10000.000000	10000.000000	10000.000000	10000.000000	
mean	1.996900	1.996900	46.07320	714.253400	
std	1.415588	0.817409	45.44845	49.749487	
min	0.000000	1.000000	1.000000	530.000000	
25%	1.000000	1.000000	6.000000	681.000000	
50%	2.000000	2.000000	12.000000	715.000000	
75%	3.000000	3.000000	99.000000	748.000000	
max	9.000000	3.000000	99.000000	850.000000	

	Premium_Adjustment_Credit	Premium_Adjustment_Region
count	10000.000000	10000.000000
mean	-11.320000	64.325000
std	48.704156	39.232618
min	-50.000000	0.000000
25%	-50.000000	50.000000
50%	-50.000000	50.000000
75%	50.000000	100.000000
max	50.000000	100.000000

[8 rows x 21 columns]

df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 27 columns):
```

#	Column	Non-Null Count	Dtype
---	-----	-----	-----
0	Age	10000 non-null	int64
1	Is_Senior	10000 non-null	int64
2	Marital_Status	10000 non-null	object
3	Married_Premium_Discount	10000 non-null	int64
4	Prior_Insurance	10000 non-null	object

5	Prior_Insurance_Premium_Adjustment	10000	non-null	int64
6	Claims_Frequency	10000	non-null	int64
7	Claims_Severity	10000	non-null	object
8	Claims_Adjustment	10000	non-null	int64
9	Policy_Type	10000	non-null	object
10	Policy_Adjustment	10000	non-null	int64
11	Premium_Amount	10000	non-null	int64
12	Safe_Driver_Discount	10000	non-null	int64
13	Multi_Policy_Discount	10000	non-null	int64
14	Bundling_Discount	10000	non-null	int64
15	Total_Discounts	10000	non-null	int64
16	Source_of_Lead	10000	non-null	object
17	Time_Since_First_Contact	10000	non-null	int64
18	Conversion_Status	10000	non-null	int64
19	Website_Visits	10000	non-null	int64
20	Inquiries	10000	non-null	int64
21	Quotes_Requested	10000	non-null	int64
22	Time_to_Conversion	10000	non-null	int64
23	Credit_Score	10000	non-null	int64
24	Premium_Adjustment_Credit	10000	non-null	int64
25	Region	10000	non-null	object
26	Premium_Adjustment_Region	10000	non-null	int64

dtypes: int64(21), object(6)

memory usage: 2.1+ MB

df.describe

```
<bound method NDFrame.describe of
Married_Premium_Discount Prior_Insurance \
Age Is_Senior Marital_Status
0      47      0      Married      86      1-5 years
1      37      0      Married      86      1-5 years
2      49      0      Married      86      1-5 years
3      62      1      Married      86      >5 years
4      36      0      Single      0      >5 years
...      ...      ...      ...      ...      ...
9995    59      1      Single      0      1-5 years
9996    18      0      Married      86      1-5 years
9997    29      0      Married      86      <1 year
9998    47      0      Single      0      <1 year
9999    49      0      Divorced      0      1-5 years
```

```
Prior_Insurance_Premium_Adjustment Claims_Frequency Claims_Severity \
0      50      0      Low
1      50      0      Low
2      50      1      Low
3      0      1      Low
4      0      2      Low
...      ...      ...      ...
9995    50      0      Low
9996    50      0      Medium
```

9997	100	0	Low
9998	100	0	Medium
9999	50	0	High

	Claims_Adjustment	Policy_Type	...	Time_Since_First_Contact	\
0	0	Full Coverage	...	10	
1	0	Full Coverage	...	22	
2	50	Full Coverage	...	28	
3	50	Full Coverage	...	4	
4	100	Full Coverage	...	14	
...	
9995	0	Full Coverage	...	6	
9996	0	Full Coverage	...	3	
9997	0	Full Coverage	...	29	
9998	0	Liability-Only	...	8	
9999	0	Liability-Only	...	11	

	Conversion_Status	Website_Visits	Inquiries	Quotes_Requested	\
0	0	5	1	2	
1	0	5	1	2	
2	0	4	4	1	
3	1	6	2	2	
4	1	8	4	2	
...	
9995	1	4	3	2	
9996	1	6	1	3	
9997	1	3	4	3	
9998	1	2	4	1	
9999	1	5	0	2	

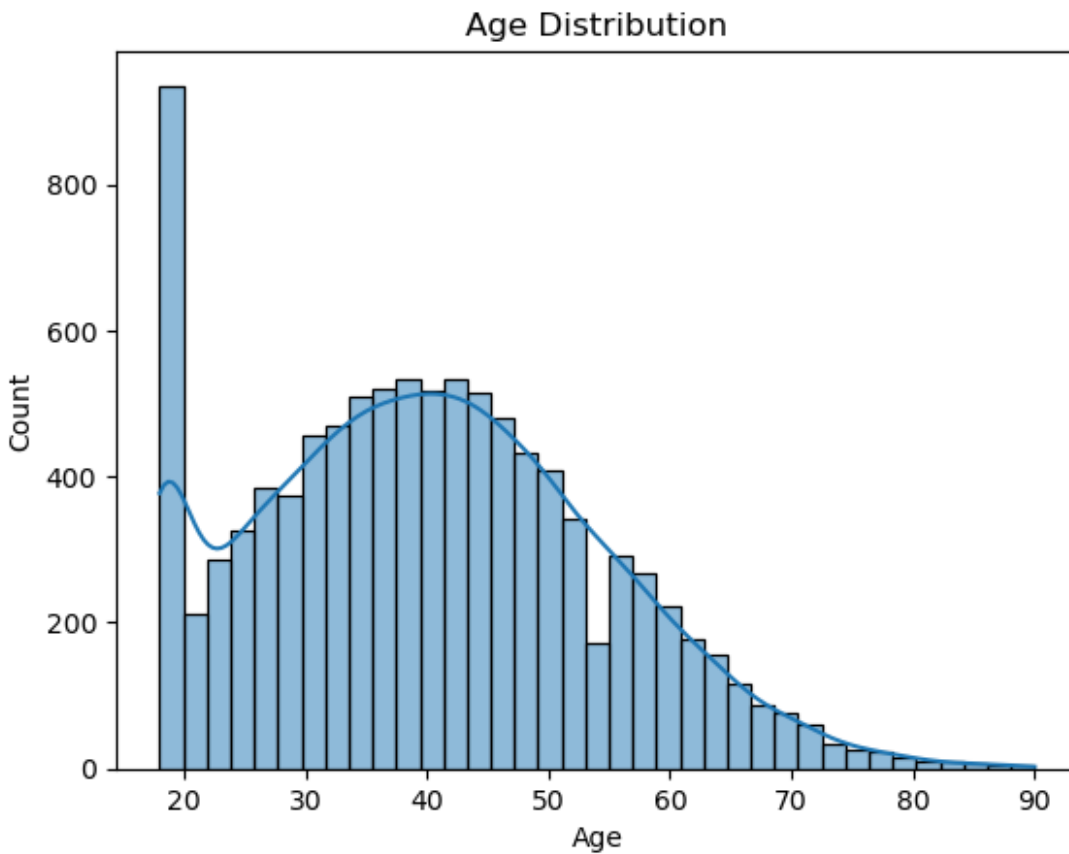
	Time_to_Conversion	Credit_Score	Premium_Adjustment_Credit	Region	\
0	99	704	-50	Suburban	
1	99	726	-50	Urban	
2	99	772	-50	Urban	
3	2	809	-50	Urban	
4	10	662	50	Suburban	
...	
9995	9	783	-50	Urban	
9996	6	667	50	Urban	
9997	3	637	50	Urban	
9998	13	676	50	Suburban	
9999	4	776	-50	Suburban	

	Premium_Adjustment_Region
0	50
1	100
2	100
3	100
4	50

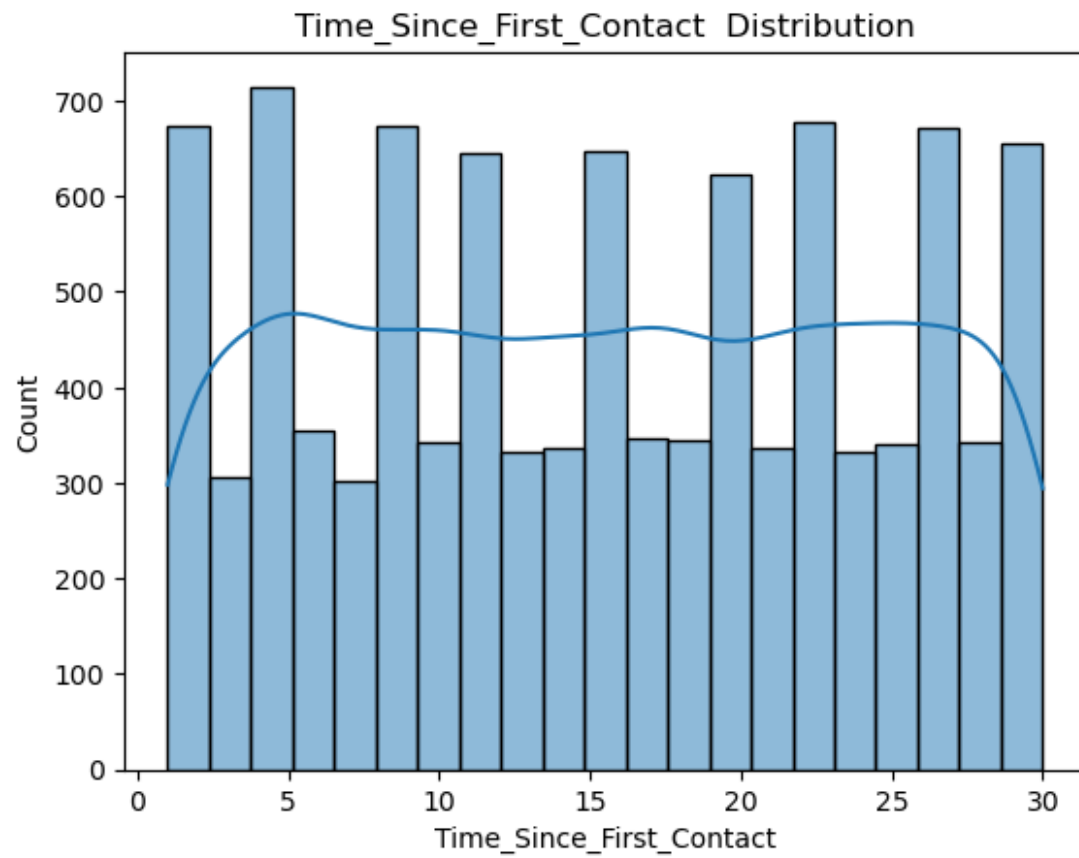
```
...
9995      100
9996      100
9997      100
9998       50
9999       50
```

