

data_exploration

April 14, 2025

1 Data Exploration

This notebook explores the dataset to understand and get an overview of the dataset:

```
[24]: import sys
from pathlib import Path
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Add parent directory to sys.path
parent_dir = Path().resolve().parent
sys.path.append(str(parent_dir))

from src.utils import load_data
from src.utils import replace_birthdate_with_age
from src.utils import plot_boxplots
```

- load data
 - load feature data

```
[25]: file_path_features = parent_dir / 'features.parquet'
feature_data = load_data(file_path_features)
#feature_data = feature_data[feature_data['Exposure'] < 1]
```

DataFrame Info:

```
<class 'pandas.core.frame.DataFrame'>
```

RangeIndex: 678013 entries, 0 to 678012

Data columns (total 12 columns):

#	Column	Non-Null Count	Dtype
0	IDpol	678013 non-null	float64
1	ClaimNb	678013 non-null	float64
2	Exposure	678013 non-null	float64
3	Area	678013 non-null	object
4	VehPower	678013 non-null	float64
5	VehAge	678013 non-null	float64
6	BonusMalus	678013 non-null	float64

```

7  VehBrand      678013 non-null object
8  VehGas        644112 non-null object
9  Density       678013 non-null float64
10 Region        678013 non-null object
11 BirthD        678013 non-null object

```

dtypes: float64(7), object(5)

memory usage: 62.1+ MB

None

#####

First 5 Rows:

	IDpol	ClaimNb	Exposure	Area	VehPower	VehAge	BonusMalus	VehBrand \
0	1.0	1.0	0.10	'D'	5.0	0.0	50.0	'B12'
1	3.0	1.0	0.77	'D'	5.0	0.0	50.0	'B12'
2	5.0	1.0	0.75	'B'	6.0	2.0	50.0	'B12'
3	10.0	1.0	0.09	'B'	7.0	0.0	50.0	'B12'
4	11.0	1.0	0.84	'B'	7.0	0.0	50.0	'B12'

	VehGas	Density	Region	BirthD
0	None	1217.0	'R82'	1967-05-08
1	Regular	1217.0	'R82'	1967-12-28
2	Diesel	54.0	'R22'	1970-08-13
3	Diesel	76.0	'R72'	1976-12-05
4	Diesel	76.0	'R72'	1976-02-29

#####

Summary Statistics:

	IDpol	ClaimNb	Exposure	VehPower \
count	6.780130e+05	678013.000000	678013.000000	678013.000000
mean	2.621857e+06	0.053247	0.528750	6.454631
std	1.641783e+06	0.240117	0.364442	2.050906
min	1.000000e+00	0.000000	0.002732	4.000000
25%	1.157951e+06	0.000000	0.180000	5.000000
50%	2.272152e+06	0.000000	0.490000	6.000000
75%	4.046274e+06	0.000000	0.990000	7.000000
max	6.114330e+06	16.000000	2.010000	15.000000

	VehAge	BonusMalus	Density
count	678013.000000	678013.000000	678013.000000
mean	7.044265	59.761502	1792.422405
std	5.666232	15.636658	3958.646564
min	0.000000	50.000000	1.000000
25%	2.000000	50.000000	92.000000
50%	6.000000	50.000000	393.000000
75%	11.000000	64.000000	1658.000000
max	100.000000	230.000000	27000.000000

```
#####
Unique Values Per Column:
IDpol          678013
ClaimNb         11
Exposure        181
Area            6
VehPower        12
VehAge          78
BonusMalus      115
VehBrand        11
VehGas          2
Density         1607
Region          22
BirthD         25775
dtype: int64
```

```
#####
Total Missing Values in DataFrame:
IDpol          0
ClaimNb         0
Exposure        0
Area            0
VehPower        0
VehAge          0
BonusMalus      0
VehBrand        0
VehGas         33901
Density         0
Region          0
BirthD          0
dtype: int64
```

```
#####
```

- load target data

```
[26]: file_path_target = parent_dir / 'target.parquet'
      target_data = load_data(file_path_target)
```

```
DataFrame Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26639 entries, 0 to 26638
Data columns (total 2 columns):
#   Column          Non-Null Count  Dtype
#
```

```

---  -----  -----  -----
0   IDpol      26639 non-null  float64
1   ClaimAmount 26639 non-null  float64
dtypes: float64(2)
memory usage: 416.4 KB
None

