Regression_with_Insurance

May 23, 2025

1 Import libraries and initial data analysis

[2183]:
```
# This Python 3 environment comes with many helpful analytics libraries
 ↪installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/
 ↪docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns
import matplotlib.pyplot as plt
import scipy.stats as stats

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list
 ↪all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that
 ↪gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved
 ↪outside of the current session
```

[2184]:
```
df_train = pd.read_csv('train.csv')
df_test = pd.read_csv('test.csv')
```

[2185]:
```
dataset = [
    (df_train, "train"),
    (df_test, "test")
]

for df, name in dataset:
```

```
    print(f"There is {df.shape[0]} rows and {df.shape[1]} columns in the {name}␣
↪dataset.")
    sum_data_duplicates = df.duplicated().sum()
    print(f"Duplicated fields in {name} dataset: {sum_data_duplicates}")
```

```
There is 1200000 rows and 21 columns in the train dataset.
Duplicated fields in train dataset: 0
There is 800000 rows and 20 columns in the test dataset.
Duplicated fields in test dataset: 0
```

[2186]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1200000 entries, 0 to 1199999
Data columns (total 21 columns):
 #   Column                Non-Null Count    Dtype
---  ------                --------------    -----
 0   id                    1200000 non-null  int64
 1   Age                   1181295 non-null  float64
 2   Gender                1200000 non-null  object
 3   Annual Income         1155051 non-null  float64
 4   Marital Status        1181471 non-null  object
 5   Number of Dependents  1090328 non-null  float64
 6   Education Level       1200000 non-null  object
 7   Occupation            841925 non-null   object
 8   Health Score          1125924 non-null  float64
 9   Location              1200000 non-null  object
 10  Policy Type           1200000 non-null  object
 11  Previous Claims       835971 non-null   float64
 12  Vehicle Age           1199994 non-null  float64
 13  Credit Score          1062118 non-null  float64
 14  Insurance Duration    1199999 non-null  float64
 15  Policy Start Date     1200000 non-null  object
 16  Customer Feedback     1122176 non-null  object
 17  Smoking Status        1200000 non-null  object
 18  Exercise Frequency    1200000 non-null  object
 19  Property Type         1200000 non-null  object
 20  Premium Amount        1200000 non-null  float64
dtypes: float64(9), int64(1), object(11)
memory usage: 192.3+ MB
```

[2187]:
```
df_train.set_index('id', inplace=True)
```

[2188]:
```
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 800000 entries, 0 to 799999
Data columns (total 20 columns):
 #   Column                Non-Null Count   Dtype
```

```
---  ------                --------------   -----
 0   id                    800000 non-null  int64
 1   Age                   787511 non-null  float64
 2   Gender                800000 non-null  object
 3   Annual Income         770140 non-null  float64
 4   Marital Status        787664 non-null  object
 5   Number of Dependents  726870 non-null  float64
 6   Education Level       800000 non-null  object
 7   Occupation            560875 non-null  object
 8   Health Score          750551 non-null  float64
 9   Location              800000 non-null  object
 10  Policy Type           800000 non-null  object
 11  Previous Claims       557198 non-null  float64
 12  Vehicle Age           799997 non-null  float64
 13  Credit Score          708549 non-null  float64
 14  Insurance Duration    799998 non-null  float64
 15  Policy Start Date     800000 non-null  object
 16  Customer Feedback     747724 non-null  object
 17  Smoking Status        800000 non-null  object
 18  Exercise Frequency    800000 non-null  object
 19  Property Type         800000 non-null  object
dtypes: float64(8), int64(1), object(11)
memory usage: 122.1+ MB
```

[2189]:

```
df_train.head()
```

[2189]:

```
     Age  Gender  Annual Income Marital Status  Number of Dependents  \
id
0   19.0  Female        10049.0        Married                   1.0
1   39.0  Female        31678.0       Divorced                   3.0
2   23.0    Male        25602.0       Divorced                   3.0
3   21.0    Male       141855.0        Married                   2.0
4   21.0    Male        39651.0         Single                   1.0

   Education Level     Occupation  Health Score  Location    Policy Type  \
id
0       Bachelor's  Self-Employed     22.598761     Urban        Premium
1         Master's            NaN     15.569731     Rural  Comprehensive
2      High School  Self-Employed     47.177549  Suburban        Premium
3       Bachelor's            NaN     10.938144     Rural          Basic
4       Bachelor's  Self-Employed     20.376094     Rural        Premium

    Previous Claims  Vehicle Age  Credit Score  Insurance Duration  \
id
0               2.0         17.0         372.0                 5.0
1               1.0         12.0         694.0                 2.0
2               1.0         14.0           NaN                 3.0
```

```
3              1.0          0.0         367.0                 1.0
4              0.0          8.0         598.0                 4.0

             Policy Start Date Customer Feedback Smoking Status  \
id
0   2023-12-23 15:21:39.134960              Poor             No
1   2023-06-12 15:21:39.111551           Average            Yes
2   2023-09-30 15:21:39.221386              Good            Yes
3   2024-06-12 15:21:39.226954              Poor            Yes
4   2021-12-01 15:21:39.252145              Poor            Yes

   Exercise Frequency Property Type  Premium Amount
id
0              Weekly         House          2869.0
1             Monthly         House          1483.0
2              Weekly         House           567.0
3               Daily     Apartment           765.0
4              Weekly         House          2022.0
```

[2190]:
```python
df_test.head()
```

[2190]:
```
        id   Age  Gender  Annual Income Marital Status  Number of Dependents  \
0  1200000  28.0  Female         2310.0            NaN                   4.0
1  1200001  31.0  Female       126031.0        Married                   2.0
2  1200002  47.0  Female        17092.0       Divorced                   0.0
3  1200003  28.0  Female        30424.0       Divorced                   3.0
4  1200004  24.0    Male        10863.0       Divorced                   2.0

  Education Level     Occupation  Health Score  Location    Policy Type  \
0      Bachelor's  Self-Employed      7.657981     Rural          Basic
1        Master's  Self-Employed     13.381379  Suburban        Premium
2             PhD     Unemployed     24.354527     Urban  Comprehensive
3             PhD  Self-Employed      5.136225  Suburban  Comprehensive
4     High School     Unemployed     11.844155  Suburban        Premium

   Previous Claims  Vehicle Age  Credit Score  Insurance Duration  \
0              NaN         19.0           NaN                 1.0
1              NaN         14.0         372.0                 8.0
2              NaN         16.0         819.0                 9.0
3              1.0          3.0         770.0                 5.0
4              NaN         14.0         755.0                 7.0

            Policy Start Date Customer Feedback Smoking Status  \
0  2023-06-04 15:21:39.245086              Poor            Yes
1  2024-04-22 15:21:39.224915              Good            Yes
2  2023-04-05 15:21:39.134960           Average            Yes
3  2023-10-25 15:21:39.134960              Poor            Yes
```

```
4  2021-11-26 15:21:39.259788           Average             No

  Exercise Frequency Property Type
0             Weekly         House
1             Rarely     Apartment
2            Monthly         Condo
3              Daily         House
4             Weekly         House
```

[2191]:

```python
for df, name in dataset:
    print(f"\n--- {name.upper()} Dataset ---")
    total_rows = df.shape[0]
    null_counts = df.isnull().sum()
    null_columns = null_counts[null_counts > 0]

    if not null_columns.empty:
        print("Columns with null values (count | %):")
        # Sort columns by null count (or percentage) in descending order
        sorted_null_columns = null_columns.sort_values(ascending=True)
        for col, count in sorted_null_columns.items():
            percent = (count / total_rows) * 100
            print(f"- {col}: {count} nulls ({percent:.2f}%)")
    else:
        print("No columns with null values.")
```

```
--- TRAIN Dataset ---
Columns with null values (count | %):
- Insurance Duration: 1 nulls (0.00%)
- Vehicle Age: 6 nulls (0.00%)
- Marital Status: 18529 nulls (1.54%)
- Age: 18705 nulls (1.56%)
- Annual Income: 44949 nulls (3.75%)
- Health Score: 74076 nulls (6.17%)
- Customer Feedback: 77824 nulls (6.49%)
- Number of Dependents: 109672 nulls (9.14%)
- Credit Score: 137882 nulls (11.49%)
- Occupation: 358075 nulls (29.84%)
- Previous Claims: 364029 nulls (30.34%)

--- TEST Dataset ---
Columns with null values (count | %):
- Insurance Duration: 2 nulls (0.00%)
- Vehicle Age: 3 nulls (0.00%)
- Marital Status: 12336 nulls (1.54%)
- Age: 12489 nulls (1.56%)
- Annual Income: 29860 nulls (3.73%)
- Health Score: 49449 nulls (6.18%)
```

```
- Customer Feedback: 52276 nulls (6.53%)
- Number of Dependents: 73130 nulls (9.14%)
- Credit Score: 91451 nulls (11.43%)
- Occupation: 239125 nulls (29.89%)
- Previous Claims: 242802 nulls (30.35%)
```

[2192]:

```python
summary_dict = {col: df[col].describe() for col in null_columns.index}

# To display the summaries:
for col, summary in summary_dict.items():
    print(f"Summary for column: {col}")
    print(summary)
    print("\n")
```

```
Summary for column: Age
count    787511.000000
mean         41.136440
std          13.537829
min          18.000000
25%          30.000000
50%          41.000000
75%          53.000000
max          64.000000
Name: Age, dtype: float64


Summary for column: Annual Income
count    770140.000000
mean      32803.871471
std       32201.063749
min           2.000000
25%        8048.000000
50%       23981.000000
75%       44660.000000
max      149997.000000
Name: Annual Income, dtype: float64


Summary for column: Marital Status
count      787664
unique          3
top        Single
freq       263705
Name: Marital Status, dtype: object


Summary for column: Number of Dependents
count    726870.000000
```

```
mean          2.009337
std           1.415241
min           0.000000
25%           1.000000
50%           2.000000
75%           3.000000
max           4.000000
Name: Number of Dependents, dtype: float64


Summary for column: Occupation
count       560875
unique           3
top       Employed
freq        188574
Name: Occupation, dtype: object


Summary for column: Health Score
count    750551.000000
mean         25.613036
std          12.206882
min           1.646561
25%          15.917353
50%          24.580164
75%          34.517766
max          57.957351
Name: Health Score, dtype: float64


Summary for column: Previous Claims
count    557198.000000
mean          1.004873
std           0.982803
min           0.000000
25%           0.000000
50%           1.000000
75%           2.000000
max           9.000000
Name: Previous Claims, dtype: float64


Summary for column: Vehicle Age
count    799997.000000
mean          9.571891
std           5.772200
min           0.000000
25%           5.000000
```

```
50%             10.000000
75%             15.000000
max             19.000000
Name: Vehicle Age, dtype: float64


Summary for column: Credit Score
count    708549.000000
mean        592.904749
std         150.116374
min         300.000000
25%         468.000000
50%         595.000000
75%         721.000000
max         849.000000
Name: Credit Score, dtype: float64


Summary for column: Insurance Duration
count    799998.000000
mean          5.018949
std           2.593759
min           1.000000
25%           3.000000
50%           5.000000
75%           7.000000
max           9.000000
Name: Insurance Duration, dtype: float64


Summary for column: Customer Feedback
count      747724
unique          3
top       Average
freq       251217
Name: Customer Feedback, dtype: object
```

2 Exploratory data analysis

2.1 Target values

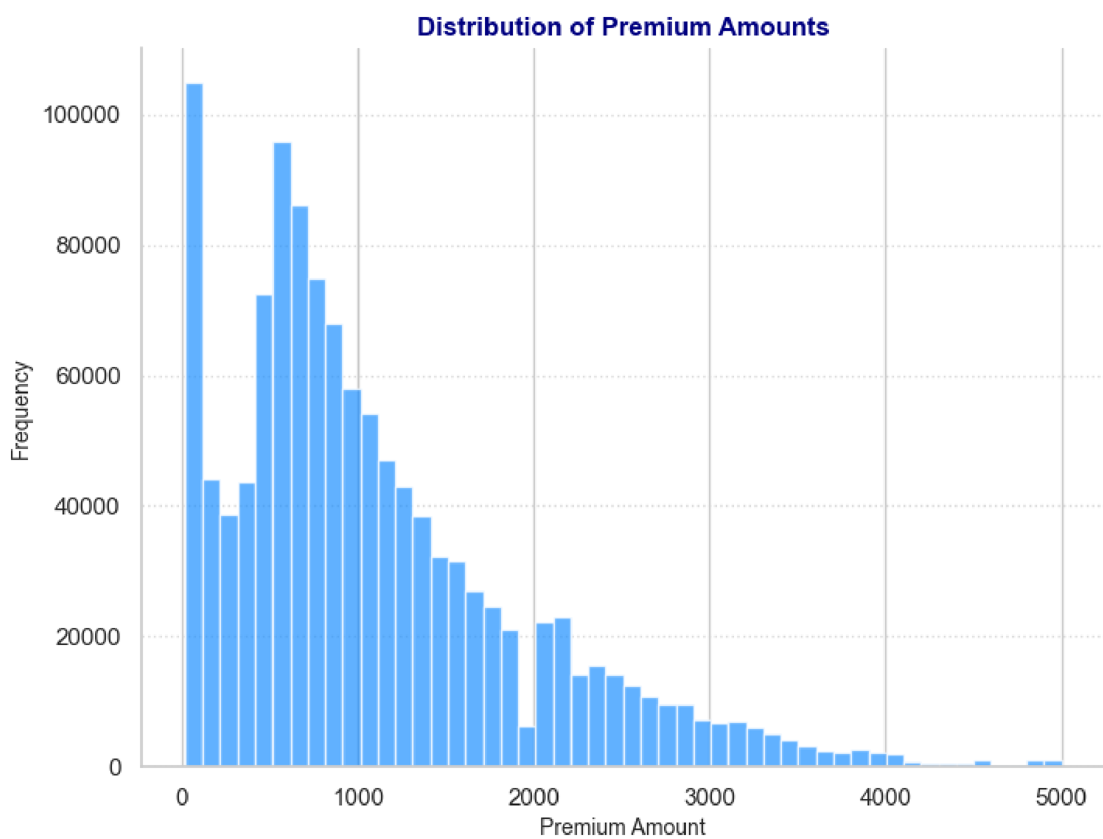
[2193]:

```
# Define style constants to match previous plots
MAIN_COLOR = 'dodgerblue'
SECONDARY_COLOR = 'navy'
TERTIARY_COLOR = 'darkorange'
```

```
EDGE_COLOR = 'white'
GRID_STYLE = dict(linestyle=':', alpha=0.7)
TEXT_COLOR = 'black'
```

[2194]:
```
def format_axes(ax, title, xlabel, ylabel):
    """Apply consistent formatting to an axis."""
    ax.set_title(title, fontsize=12, fontweight='bold', color=SECONDARY_COLOR)
    ax.set_xlabel(xlabel, fontsize=10)
    ax.set_ylabel(ylabel, fontsize=10)
    # Optionally, remove top and right spines for a cleaner look
    ax.spines['top'].set_visible(False)
    ax.spines['right'].set_visible(False)
    ax.set_axisbelow(True)
    ax.yaxis.grid(True, **GRID_STYLE)
```

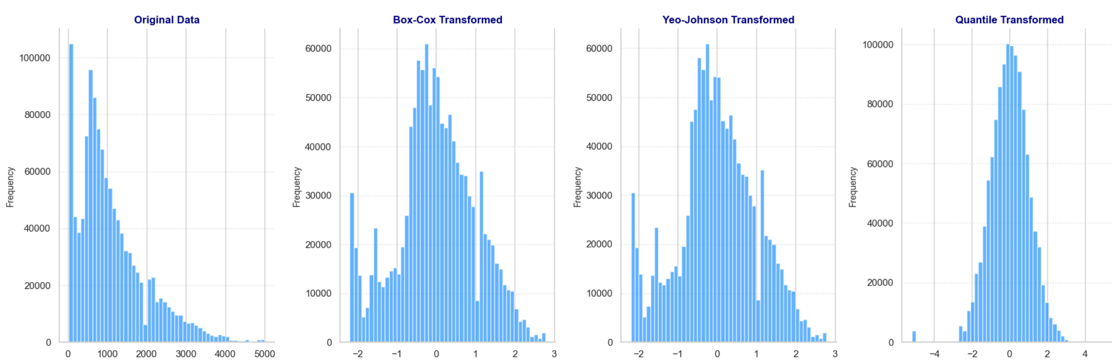
[2195]:
```
plt.figure(figsize=(8, 6))
ax = plt.gca()
ax.hist(df_train["Premium Amount"], bins=50, edgecolor=EDGE_COLOR,␣
 ↪color=MAIN_COLOR, alpha=0.7)
format_axes(ax, 'Distribution of Premium Amounts', 'Premium Amount',␣
 ↪'Frequency')
plt.show()
```

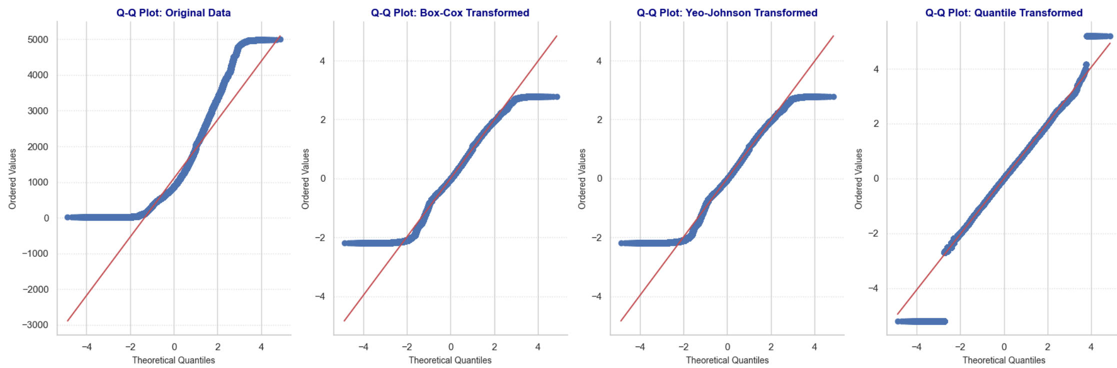


[2196]:
```
plt.figure(figsize=(6, 6))
ax = plt.gca()
stats.probplot(df_train["Premium Amount"], dist="norm", plot=ax)
format_axes(ax, 'Normal Q-Q plot Sale Prices', 'Theoretical Quantiles',␣
 ↪'Ordered Values')
plt.show()
```

[2197]:
```
from sklearn.preprocessing import PowerTransformer, QuantileTransformer
# Initialize transformers
transformers = {
    'Box-Cox': PowerTransformer(method='box-cox', standardize=True),
    'Yeo-Johnson': PowerTransformer(method='yeo-johnson', standardize=True),
```