```
[10000 rows x 27 columns]>
```

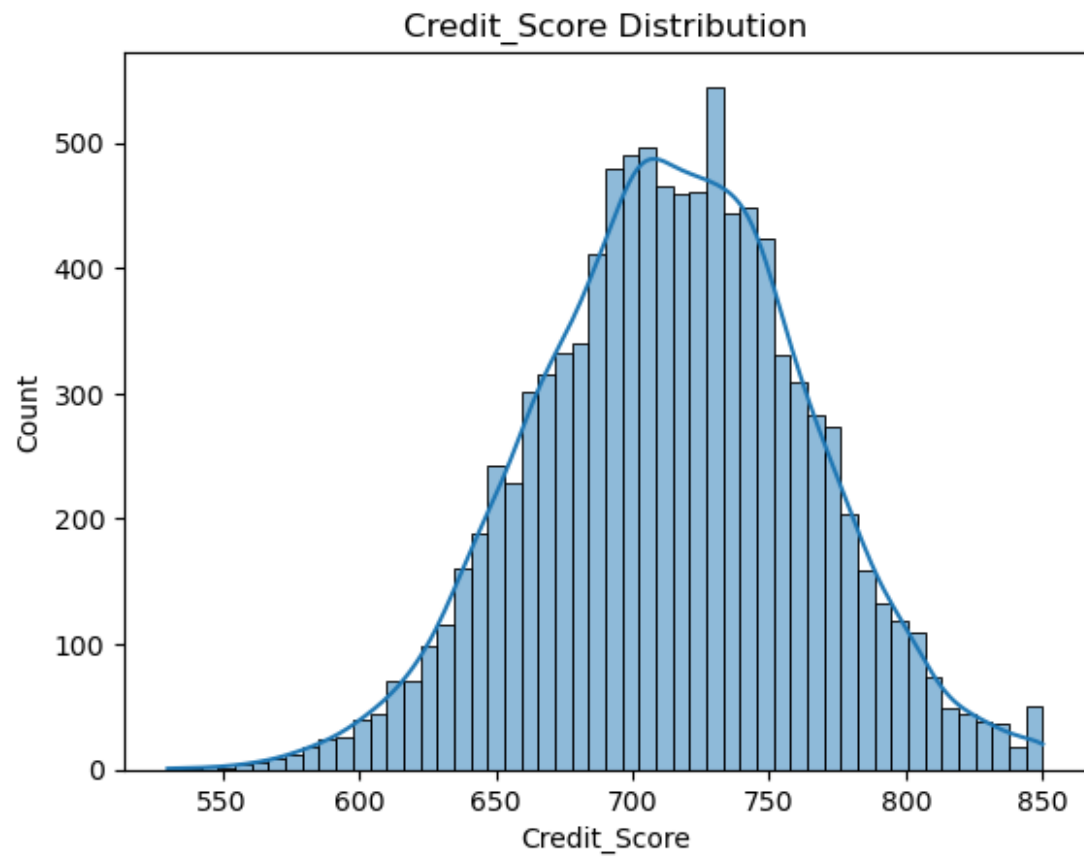
```
# Univariate Analysis: Numerical
sns.histplot(df['Age'], kde=True).set_title('Age Distribution')
plt.show()
```



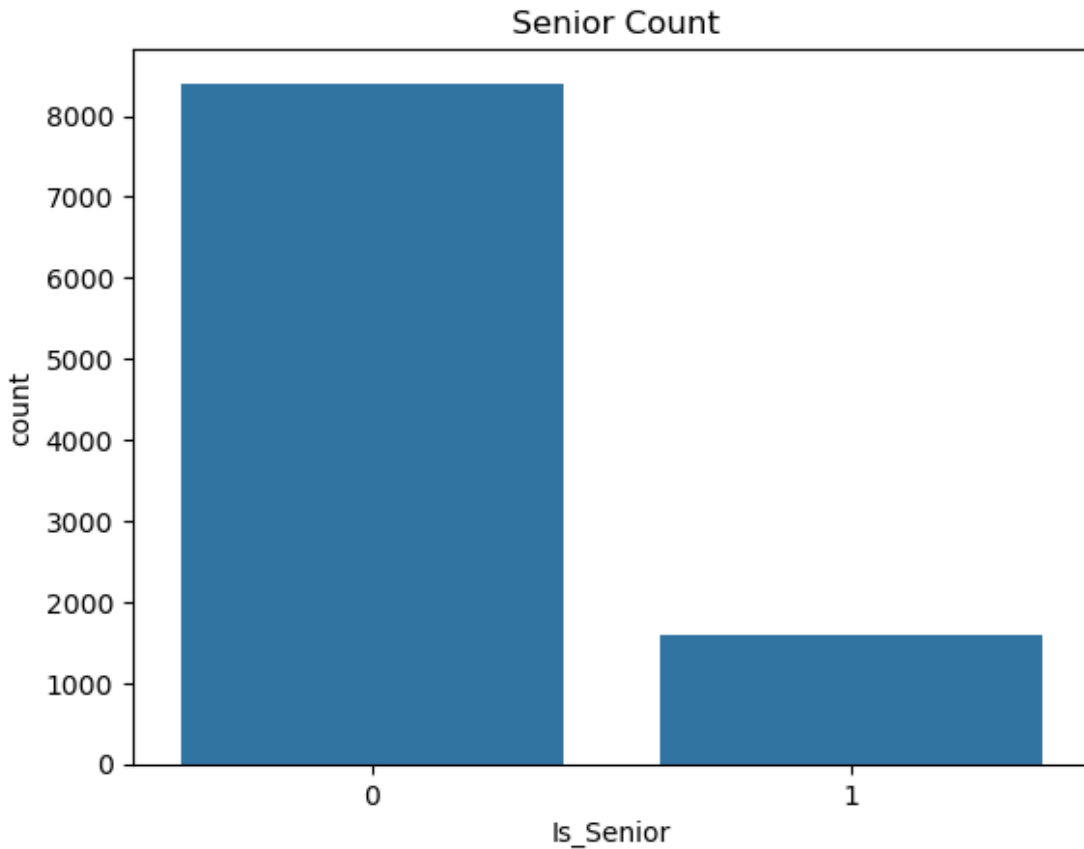
```
# Univariate Analysis: Numerical
sns.histplot(df['Time_Since_First_Contact'],
kde=True).set_title('Time_Since_First_Contact Distribution')
plt.show()
```



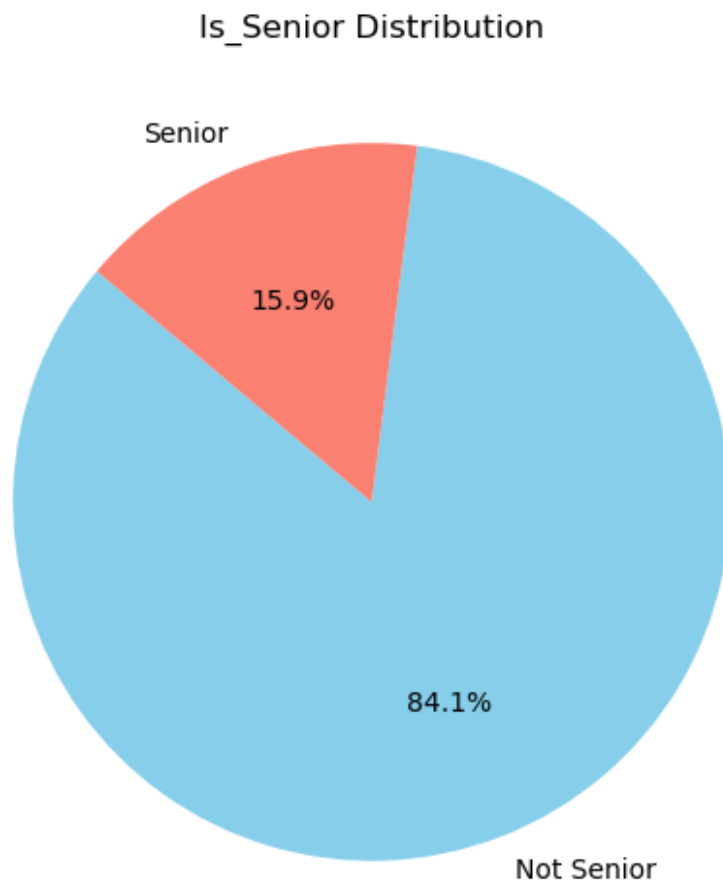
```
# Univariate Analysis: Numerical
sns.histplot(df['Credit_Score'], kde=True).set_title('Credit_Score
Distribution')
plt.show()
```



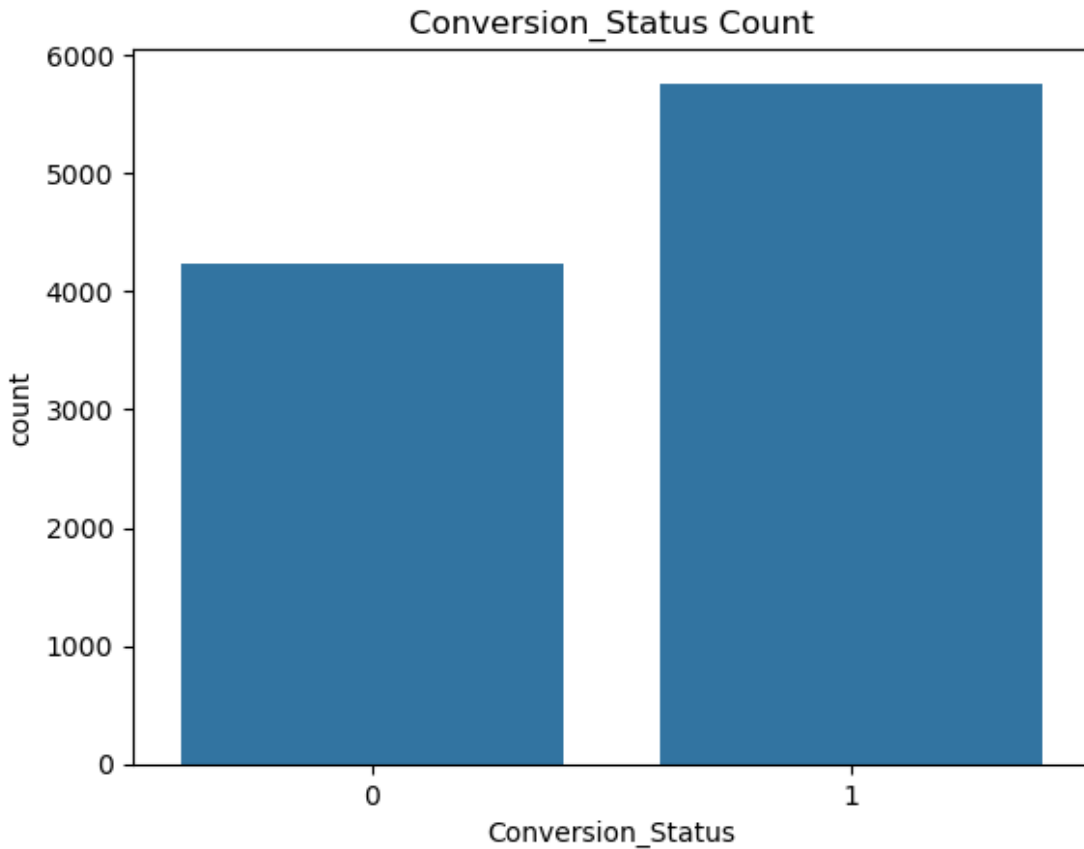
```
# Univariate Analysis: Categorical  
sns.countplot(x='Is_Senior', data=df).set_title(' Senior Count')  
plt.show()
```