```

```
#####
```

First 5 Rows:

```

      IDpol  ClaimAmount
0      1552.0         995.20
1  1010996.0        1128.12
2  4024277.0        1851.11
3  4007252.0        1204.00
4  4046424.0        1204.00

```

```
#####
```

Summary Statistics:

```

      IDpol  ClaimAmount
count  2.663900e+04  2.663900e+04
mean    2.279864e+06  2.278536e+03
std      1.577202e+06  2.929748e+04
min      1.390000e+02  1.000000e+00
25%      1.087642e+06  6.868100e+02
50%      2.137413e+06  1.172000e+03
75%      3.180162e+06  1.228080e+03
max      6.113971e+06  4.075401e+06

```

```
#####
```

Unique Values Per Column:

```

IDpol      24950
ClaimAmount 12369
dtype: int64

```

```
#####
```

Total Missing Values in DataFrame:

```

IDpol      0
ClaimAmount 0
dtype: int64

```

```
#####
```

- merge two data sets

```
[27]: # # sum ClaimAmount over identical IDs
target_data = target_data.groupby('IDpol', as_index=False).agg({'ClaimAmount': ↵
    ↵ 'sum'})

feature_data["IDpol"] = feature_data["IDpol"].astype(int)
feature_data.set_index("IDpol", inplace=True)
# merge features and target data
df = pd.merge(feature_data, target_data, on='IDpol', how='left')

df['ClaimAmount'] = df['ClaimAmount'].fillna(0)
# Drop the IDpol column
df = df.drop(columns=['IDpol'])
```

- Data imputation
 - Convert birthdates to ages in year
 - Fill Missing Values with a New Category in VehGas

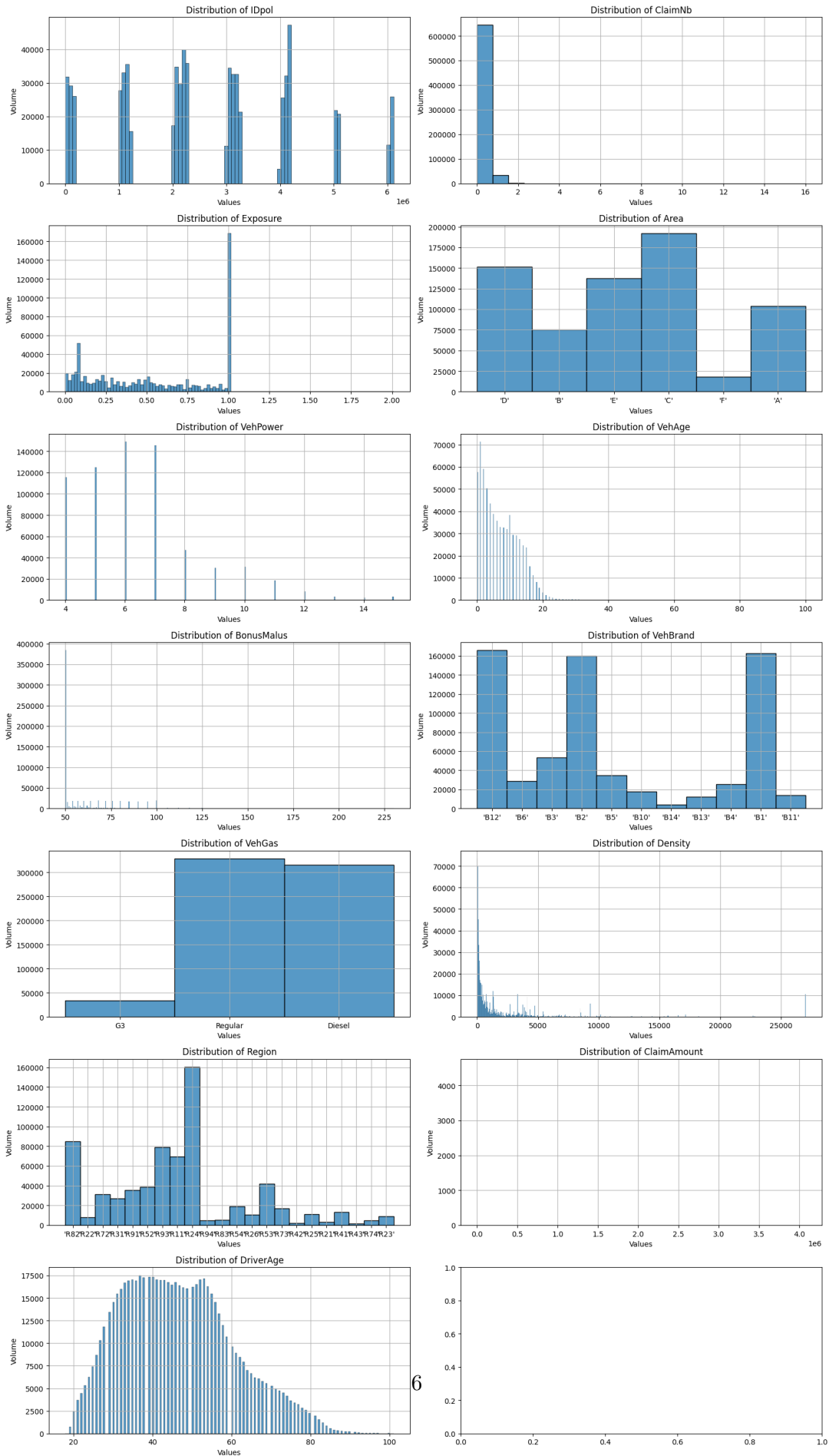
```
[28]: df['VehGas'] = df['VehGas'].fillna('G3')
df = replace_birthdate_with_age(df, 'BirthD', reference_date='2023-01-01')
```