```python
    'Quantile': QuantileTransformer(output_distribution='normal')
}

# Apply transformations and store results
transformed_data = {'Original': df_train["Premium Amount"]}
for name, transformer in transformers.items():
    transformed_data[name] = transformer.fit_transform(df_train[["Premium Amount"]]).flatten()

# Plot histograms
fig, axes = plt.subplots(1, 4, figsize=(18, 6))
for ax, (name, data) in zip(axes, transformed_data.items()):
    ax.hist(data, bins=50, edgecolor=EDGE_COLOR, color=MAIN_COLOR, alpha=0.7)
    format_axes(ax, f"{name} Data" if name == 'Original' else f"{name} Transformed",
                "Premium Amount" if name == 'Original' else "Transformed Value", "Frequency")
plt.tight_layout()
plt.show()

# Plot Q-Q plots
fig, axes = plt.subplots(1, 4, figsize=(18, 6))
for ax, (name, data) in zip(axes, transformed_data.items()):
    stats.probplot(data, dist="norm", plot=ax)
    format_axes(ax, f'Q-Q Plot: {name} Data' if name == 'Original' else f'Q-Q Plot: {name} Transformed',
                'Theoretical Quantiles', 'Ordered Values')
plt.tight_layout()
plt.show()
```





[2198]:
```python
df_train["Premium Amount"].describe()
```

[2198]:
```
count    1.200000e+06
mean     1.102545e+03
std      8.649989e+02
min      2.000000e+01
25%      5.140000e+02
50%      8.720000e+02
75%      1.509000e+03
max      4.999000e+03
Name: Premium Amount, dtype: float64
```

2.2 Numerical values

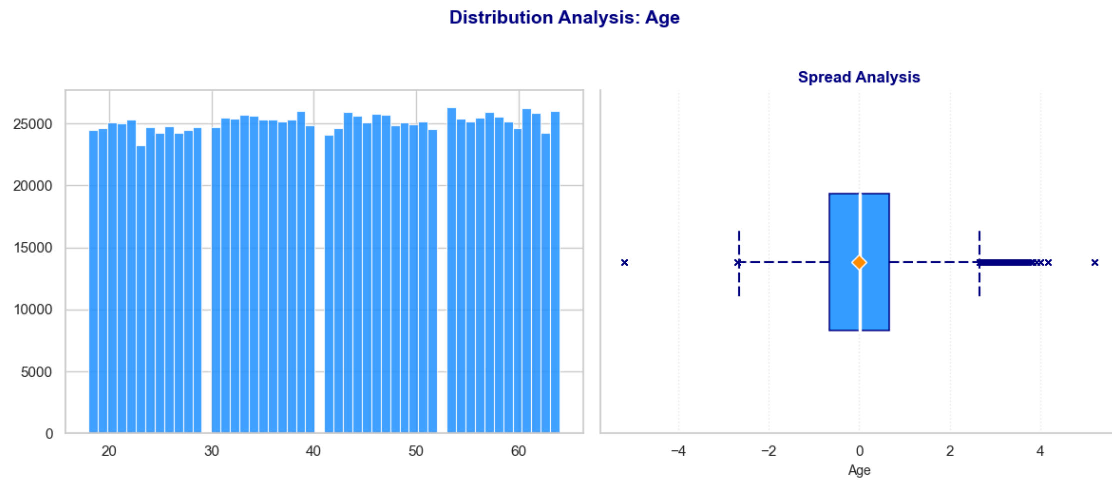
[2199]:
```python
columns_numerical_values = df_train.select_dtypes("number").
 ↪drop(columns=["Premium Amount"])
columns_numerical_values.count()
```

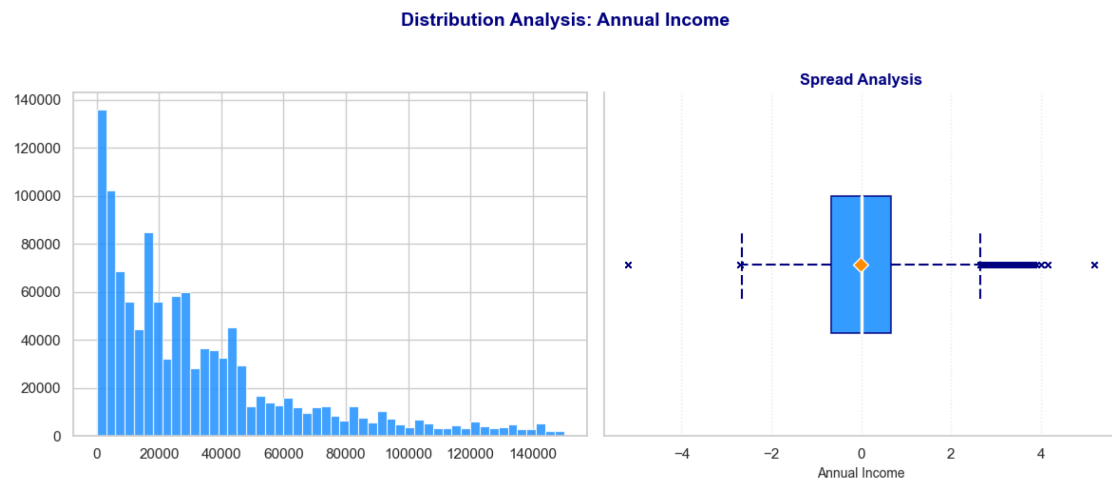
[2199]:
```
Age                     1181295
Annual Income           1155051
Number of Dependents    1090328
Health Score            1125924
Previous Claims          835971
Vehicle Age             1199994
Credit Score            1062118
Insurance Duration      1199999
dtype: int64
```

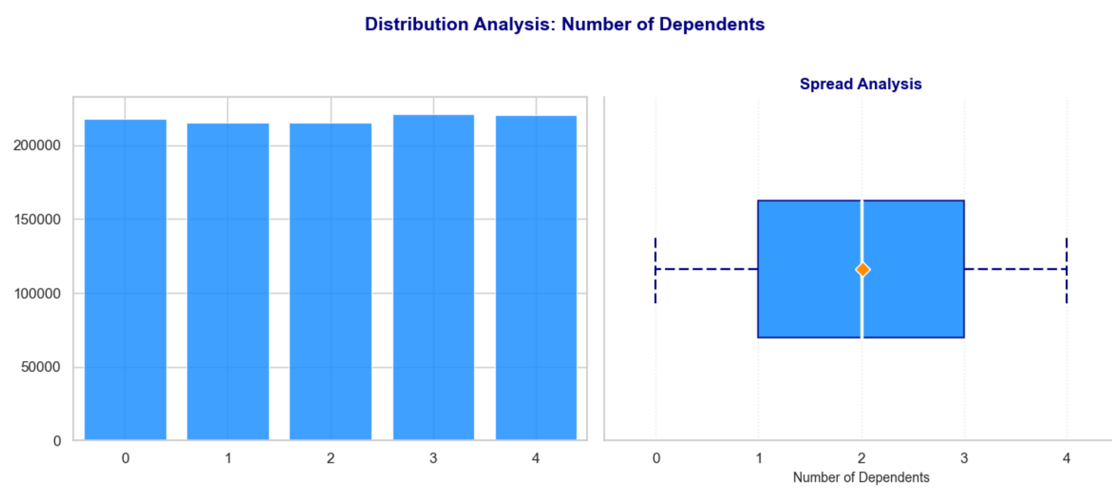
[2200]:
```python
from matplotlib.ticker import MultipleLocator

for col in columns_numerical_values.columns:
    plt.figure(figsize=(12, 5))
    sns.set_theme(style="whitegrid")
    plt.suptitle(f'Distribution Analysis: {col}', y=1.02,
```

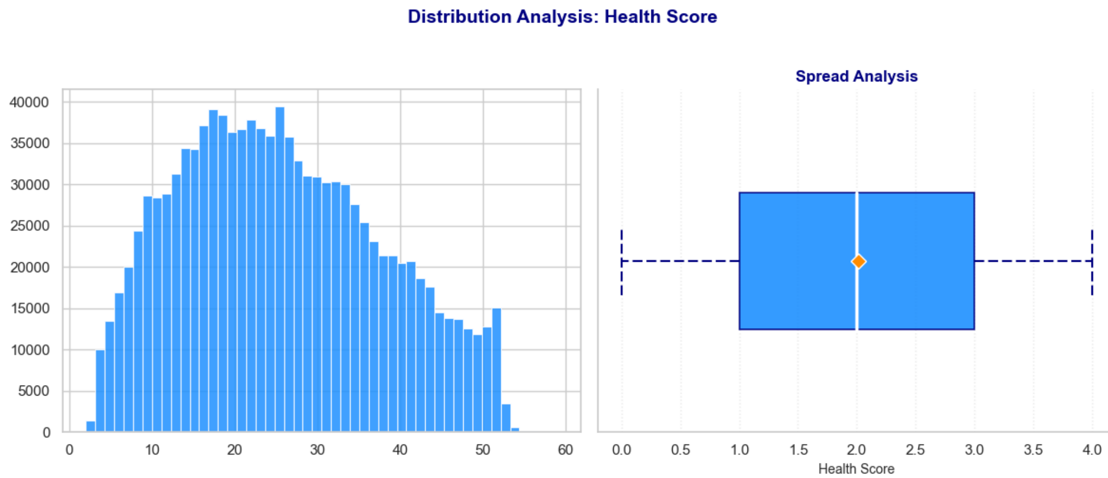
```
                  fontsize=14, fontweight='semibold', color=SECONDARY_COLOR)