```
# Univariate Pie Chart: Senior distribution
depression_counts = df['Is_Senior'].value_counts()
plt.figure(figsize=(6, 6))
plt.pie(depression_counts, labels=['Not Senior', 'Senior'],
        autopct='%1.1f%%', startangle=140, colors=['skyblue', 'salmon'])
plt.title('Is_Senior Distribution')
plt.show()
```

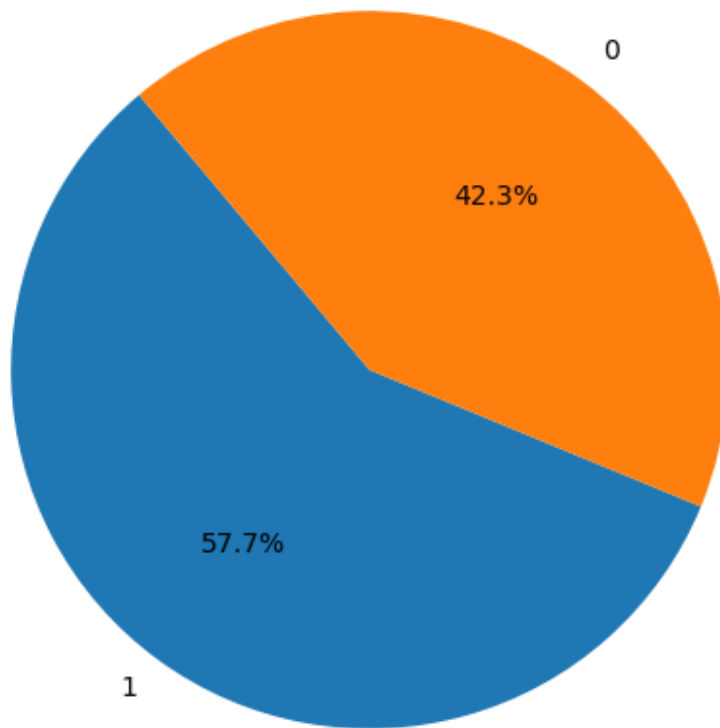


```
# Univariate Analysis: Categorical  
sns.countplot(x='Conversion_Status', data=df).set_title('Conversion_Status  
Count')  
plt.show()
```

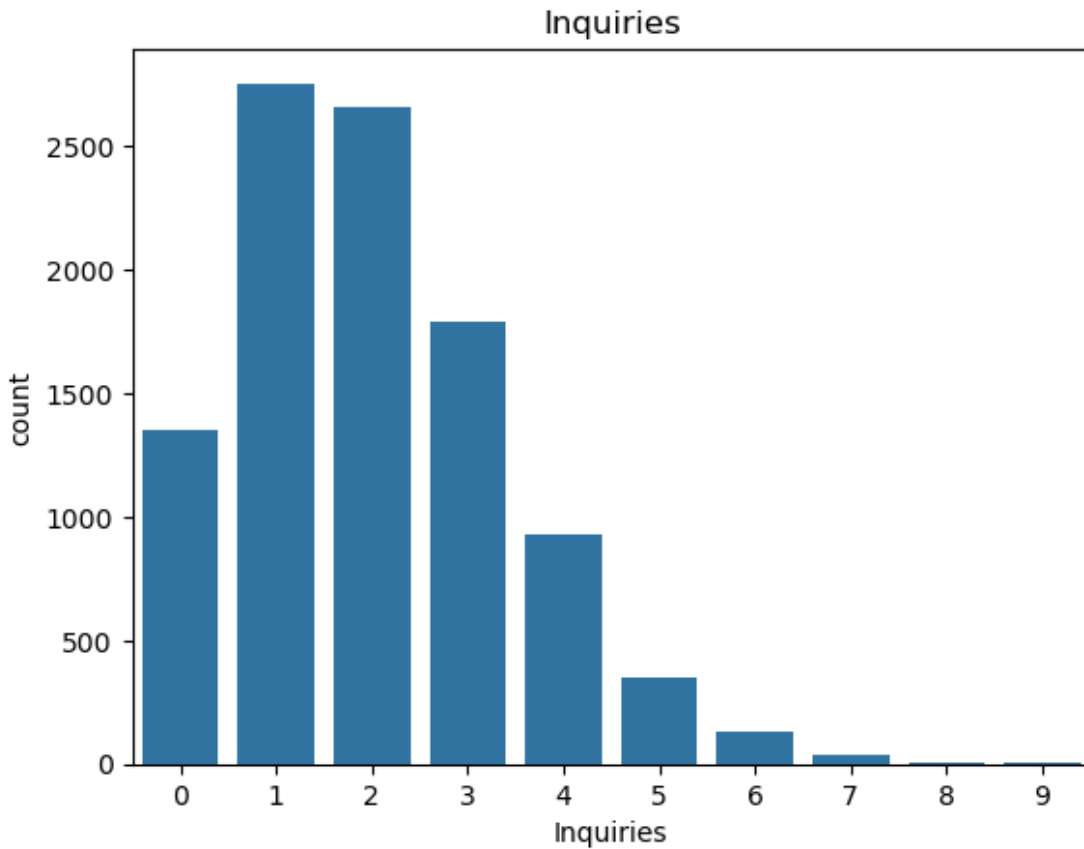


```
# Univariate Pie Chart: Conversion Status distribution
gender_counts = df['Conversion_Status'].value_counts()
plt.figure(figsize=(6, 6))
plt.pie(gender_counts, labels=gender_counts.index, autopct='%1.1f%%',
startangle=130)
plt.title('Conversion Status Distribution')
plt.show()
```

Conversion Status Distribution

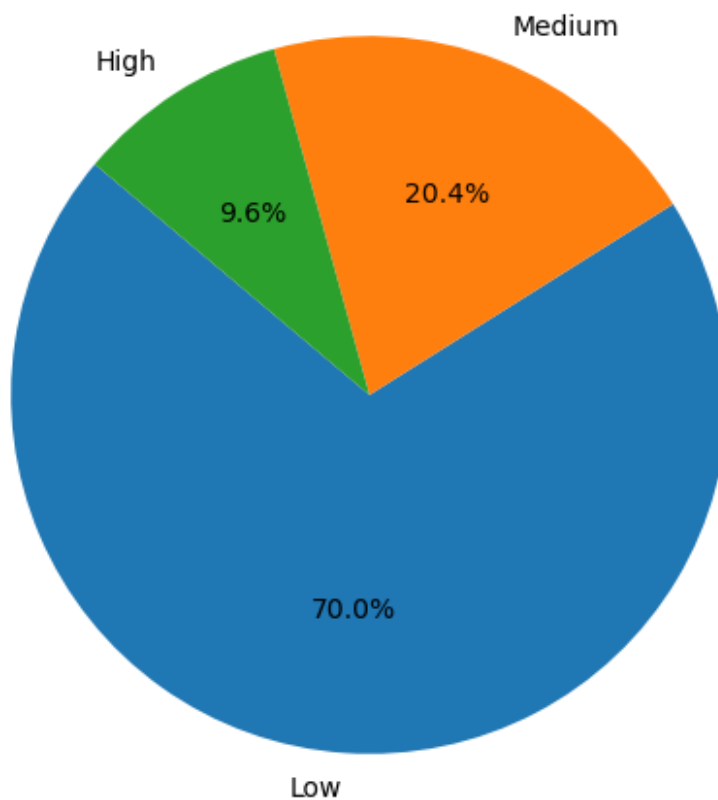