- Feature distribution

```
[16]: # plot the distribution of each feature
num_columns = len(df.columns)
fig, axes = plt.subplots(nrows=(num_columns + 1) // 2, ncols=2, figsize=(16, 4 ↵
    ↵ * ((num_columns + 1) // 2)))
axes = axes.flatten()

# Plot each column's distribution
for i, column in enumerate(df.columns):
    sns.histplot(df[column], kde=False, ax=axes[i])
    axes[i].set_title(f'Distribution of {column}')
    axes[i].set_xlabel('Values')
    axes[i].set_ylabel('Volume')
    axes[i].grid(True)
    #axes[i].set_xlim(df[column].min(), df[column].max())

# Adjust layout
plt.tight_layout()
plt.show()
```



- factorize the categorical features

```
[32]: # List of categorical columns to factorize
categorical_columns = ['Area', 'Region', 'VehGas', 'VehBrand']

# Factorize each categorical column
for column in categorical_columns:
    df[column] = pd.factorize(df[column])[0]

# Display the updated DataFrame
#print(df.head())
```

- Boxplot to detect outliers

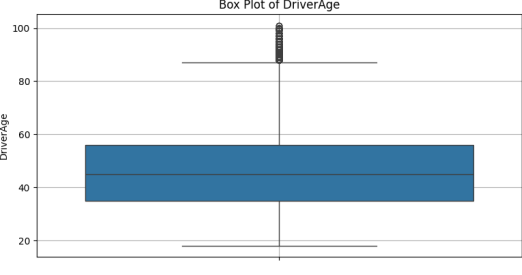
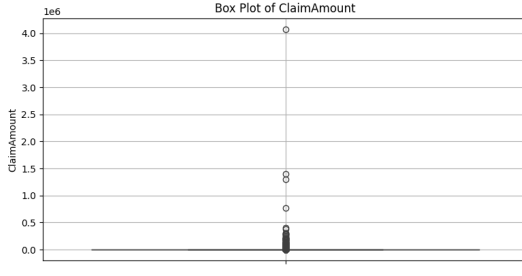
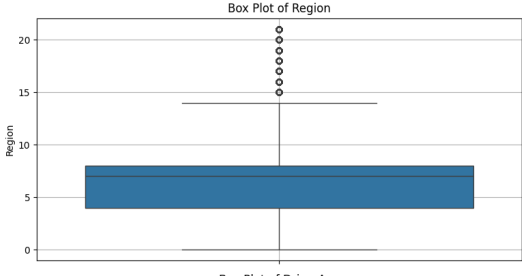