    # Left subplot: Histogram
    ax1 = plt.subplot(1, 2, 1)

    if col in ['Number of Dependents', 'Previous Claims', 'Vehicle Age',␣
↪'Insurance Duration']:
        data = columns_numerical_values[col].dropna().astype(int)
        min_val = data.min()
        max_val = data.max()

        # Calculate value counts for perfect alignment
        value_counts = data.value_counts().sort_index()
        bins = np.arange(min_val - 0.5, max_val + 1.5, 1)

        # Plot with narrow bars (rwidth=0.8) and perfect alignment
        plt.hist(data, bins=bins,
                 color=MAIN_COLOR, edgecolor=EDGE_COLOR, linewidth=0.8,
                 density=False, alpha=0.85, align='mid', rwidth=0.8)

        ax1.set_xlim(min_val - 0.5, max_val + 0.5)
        ax1.xaxis.set_major_locator(MultipleLocator(1))

        # Set exact integer labels from data
        ax1.set_xticks(np.arange(min_val, max_val + 1, 1))

    else:
        # Continuous case remains unchanged
        plt.hist(columns_numerical_values[col].dropna(), bins=50,
                 color=MAIN_COLOR, edgecolor=EDGE_COLOR, linewidth=0.8,
                 density=False, alpha=0.85)

    # Right subplot: Boxplot
    ax2 = plt.subplot(1, 2, 2)

    # Create compact boxplot
    bp = plt.boxplot(data if 'data' in locals() else␣
↪columns_numerical_values[col].dropna(),
                     vert=False,
                     widths=0.4,  # Narrower box width
                     patch_artist=True,
                     showmeans=True,
                     meanprops=dict(marker='D', markersize=8,
                                    markeredgecolor=EDGE_COLOR,
                                    markerfacecolor=TERTIARY_COLOR))

    # Enhanced boxplot styling
```

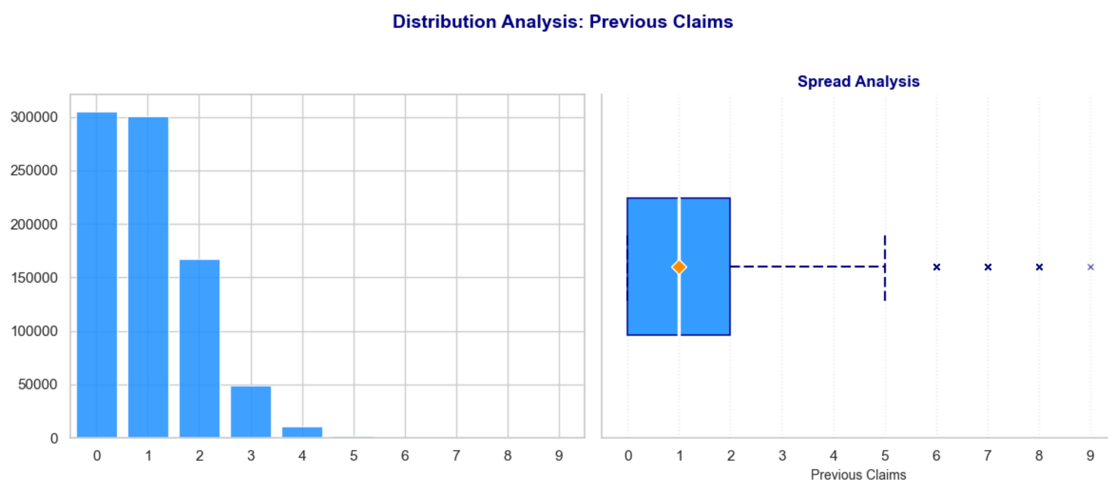
```python
    for box in bp['boxes']:
        box.set(facecolor=MAIN_COLOR,
                edgecolor=SECONDARY_COLOR,
                linewidth=1.2,
                alpha=0.9)

    # Whisker and cap styling
    for element in ['whiskers', 'caps']:
        for line in bp[element]:
            line.set(color=SECONDARY_COLOR,
                    linewidth=1.5,
                    linestyle=(0, (5, 2)))  # Custom dash pattern

    # Median line styling
    for median in bp['medians']:
        median.set(color=EDGE_COLOR,
                  linewidth=2.5,
                  solid_capstyle='round')

    # Outlier styling
    for flier in bp['fliers']:
        flier.set(marker='x',
                 markersize=5,
                 markeredgecolor=SECONDARY_COLOR,
                 alpha=0.6)

    # Axis synchronization with histogram
    if col in ['Number of Dependents', 'Previous Claims', 'Vehicle Age',␣
↪'Insurance Duration']:
        ax2.set_xlim(min_val - 0.5, max_val + 0.5)
        ax2.xaxis.set_major_locator(MultipleLocator(1))
        ax2.set_xticks(np.arange(min_val, max_val + 1, 1))

    format_axes(ax2, "Spread Analysis", col, "")
    ax2.grid(**{**GRID_STYLE, 'alpha': 0.4})
    ax2.set_yticks([])