```
# Univariate Analysis: Categorical  
sns.countplot(x='Inquiries', data=df).set_title('Inquiries')  
plt.show()
```



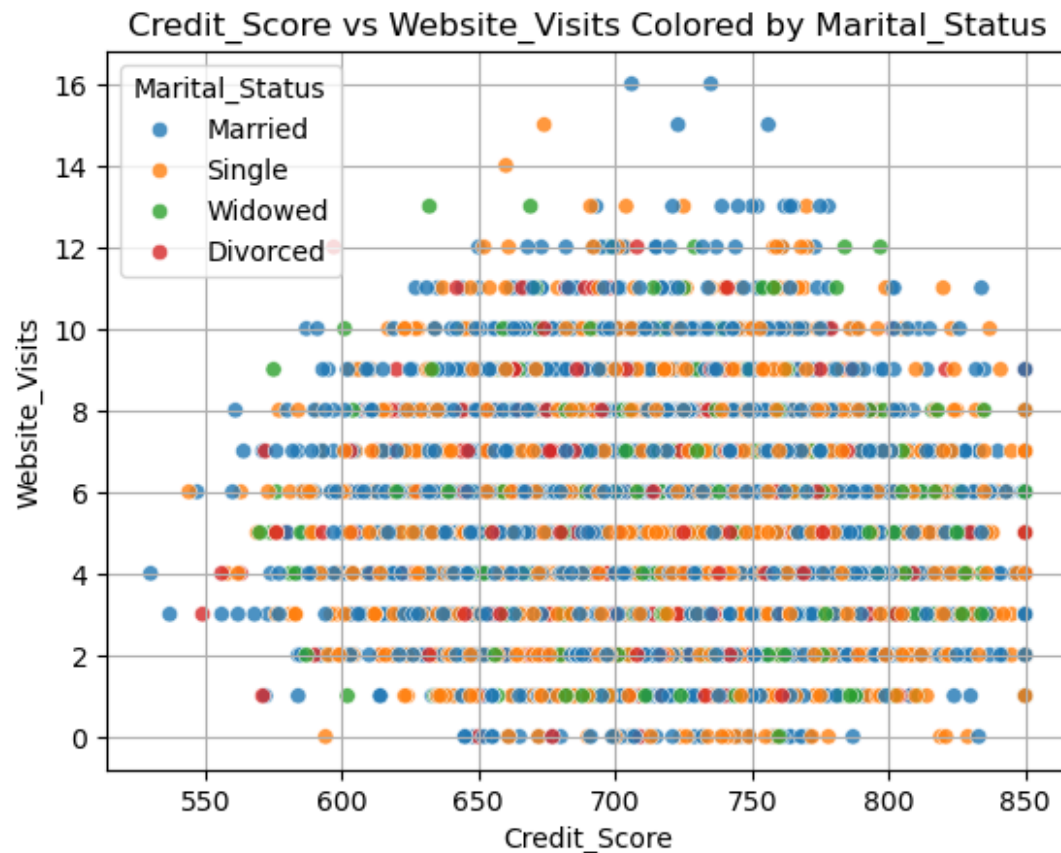
```
# Univariate Pie Chart: Claims_Severity
diet_counts = df['Claims_Severity'].value_counts()
plt.figure(figsize=(6, 6))
plt.pie(diet_counts, labels=diet_counts.index, autopct='%1.1f%%',
startangle=140)
plt.title('Claims Severity Distribution')
plt.show()
```

Claims Severity Distribution

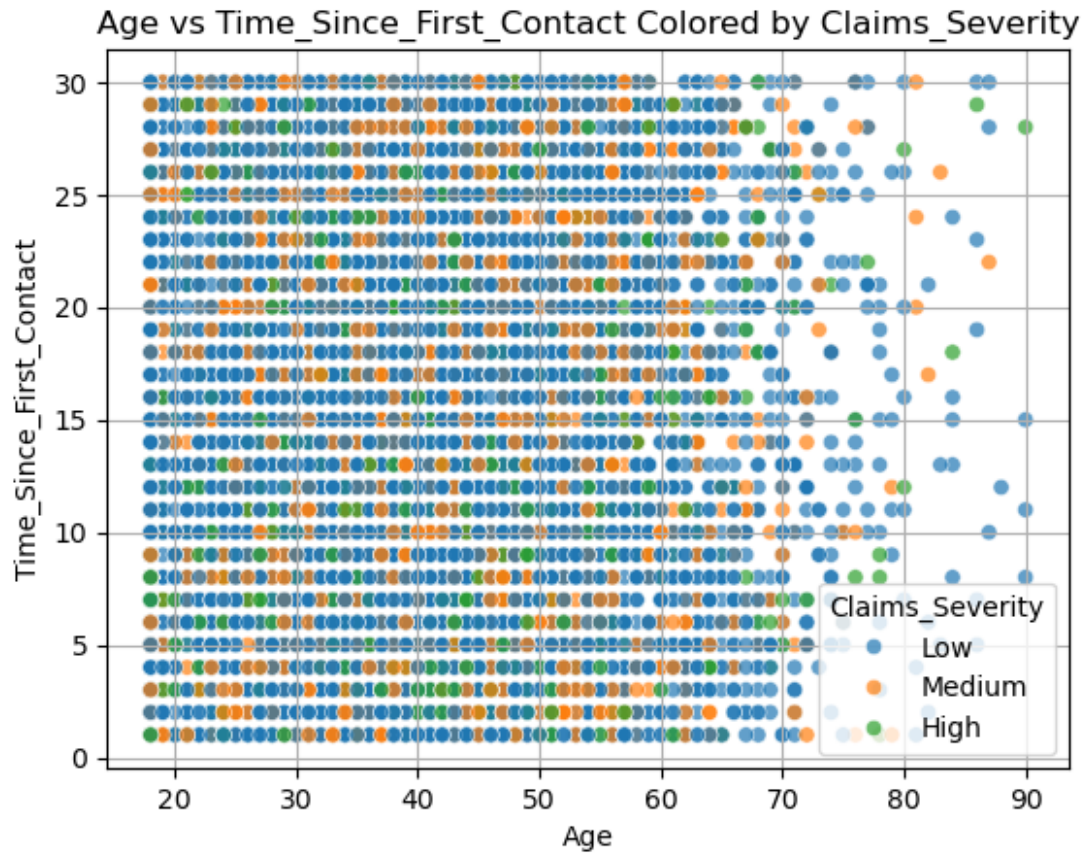


```
# Clean column names to remove any leading/trailing spaces
df.columns = df.columns.str.strip()

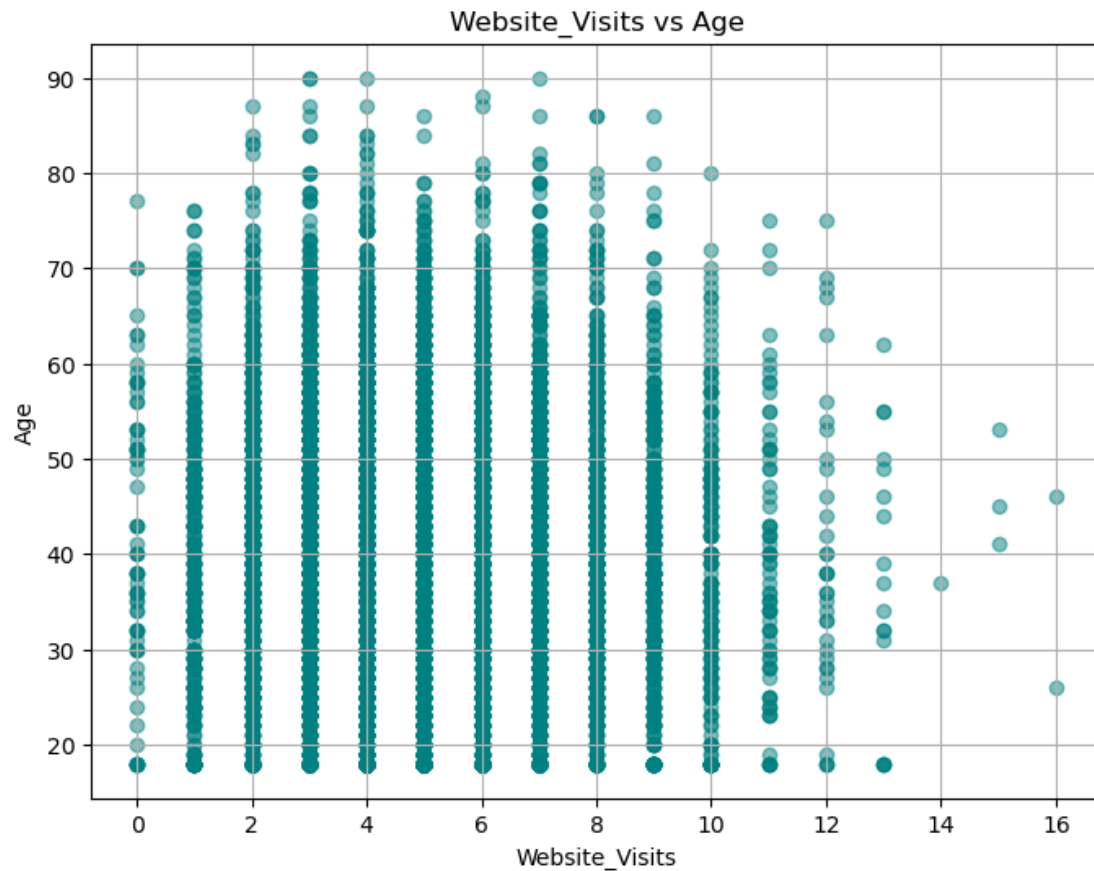
# Credit_Score vs Website_Visits Colored by Marital_Status scatter plot
sns.scatterplot(x='Credit_Score', y='Website_Visits', hue='Marital_Status',
data=df, alpha=0.8)
plt.title('Credit_Score vs Website_Visits Colored by Marital_Status')
plt.xlabel('Credit_Score')
plt.ylabel('Website_Visits')
plt.grid(True)
plt.show()
```