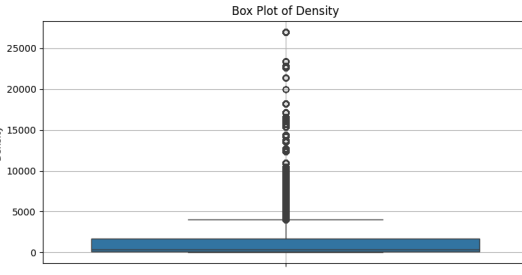
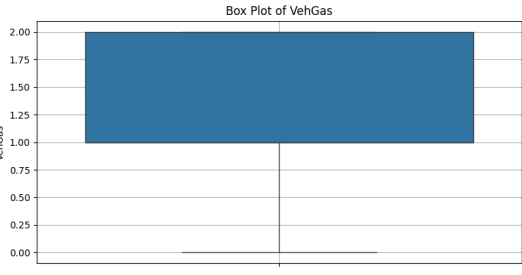
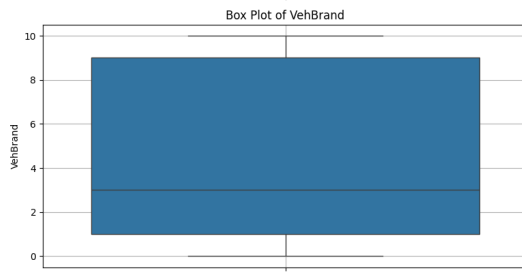
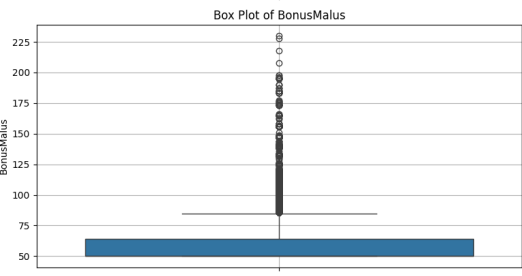
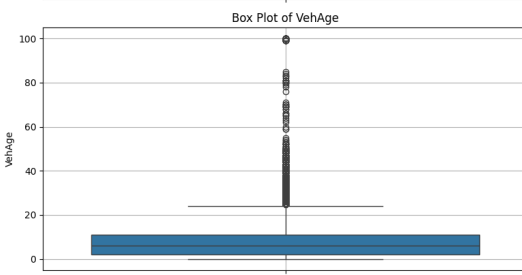
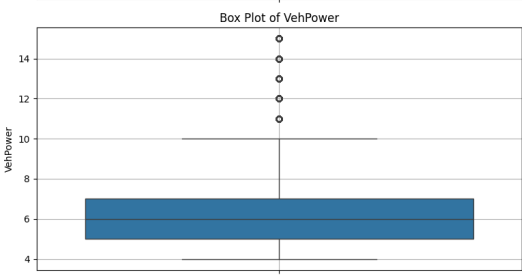
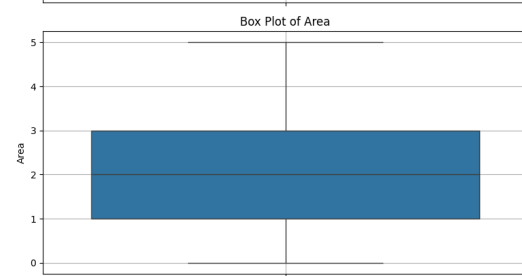
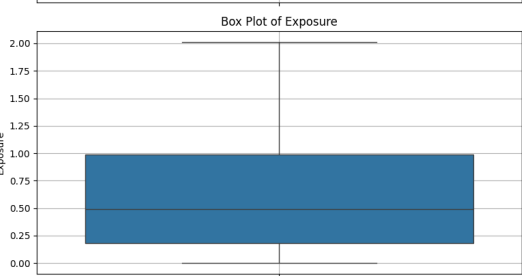
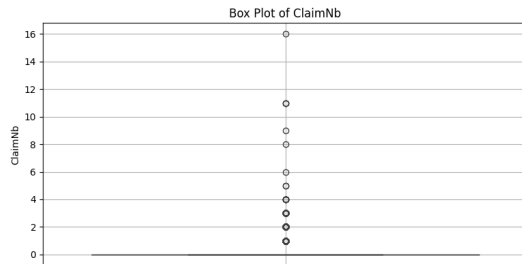
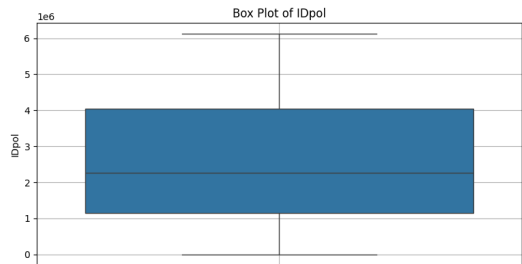
```
[18]: # Select numerical columns
numerical_columns = df.select_dtypes(include=['number']).columns

# Create subplots for box plots
num_columns = len(numerical_columns)
fig, axes = plt.subplots(nrows=(num_columns + 1) // 2, ncols=2, figsize=(16, 4
    ↳ ((num_columns + 1) // 2)))
axes = axes.flatten()

# Plot each numerical column as a box plot
for i, column in enumerate(numerical_columns):
    sns.boxplot(data=df, y=column, ax=axes[i])
    axes[i].set_title(f'Box Plot of {column}')
    axes[i].set_ylabel(column)
    axes[i].grid(True)

# Hide unused subplots if the number of columns is odd
for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

# Adjust layout
plt.tight_layout()
plt.show()
```