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

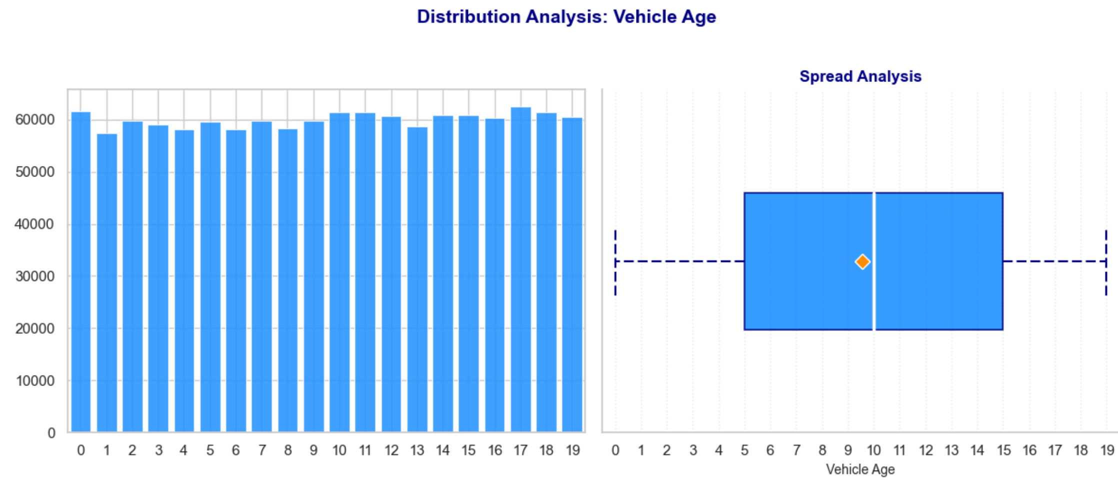

Distribution Analysis: Age
Spread Analysis
Age

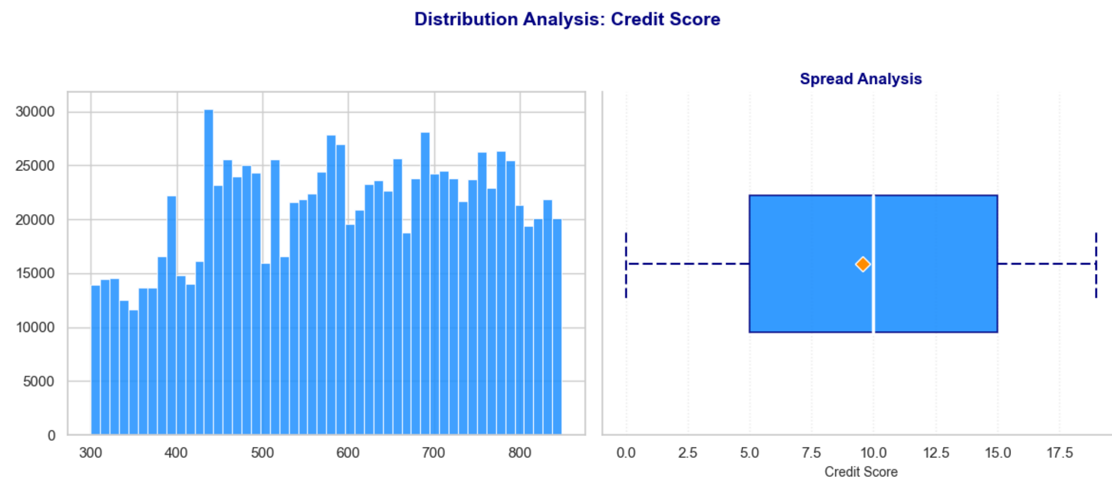

Distribution Analysis: Annual Income
Spread Analysis
Annual Income

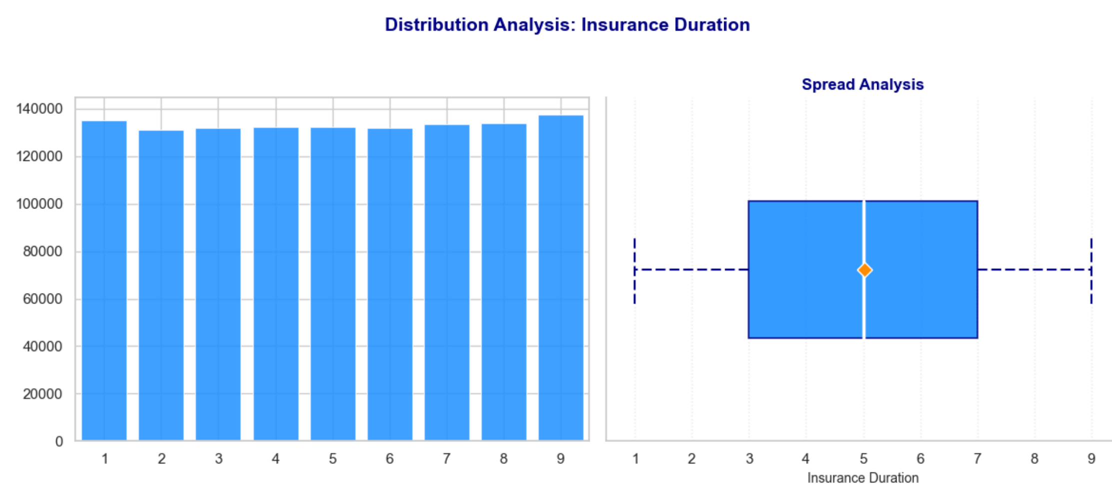

Distribution Analysis: Number of Dependents
Spread Analysis
Number of Dependents


Distribution Analysis: Health Score
Spread Analysis
Health Score


Distribution Analysis: Previous Claims
Spread Analysis
Previous Claims


Distribution Analysis: Vehicle Age
Spread Analysis
Vehicle Age


Distribution Analysis: Credit Score
Spread Analysis
Credit Score


Distribution Analysis: Insurance Duration
Spread Analysis
Insurance Duration

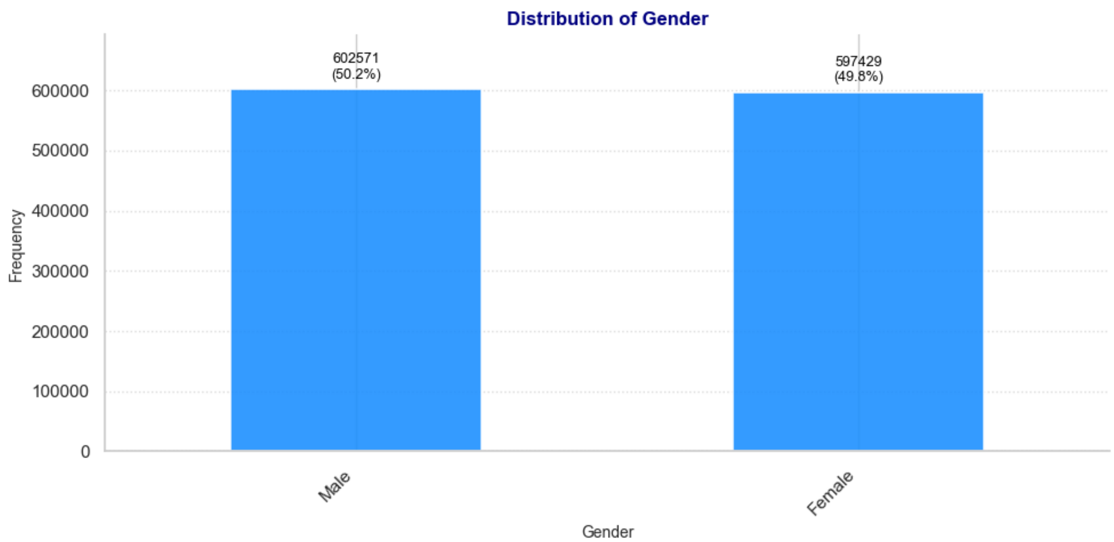
2.3 Categorical values

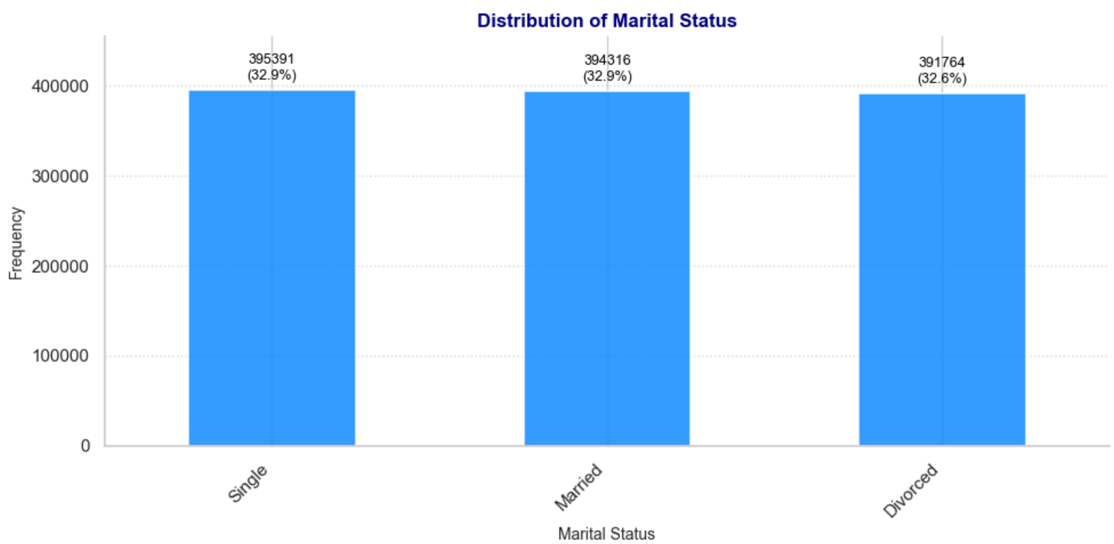
[2201]:
```
columns_object_values = df_train.select_dtypes("object")
columns_object_values.count()
```

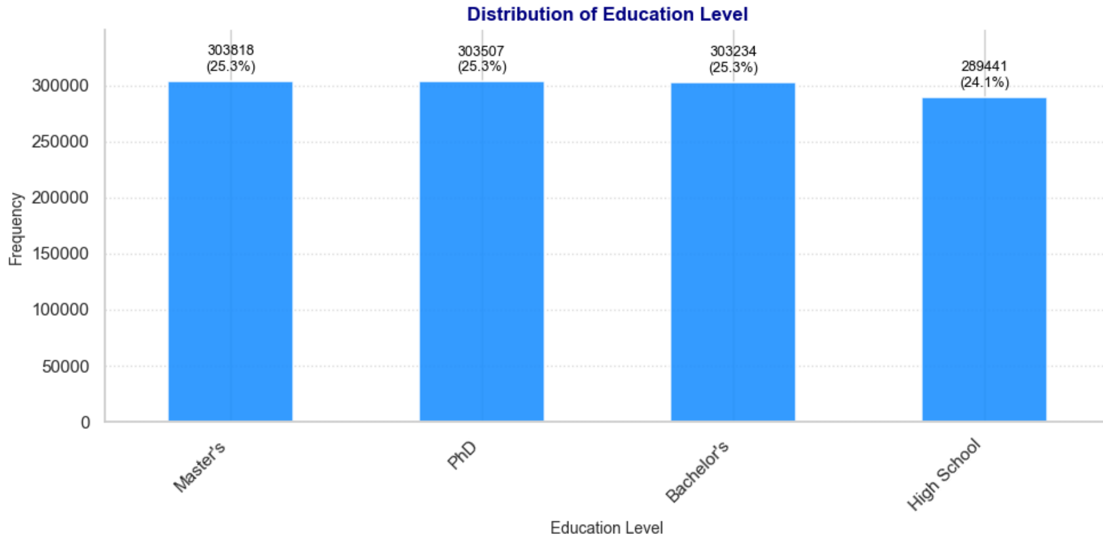
[2201]:
```
Gender                 1200000
Marital Status         1181471
Education Level        1200000
Occupation              841925
Location               1200000
Policy Type            1200000
Policy Start Date      1200000
Customer Feedback      1122176
Smoking Status         1200000
Exercise Frequency     1200000
Property Type          1200000
dtype: int64
```