```
# Scatter plot colored by Claims_Severity
df.columns = df.columns.str.strip()
sns.scatterplot(x='Age', y='Time_Since_First_Contact', hue='Claims_Severity',
data=df, alpha=0.7)
plt.title('Age vs Time_Since_First_Contact Colored by Claims_Severity')
plt.xlabel('Age')
plt.ylabel('Time_Since_First_Contact')
plt.grid(True)
plt.show()
```

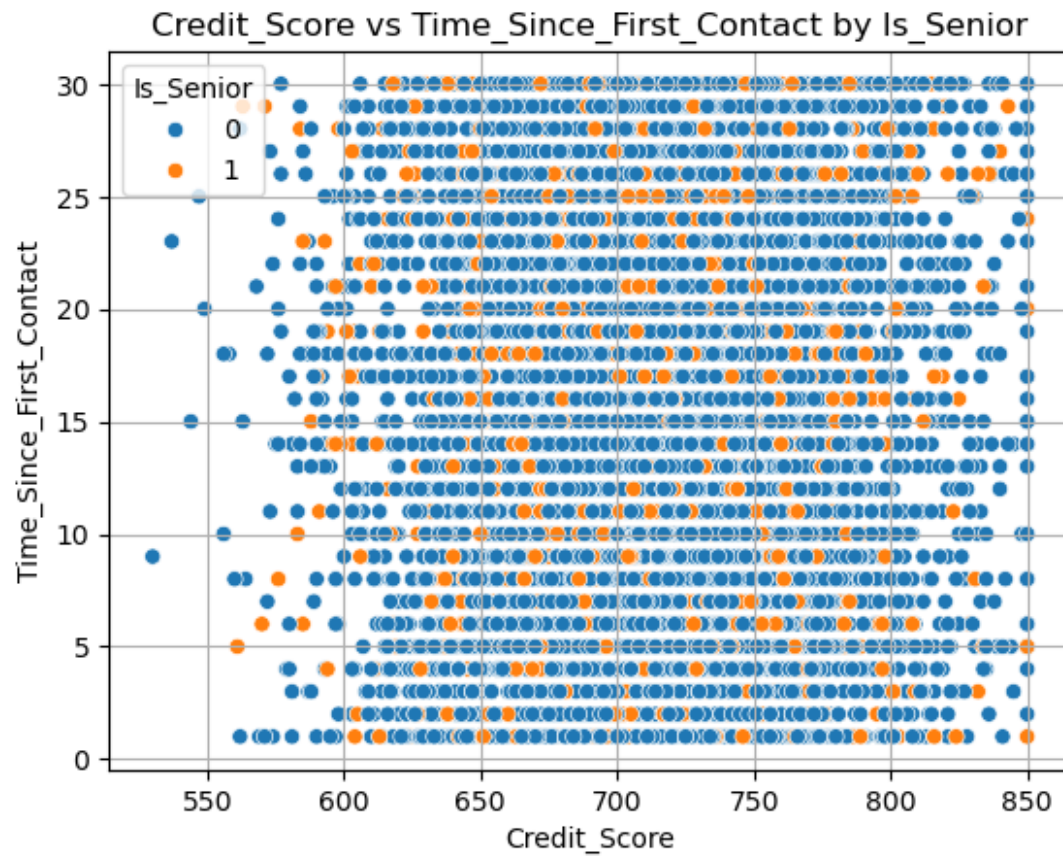


```
# Website_Visits vs Age scatter plot
plt.figure(figsize=(8, 6))
plt.scatter(df['Website_Visits'], df['Age'], color='teal', alpha=0.5)
plt.title('Website_Visits vs Age')
plt.xlabel('Website_Visits')
plt.ylabel('Age')
plt.grid(True)
plt.show()
```

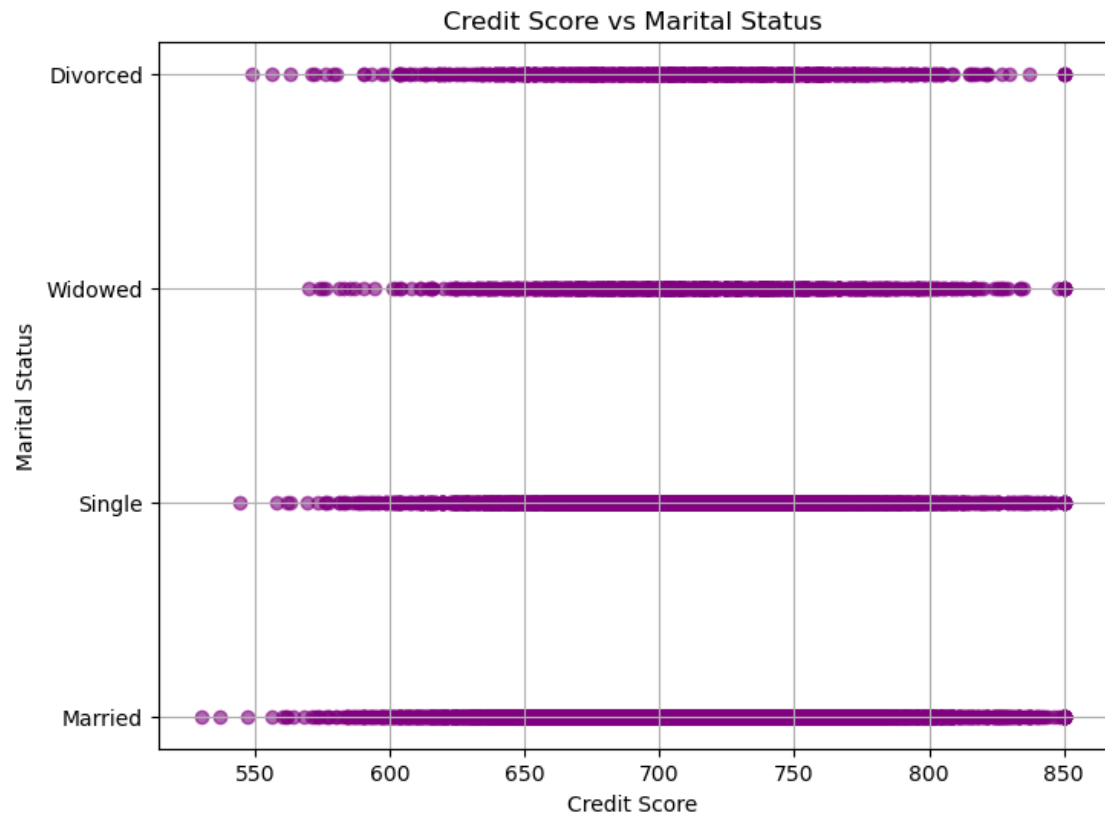