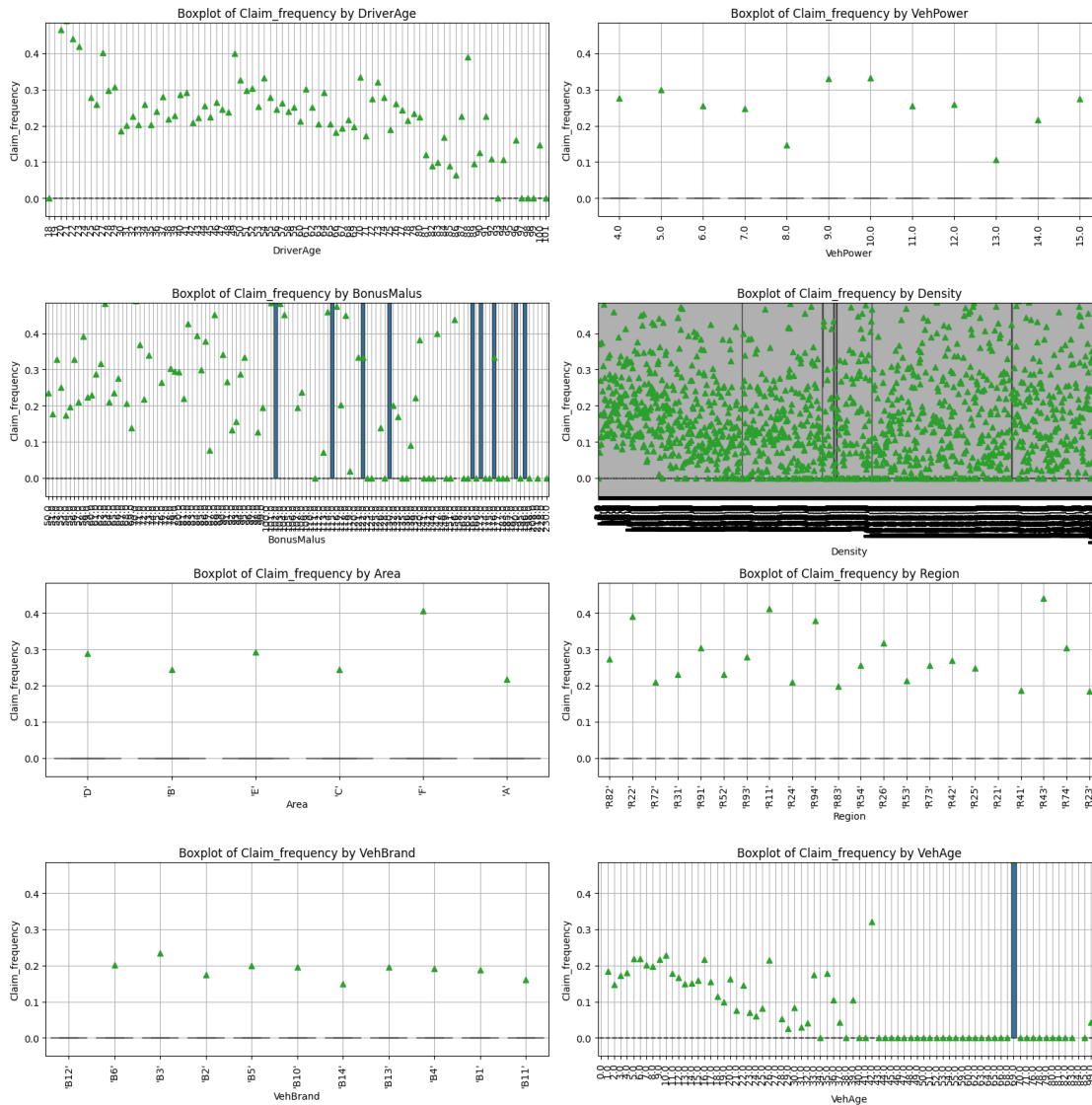
1.0.1 feature engineering

- define the loss amount

```
[29]: df['LossAmount_frequency'] = df['ClaimAmount'] / df['Exposure']  
df['Claim_frequency'] = df['ClaimNb'] / df['Exposure']
```

- observe dependency of Loss_amount_frequency/ Claim_frequency on variables