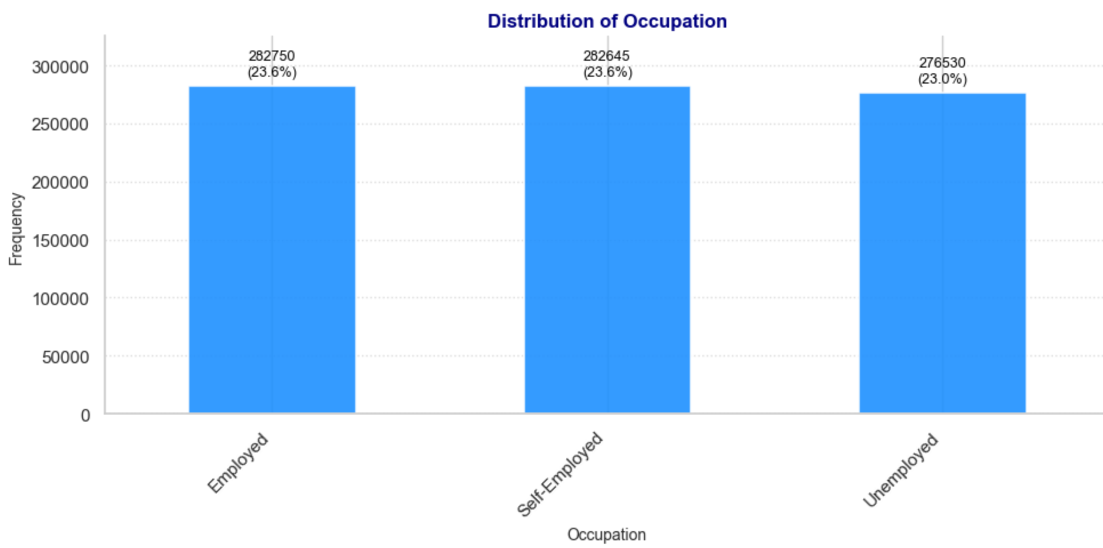
[2202]:
```
# Drop unnecessary column
columns_object_values = columns_object_values.drop(columns=['Policy Start␣
↪Date'])

# Generate bar plots for categorical columns
for col in columns_object_values.columns:
    plt.figure(figsize=(10, 5))

    # Get value counts and percentages
    counts = columns_object_values[col].value_counts()
    percentages = (counts / len(columns_object_values[col])) * 100

    # Create bar plot
    ax = counts.plot(kind="bar",
                     color=MAIN_COLOR,
                     edgecolor=EDGE_COLOR,
                     linewidth=1.2,
                     alpha=0.9,
                     rot=0)

    # Add value labels on bars
    for i, (count, percentage) in enumerate(zip(counts, percentages)):
        ax.text(i, count + 0.02 * max(counts),
                f"{count}\n({percentage:.1f}%)",
                ha='center', va='bottom',
                color=TEXT_COLOR,
```