```
df.columns = df.columns.str.strip()
```

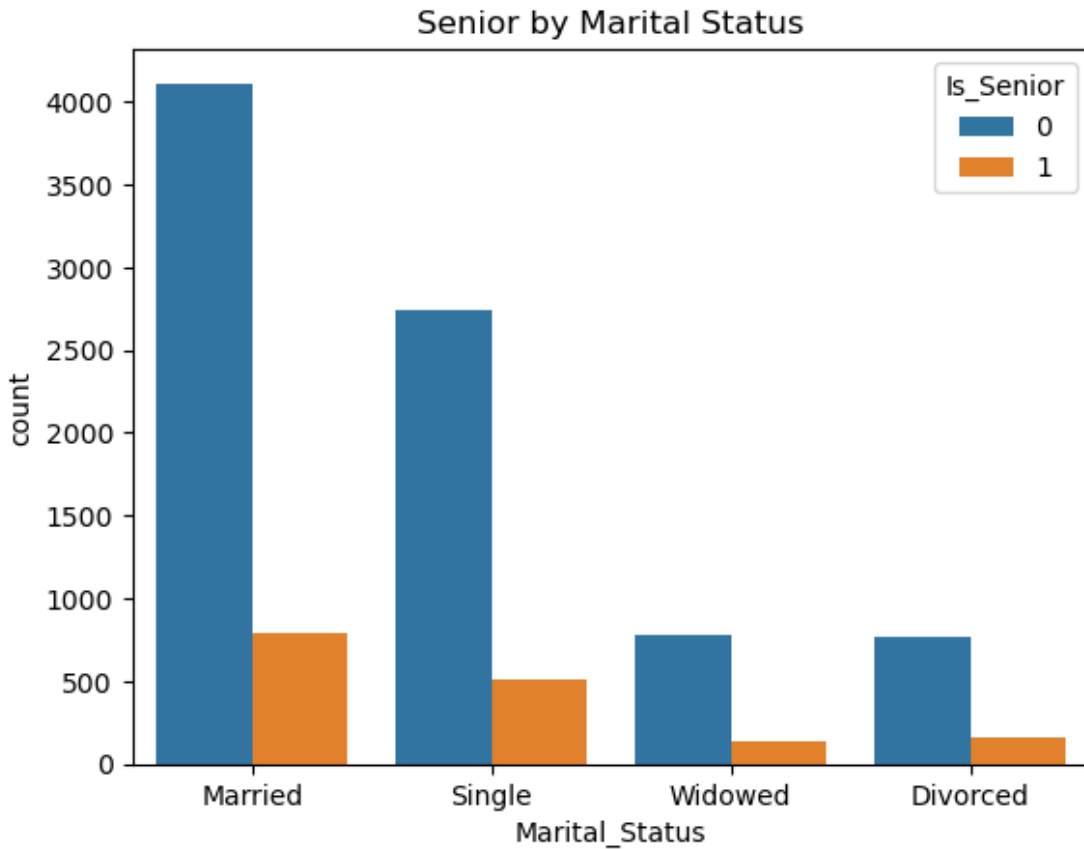
```
# Scatter plot with hue based on Conversion_Status
sns.scatterplot(x='Credit_Score', y='Time_Since_First_Contact',
hue='Is_Senior', data=df)
plt.title('Credit_Score vs Time_Since_First_Contact by Is_Senior')
plt.xlabel('Credit_Score')
plt.ylabel('Time_Since_First_Contact')
plt.grid(True)
plt.show()
```



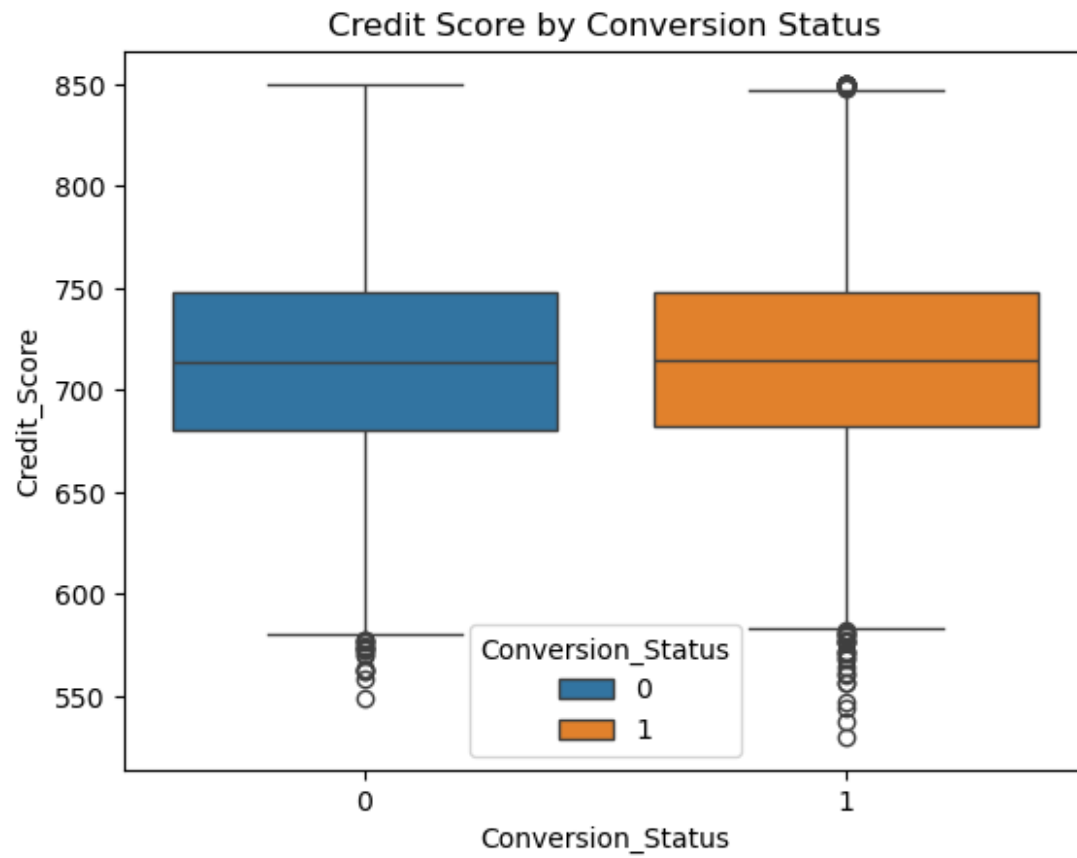
```
# Scatter plot (Credit_Score vs Website_Visits)
plt.figure(figsize=(8, 6))
plt.scatter(df['Credit_Score'], df['Marital_Status'], alpha=0.6, c='purple')
plt.title('Credit Score vs Marital Status')
plt.xlabel('Credit Score')
plt.ylabel('Marital Status')
plt.grid(True)
plt.show()
```



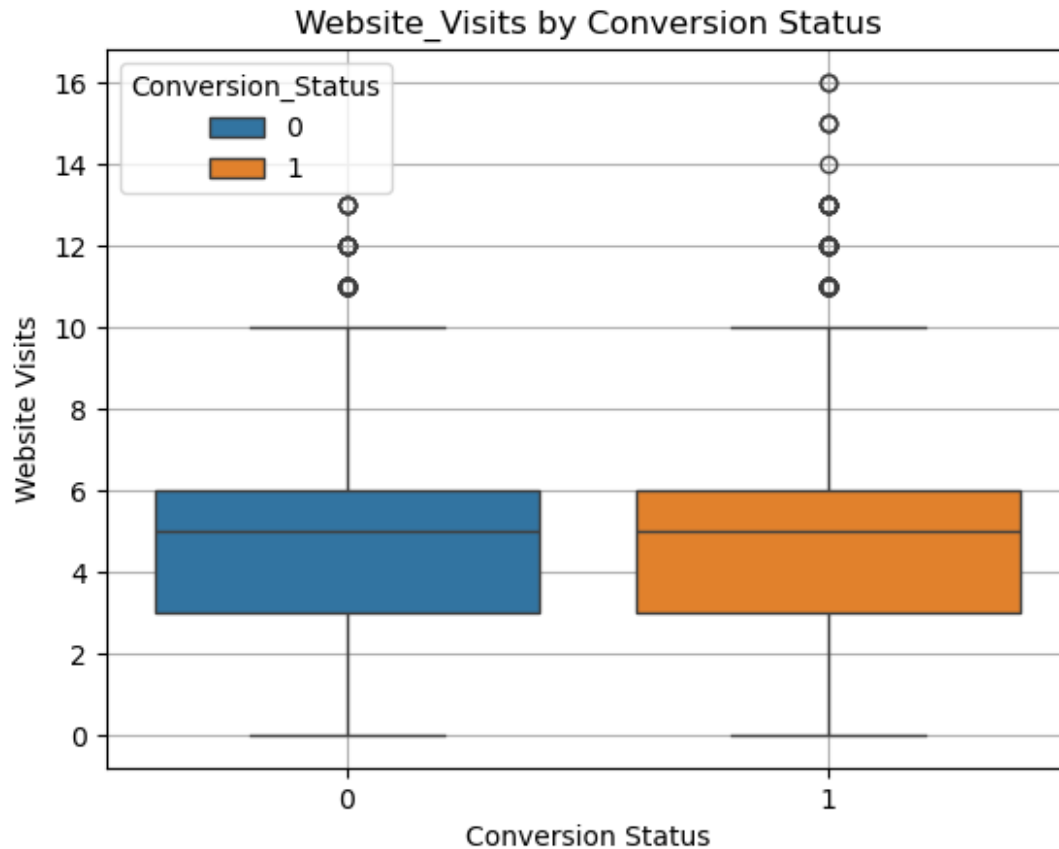
```
# Bivariate Analysis Marital Status vs Senior  
sns.countplot(x='Marital_Status', hue='Is_Senior', data=df)  
plt.title('Senior by Marital Status')  
plt.show()
```



```
# Bivariate Analysis Depression vs Credit_Score
sns.boxplot(x='Conversion_Status', y='Credit_Score', hue='Conversion_Status',
data=df)
plt.title('Credit Score by Conversion Status')
plt.show()
```



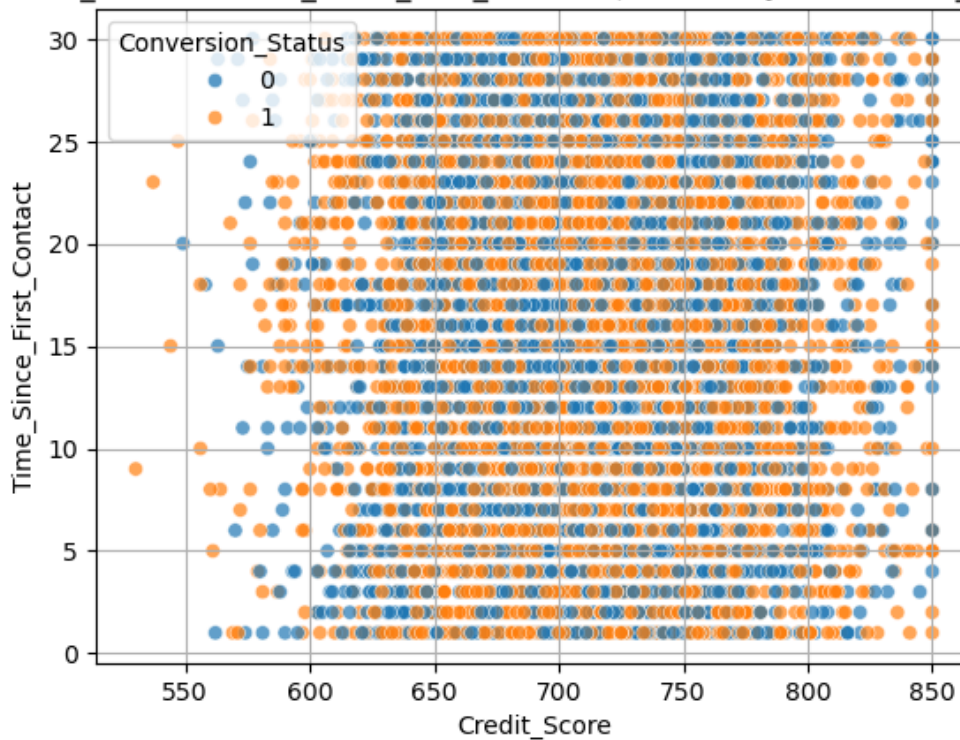
```
# Bivariate Analysis: Conversion_Status vs Website_Visits
sns.boxplot(x='Conversion_Status', y='Website_Visits',
hue='Conversion_Status', data=df)
plt.title('Website_Visits by Conversion Status')
plt.xlabel('Conversion Status')
plt.ylabel('Website_Visits')
plt.grid(True)
plt.show()
```



Scatter Plot (Bivariate): Credit_Score vs Time_Since_First_Contact, colored by Conversion_Status

```
sns.scatterplot(x='Credit_Score', y='Time_Since_First_Contact',  
hue='Conversion_Status', data=df, alpha=0.7)  
plt.title('Credit_Score vs Time_Since_First_Contact (Colored by  
Conversion_Status)')  
plt.xlabel('Credit_Score')  
plt.ylabel('Time_Since_First_Contact')  
plt.grid(True)  
plt.show()
```

Credit_Score vs Time_Since_First_Contact (Colored by Conversion_Status)



```
import matplotlib.pyplot as plt

# Clean column names (remove spaces)
df.columns = df.columns.str.strip()

# Show unique values for debugging
print("Is_Senior values:", df['Is_Senior'].unique())
print("Conversion_Status values:", df['Conversion_Status'].unique())