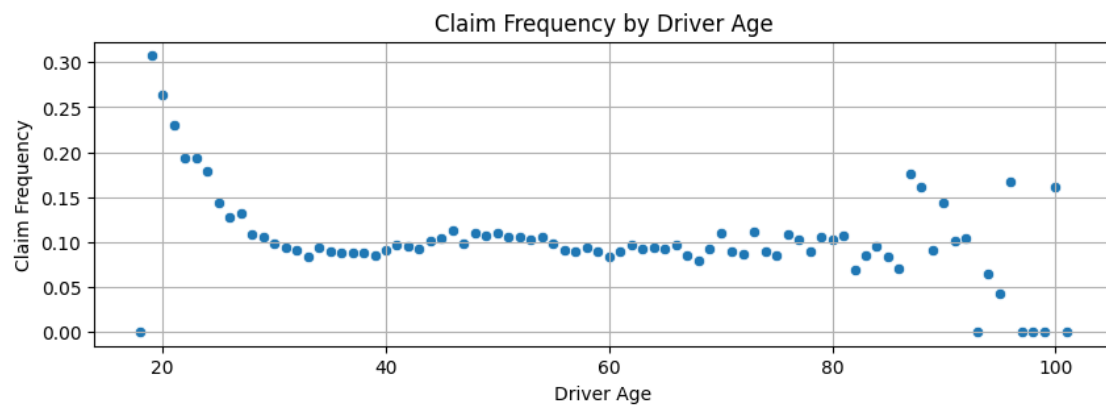
```
[7]: # Example usage:  
plot_boxplots(['DriverAge', 'VehPower', 'BonusMalus', 'Density', 'Area',  
↳ 'Region', 'VehBrand', 'VehAge'],  
              'Claim_frequency',  
              df)
```