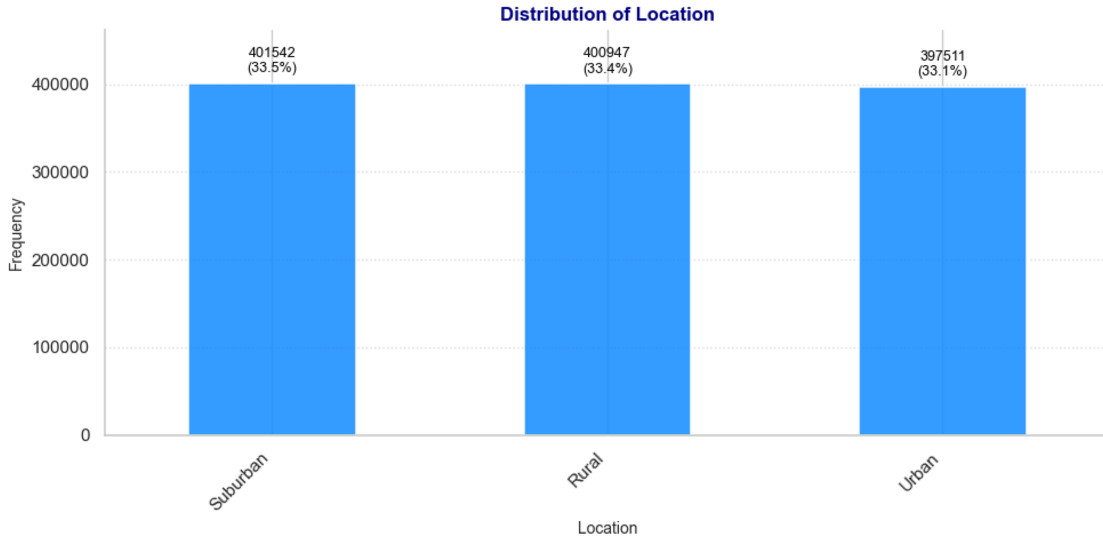
```
            fontsize=9,
            linespacing=1.2)

# Apply formatting
format_axes(ax, f"Distribution of {col}", col, "Frequency")
plt.xticks(rotation=45, ha='right')
plt.ylim(0, max(counts) * 1.15)

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

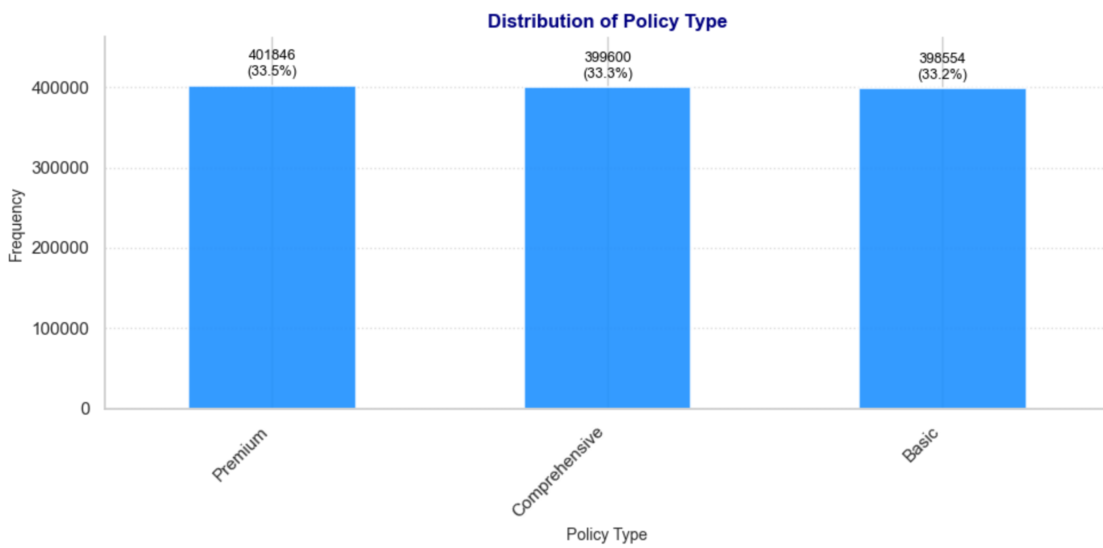


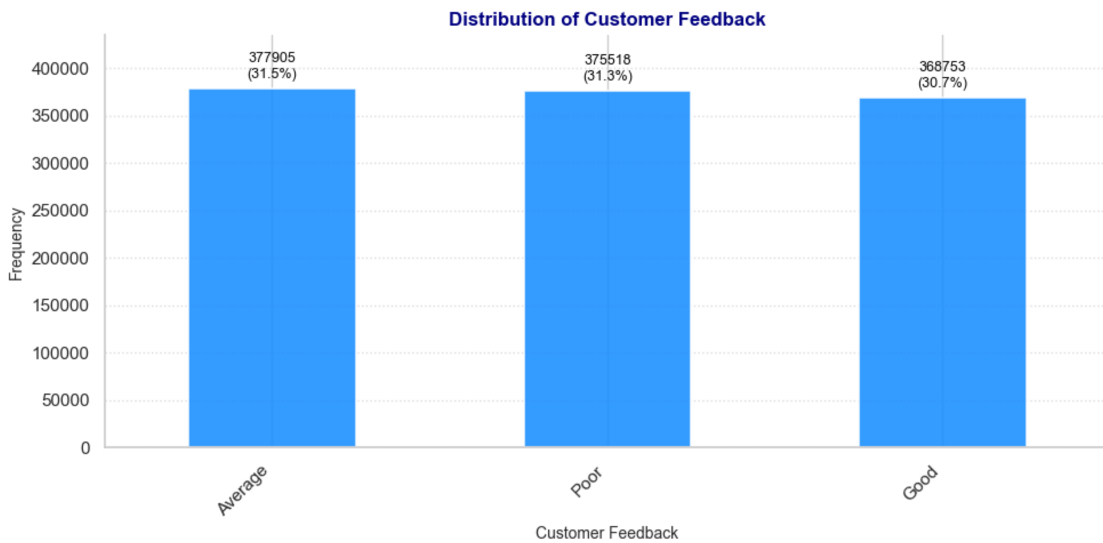


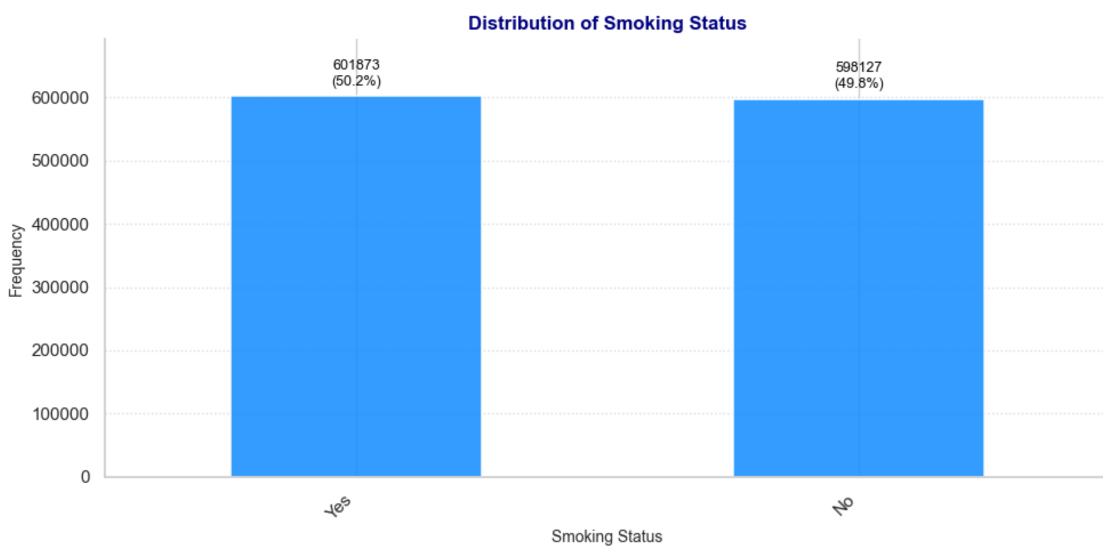

Distribution of Education Level
303818
(25.3%)
303507
(25.3%)
303234
(25.3%)
289441
(24.1%)
Frequency
0
50000
100000
150000
200000
250000
300000
Master's
PhD
Bachelor's
High School
Education Level

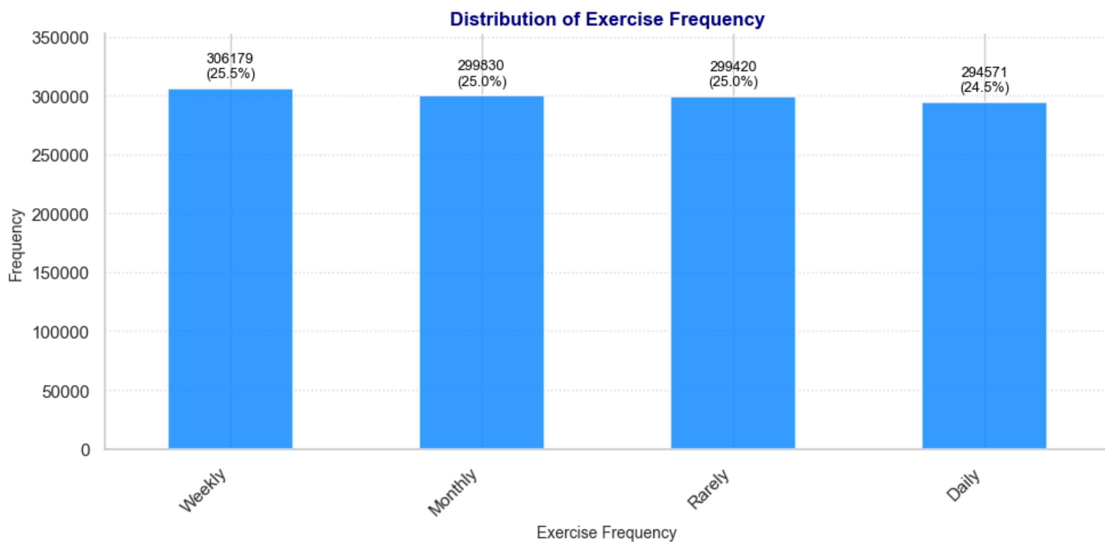

Distribution of Occupation
282750
(23.6%)
282645
(23.6%)
276530
(23.0%)
Frequency
0
50000
100000
150000
200000
250000
300000
Employed
Self-Employed
Unemployed
Occupation

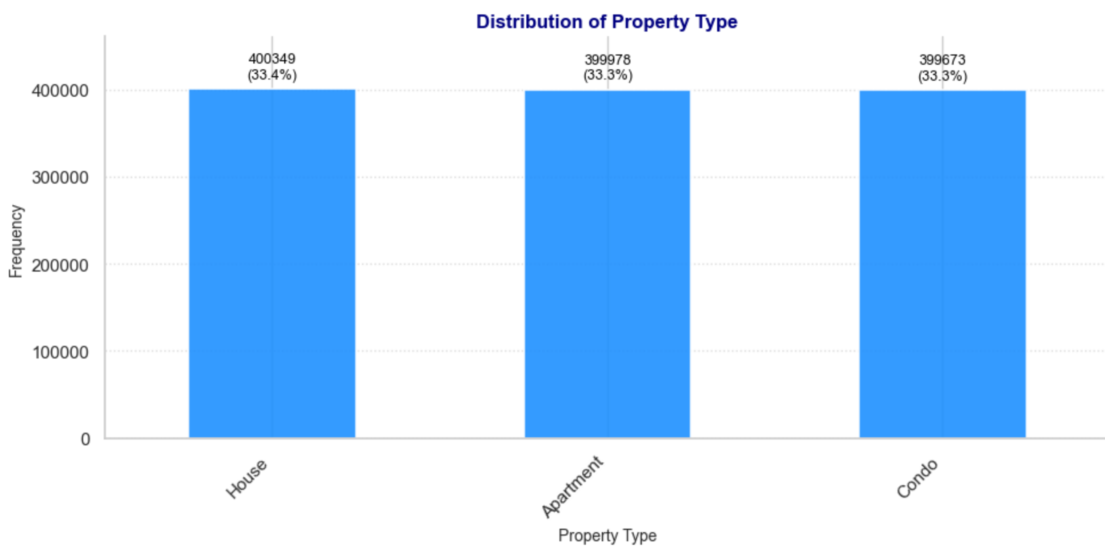

Distribution of Location
401542
(33.5%)
400947
(33.4%)
397511
(33.1%)
400000
300000
200000
100000
0
Frequency
Suburban
Rural
Urban
Location


Distribution of Policy Type
401846
(33.5%)
399600
(33.3%)
398554
(33.2%)
400000
300000
200000
100000
0
Frequency
Premium
Comprehensive
Basic
Policy Type


Distribution of Customer Feedback
377905
(31.5%)
375518
(31.3%)
368753
(30.7%)
400000
350000
300000
250000
200000
150000
100000
50000
0
Frequency
Average
Poor
Good
Customer Feedback


Distribution of Smoking Status
601873
(50.2%)
598127
(49.8%)
600000
500000
400000
300000
200000
100000
0
Frequency
Yes
No
Smoking Status



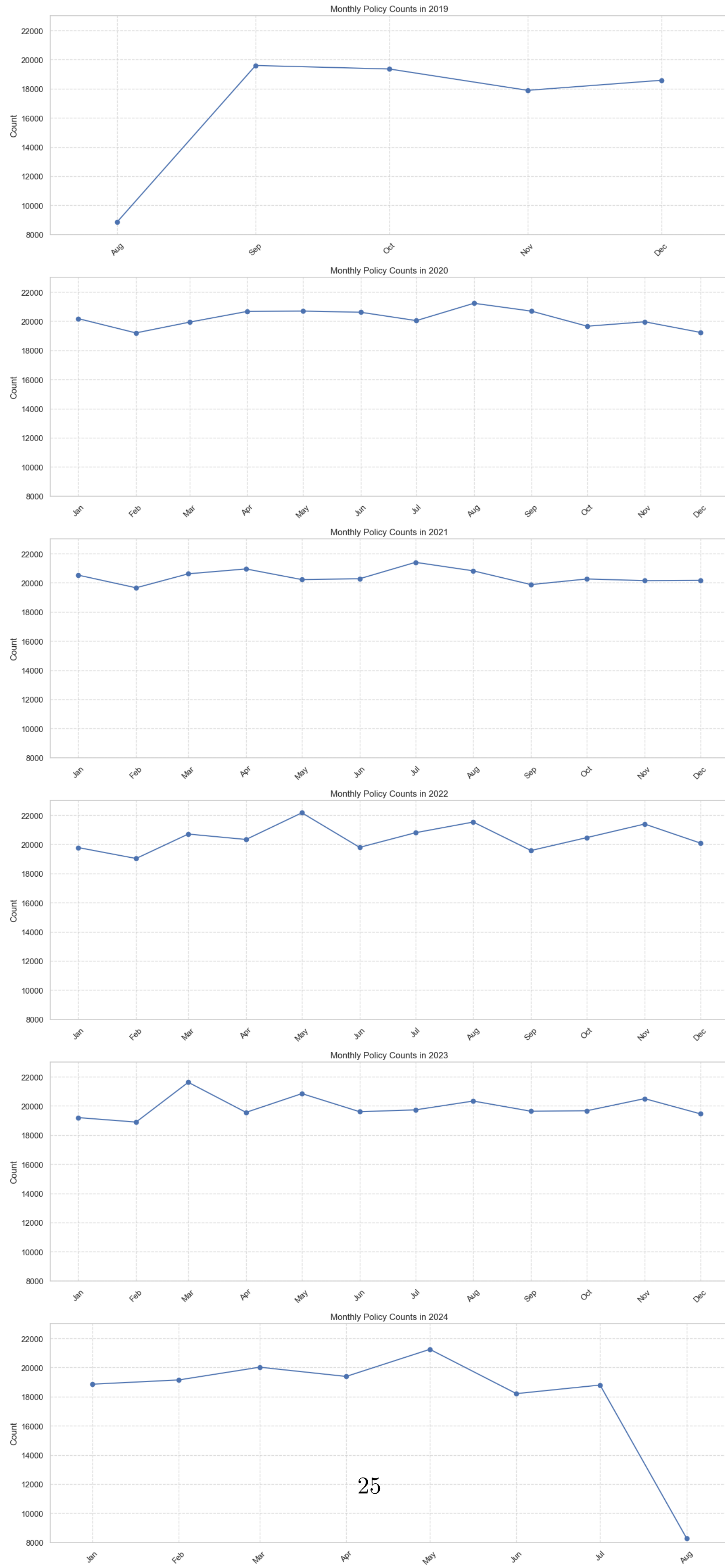


2.4 Time series values

[2203]:
```
df_train['Policy Start Date'] = pd.to_datetime(df_train['Policy Start Date'])
```

[2204]:
```
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import pandas as pd