# Filter for Male (1) and Female (0) - check if they are int or str
male_df = df[df['Is_Senior'].astype(str) == '1']
female_df = df[df['Is_Senior'].astype(str) == '0']

# Get counts
male_counts = male_df['Conversion_Status'].value_counts()
female_counts = female_df['Conversion_Status'].value_counts()

# ----- Male Pie -----
if not male_counts.empty:
    plt.figure(figsize=(6, 6))
    plt.pie(male_counts, labels=male_counts.index, autopct='%1.1f%%',
    colors=['lightgreen', 'lightcoral'])
    plt.title('Conversion_Status Distribution in Male Students')
    plt.axis('equal') # Make pie chart round
    plt.tight_layout()
```

```

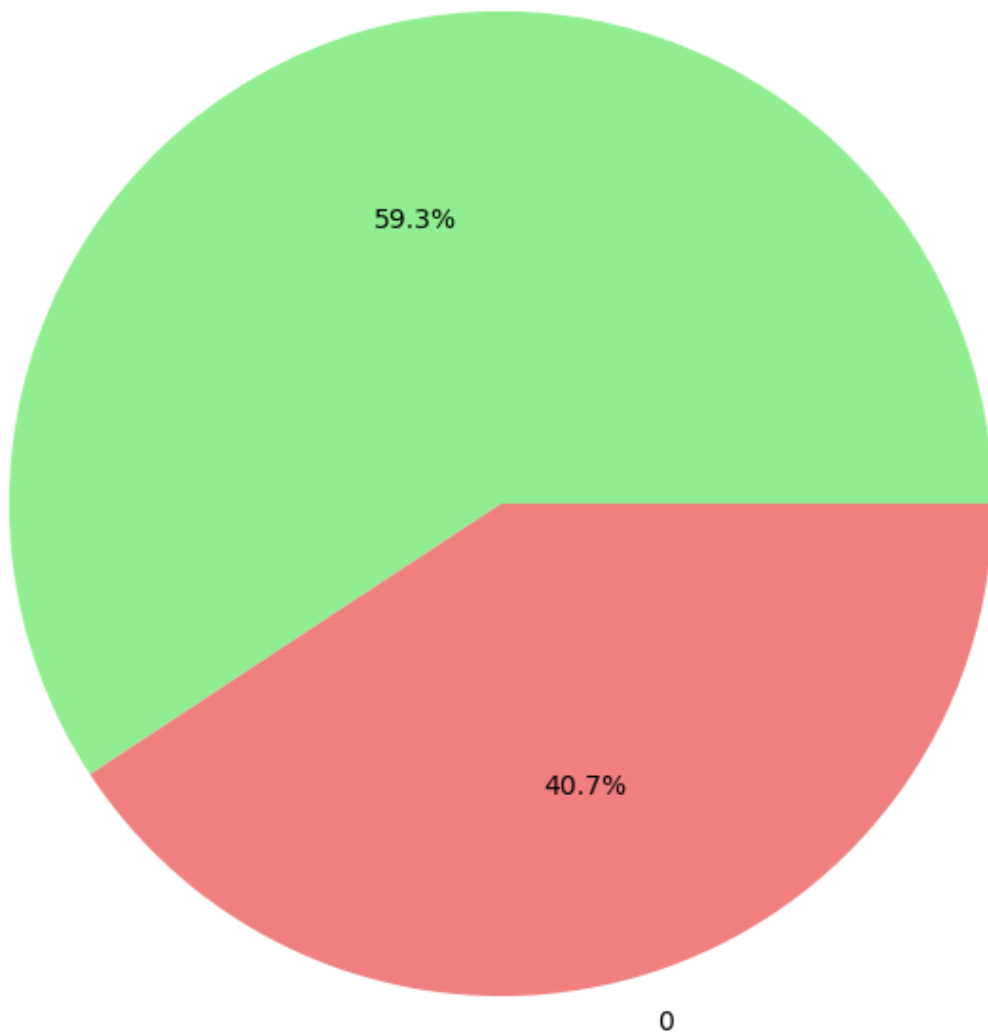
plt.show()
else:
    print("⚠ No Conversion_Status data found for Male students.")

# ----- Female Pie -----
if not female_counts.empty:
    plt.figure(figsize=(6, 6))
    plt.pie(female_counts, labels=female_counts.index, autopct='%1.1f%%',
    colors=['lightblue', 'plum'])
    plt.title('Conversion_Status Distribution in Female Students')
    plt.axis('equal') # Make pie chart round
    plt.tight_layout()
    plt.show()
else:
    print("⚠ No Conversion_Status data found for Female students.")