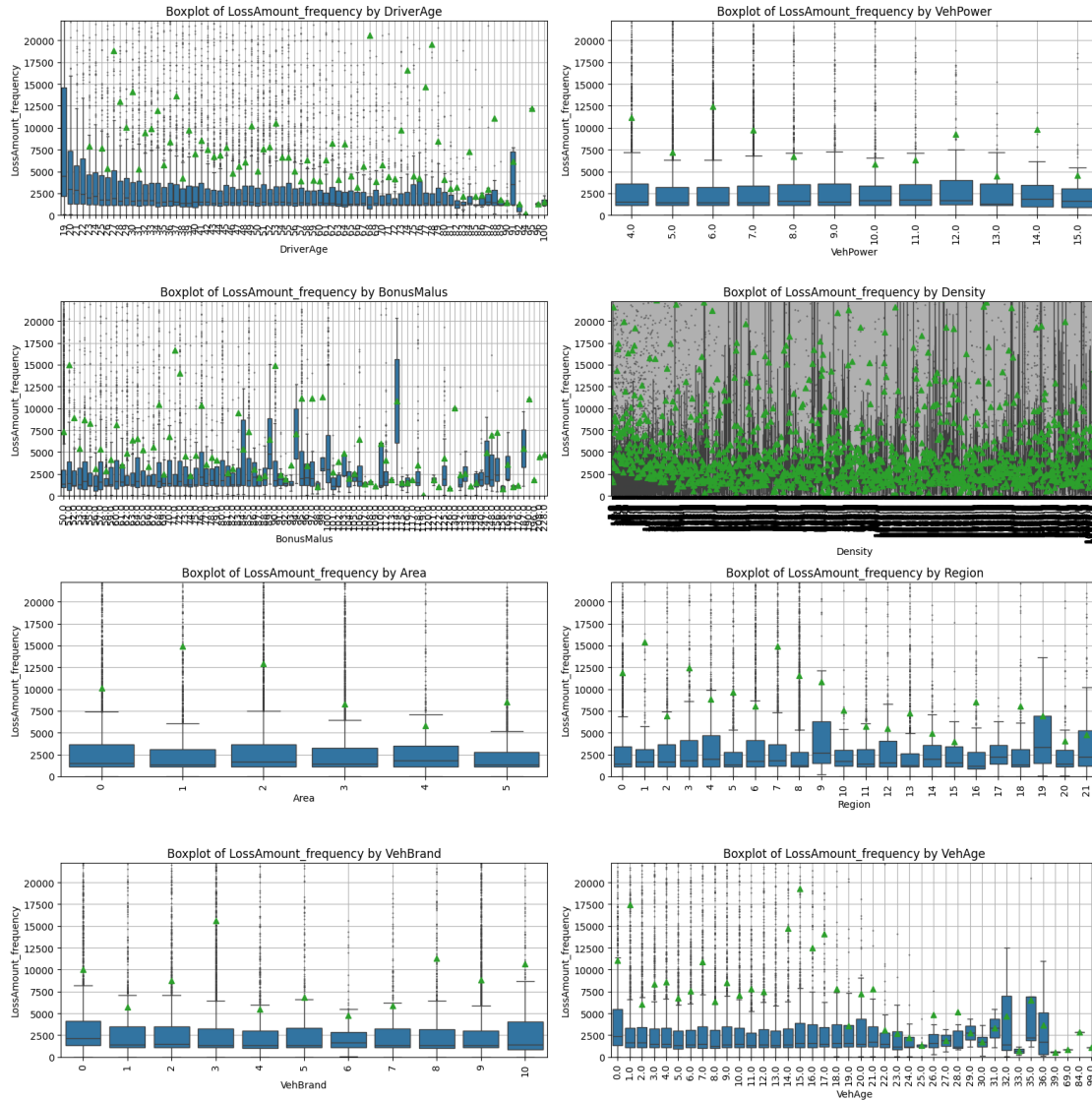
- pool of data by Driver age shows Claim frequency to age!

```
[ ]: # sum of ClaimNb and Exposure when grouping by DriverAge
grouped_df = df.groupby('DriverAge').agg({'ClaimNb': 'sum', 'Exposure': 'sum'}).
↪reset_index()
# calculate the claim frequency
grouped_df['Claim_frequency'] = grouped_df['ClaimNb'] / grouped_df['Exposure']
# plot the claim frequency by driver age
plt.figure(figsize=(10, 2))
sns.scatterplot(data=grouped_df, x='DriverAge', y='Claim_frequency')
plt.title('Claim Frequency by Driver Age')
plt.xlabel('Driver Age')
plt.ylabel('Claim Frequency')
```

```
plt.grid()
plt.show()
```