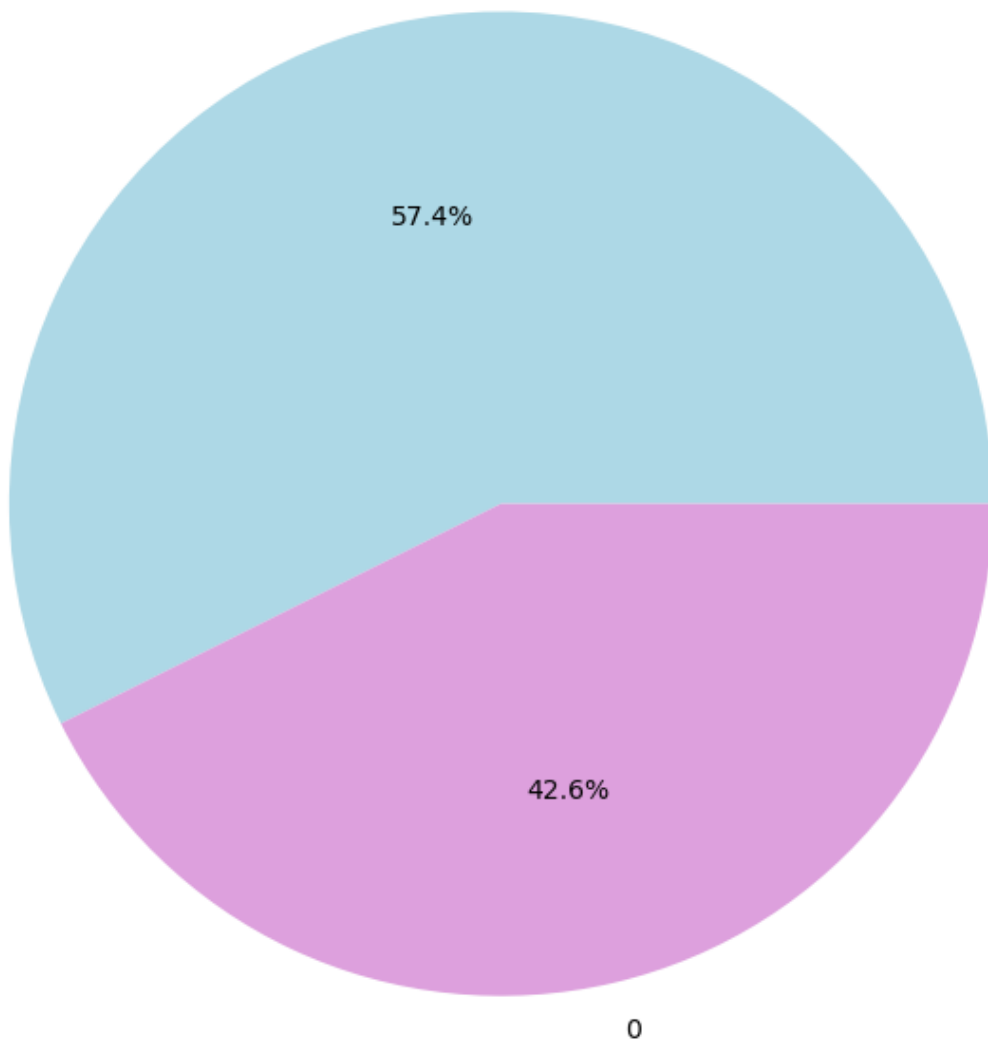
Is_Senior values: [0 1]
Conversion_Status values: [0 1]

```

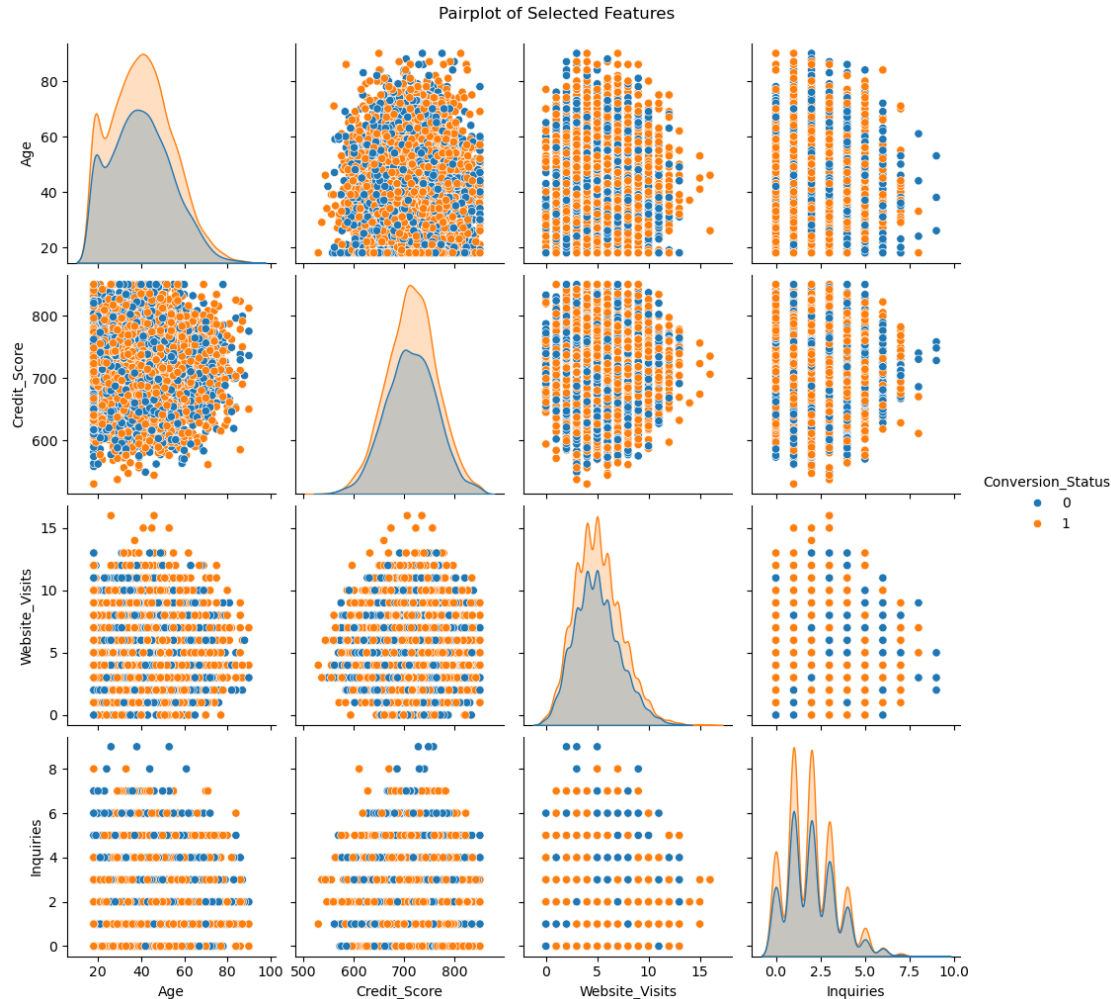

Conversion_Status Distribution in Male Students
1



Conversion_Status Distribution in Female Students



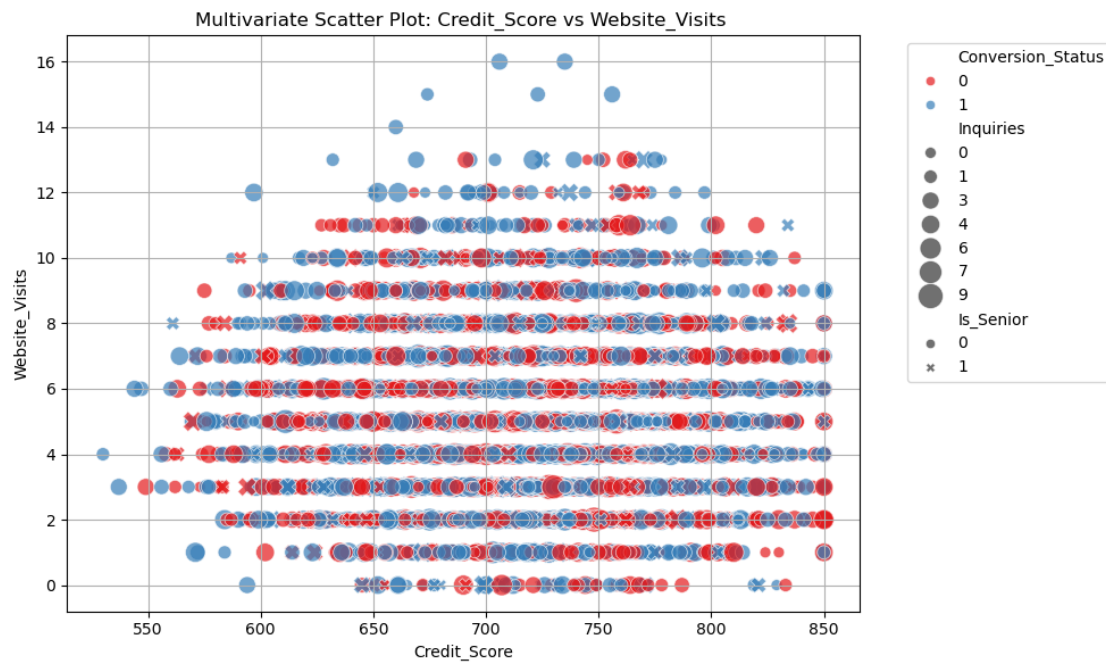
```
# Pairplot with Depression hue Multivariate Analysis
selected_columns = ['Age', 'Credit_Score', 'Website_Visits', 'Inquiries',
'Conversion_Status']
sns.pairplot(df[selected_columns], hue='Conversion_Status')
plt.suptitle("Pairplot of Selected Features", y=1.02)
plt.show()
```



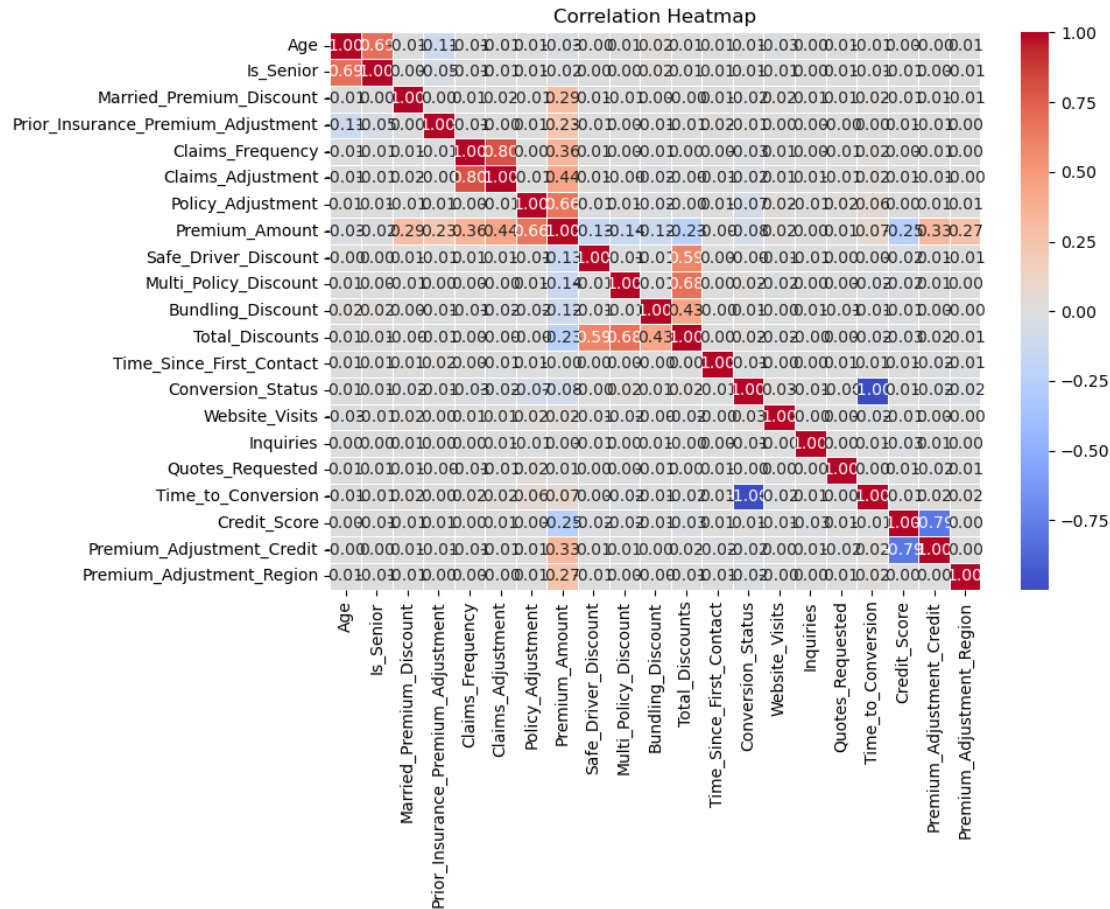
```
# Multivariate Scatter Plot
plt.figure(figsize=(10, 6))
sns.scatterplot(
    x='Credit_Score',
    y='Website_Visits',
    hue='Conversion_Status',
    size='Inquiries',
    style='Is_Senior',
    data=df,
    palette='Set1',
    sizes=(50, 250), # size range for points
    alpha=0.7
)

plt.title('Multivariate Scatter Plot: Credit_Score vs Website_Visits ')
plt.xlabel('Credit_Score')
plt.ylabel('Website_Visits ')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid(True)
```

```
plt.tight_layout()
plt.show()
```



```
# Correlation Heatmap
plt.figure(figsize=(10, 8)) # Optional: set figure size for better
readability
corr_matrix = df.corr(numeric_only=True)
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f",
linewidths=0.5)
plt.title('Correlation Heatmap')
plt.tight_layout()
plt.show()
```



Conclusion

In this analysis, we looked closely at a sales dataset by creating visual representations of important variables like 'Units Sold' and 'Unit Price' using histograms and boxplots. The histogram for 'Unit Price' showed us how prices are spread out across different products, helping us see where most prices fall and if there are any unusual pricing patterns. The boxplot for 'Unit Price' highlighted the average price, the range of prices, and any outliers that might indicate pricing issues. Similarly, examining 'Units Sold' gave us insights into which products are popular and helped us spot any unusual sales figures that might need further attention.

These visual tools not only helped us understand the data better but also provided a basis for making smart business decisions. By recognizing trends in sales and pricing, companies can adjust their strategies to meet customer needs, manage inventory more effectively, and improve overall sales performance.

Final Thoughts

Understanding how products are selling and how they are priced is essential for making good business choices. The insights from this analysis can guide businesses in managing their stock, changing prices, and boosting sales. For example, if we find that some products are selling well at low prices, it might be a good idea to raise those prices to increase profits. On the other hand, if some products are priced high but not selling well, they might need discounts or promotions to attract buyers.

Looking ahead, we could dive deeper into the data by exploring relationships between different factors, breaking down sales by product categories, or analyzing sales trends over time. Adding information about customer preferences and buying habits could also enhance our understanding and help create more effective marketing strategies.

Overall, using visual tools to analyze data has shown to be a powerful way to uncover important insights. By continually examining and interpreting sales data, businesses can stay flexible and responsive to changes in the market, ultimately leading to growth and success in a competitive environment.