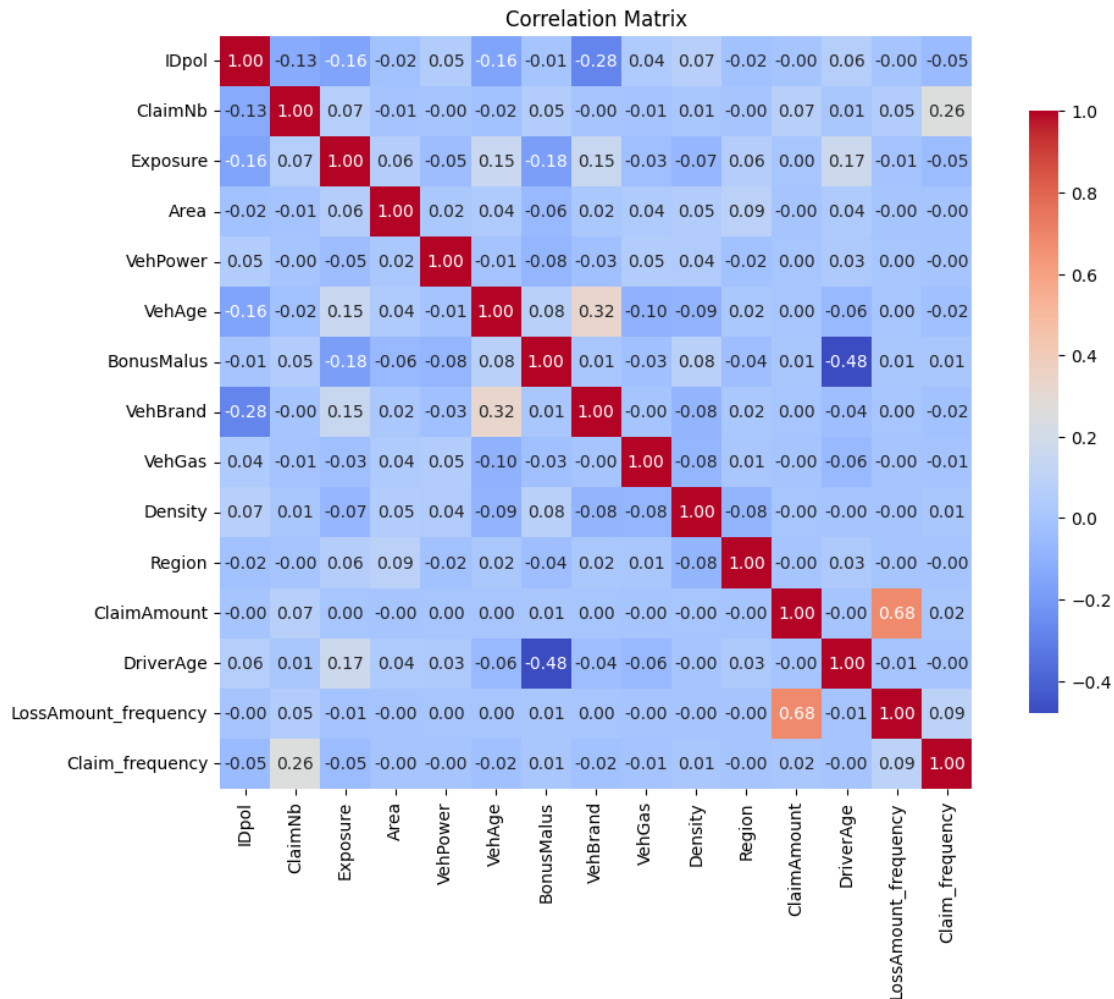


```
[35]: df = df[df['LossAmount_frequency'] > 0]
plot_boxplots(['DriverAge', 'VehPower', 'BonusMalus', 'Density', 'Area', '
↪ 'Region', 'VehBrand', 'VehAge'], 'LossAmount_frequency', df)
```



- Feature correlations

```
[33]: df.corr(method='pearson').style.background_gradient(cmap='coolwarm', axis=None).
      ↪format(precision=2)
      # Plot the correlation matrix
      plt.figure(figsize=(12, 8))
      sns.heatmap(df.corr(), annot=True, fmt=".2f", cmap='coolwarm', square=True,
      ↪cbar_kws={"shrink": .8})
      plt.title('Correlation Matrix')
      plt.show()
```



- Scatter plot

```
[49]: df.loc[:, "ClaimNb"] = df['ClaimNb'].clip(upper=5)
df2 = df[df['IDpol'] < 100000]
# Scatter plot with Claim Amount vs Exposure and IDpol as color and ClaimNb as size
plt.figure(figsize=(15, 10))
plt.subplot(2, 1, 1)
scatter_plot = sns.scatterplot(data=df, x='Exposure', y='ClaimAmount',
    hue='IDpol', size='ClaimNb', sizes=(10, 200), alpha=0.5)
scatter_plot.set_ylim(0, 4000)
#scatter_plot.legend().remove()

plt.subplot(2, 1, 2)
```

```

scatter_plot2 = sns.scatterplot(data=df2, x='Exposure', y='ClaimAmount',
    ↪ hue='IDpol', size='ClaimNb', sizes=(20, 200), alpha=0.5)
scatter_plot2.set_ylim(0, 4000)
scatter_plot2.legend_.remove()

plt.show()

```