# Załóżmy, że df_train ma kolumny 'Policy Start Date' i np. 'Other Columns'
# Grupa po roku i miesiącu bez ustawiania indeksu
```

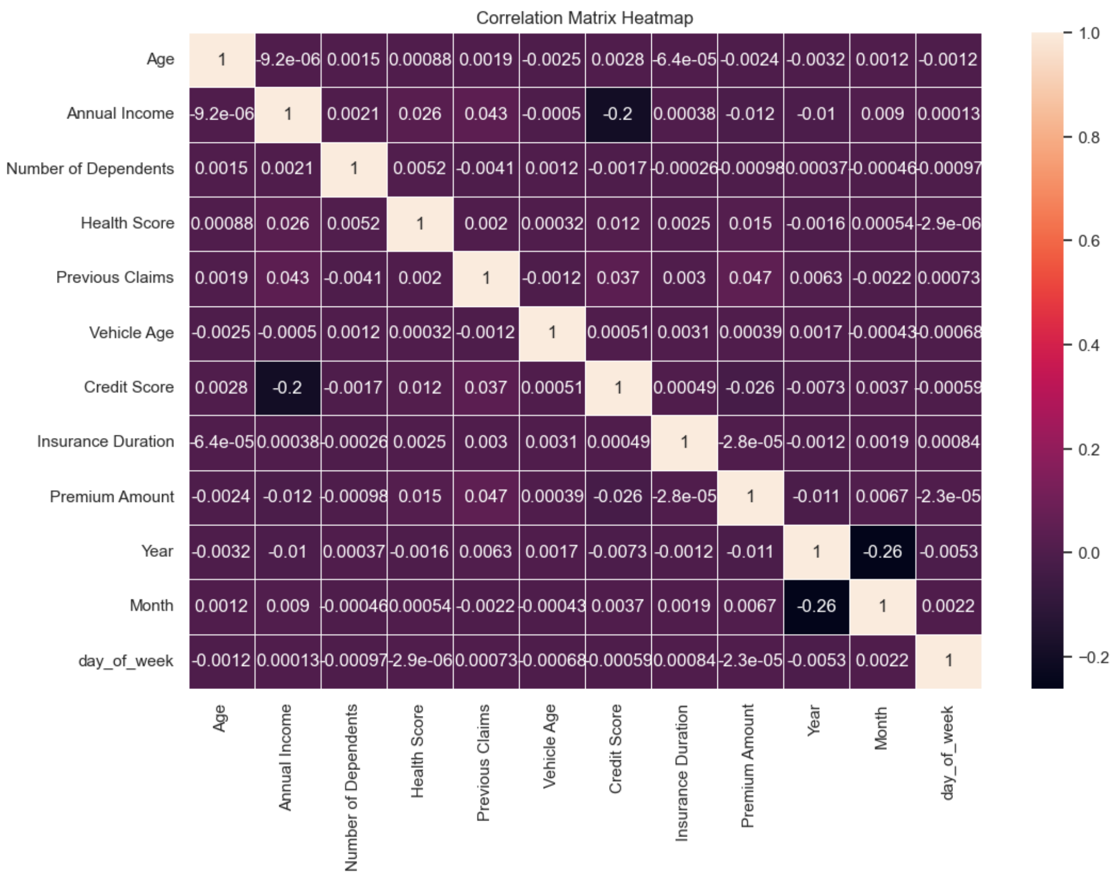
```python
df_train['Year'] = df_train['Policy Start Date'].dt.year
df_train['Month'] = df_train['Policy Start Date'].dt.month

# Liczymy liczbę polityk w każdym miesiącu
monthly_counts = df_train.groupby(['Year', 'Month']).size()

# Tworzymy wykresy dla każdego roku
years = monthly_counts.index.get_level_values('Year').unique()
n_years = len(years)

fig, axes = plt.subplots(n_years, 1, figsize=(14, 5 * n_years))

for i, year in enumerate(years):
    # Wybieramy dane dla konkretnego roku
    year_data = monthly_counts[monthly_counts.index.get_level_values('Year') ==␣
 ↪year]

    # Tworzymy daty z roku i miesiąca
    dates = pd.to_datetime(year_data.index.map(lambda x: f'{x[0]}-{x[1]:
 ↪02d}-01'))

    # Określamy zakres danych
    start_date = dates.min()
    end_date = dates.max()

    # Tworzymy wykres
    axes[i].plot(dates, year_data.values, marker='o', linestyle='-')
    axes[i].set_title(f'Monthly Policy Counts in {year}')
    axes[i].set_ylabel('Count')
    axes[i].set_ylim(8000, 23000)

    # Ustawiamy zakres osi X na podstawie danych (nie całego roku)
    axes[i].set_xlim(start_date - pd.DateOffset(days=15), end_date + pd.
 ↪DateOffset(days=15))

    # Formatowanie osi X
    axes[i].xaxis.set_major_locator(mdates.MonthLocator())
    axes[i].xaxis.set_major_formatter(mdates.DateFormatter('%b'))
    axes[i].tick_params(axis='x', rotation=45)
    axes[i].grid(True, linestyle='--', alpha=0.7)

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


Monthly Policy Counts in 2019
Count
8000 10000 12000 14000 16000 18000 20000 22000
Aug Sep Oct Nov Dec
Monthly Policy Counts in 2020
Count
8000 10000 12000 14000 16000 18000 20000 22000
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Monthly Policy Counts in 2021
Count
8000 10000 12000 14000 16000 18000 20000 22000
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Monthly Policy Counts in 2022
Count
8000 10000 12000 14000 16000 18000 20000 22000
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Monthly Policy Counts in 2023
Count
8000 10000 12000 14000 16000 18000 20000 22000
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Monthly Policy Counts in 2024
Count
8000 10000 12000 14000 16000 18000 20000 22000
Jan Feb Mar Apr May Jun Jul Aug

[2205]:
```
df_train['Policy Start Date'] = pd.to_datetime(df_train['Policy Start Date'])

df_train['Year'] = df_train['Policy Start Date'].dt.year
df_train['Month'] = df_train['Policy Start Date'].dt.month
df_train['day_of_week'] = df_train['Policy Start Date'].dt.dayofweek  # 0 -␣
 ↪Poniedziałek, 6 - Niedziela
# Function to assign time of day category
def get_time_of_day_category(time):
    hour = time.hour
    if 20 <= hour < 24 or 0 <= hour < 6:
        return 'Night'
    elif 6 <= hour < 12:
        return 'Morning'
    elif 12 <= hour < 14:
        return 'Noon'
    elif 14 <= hour < 20:
        return 'Afternoon'

# Create a new column for time of day category
df_train['time_of_day_category'] = df_train['Policy Start Date'].
 ↪apply(get_time_of_day_category)
```

2.5 Correlation matrix

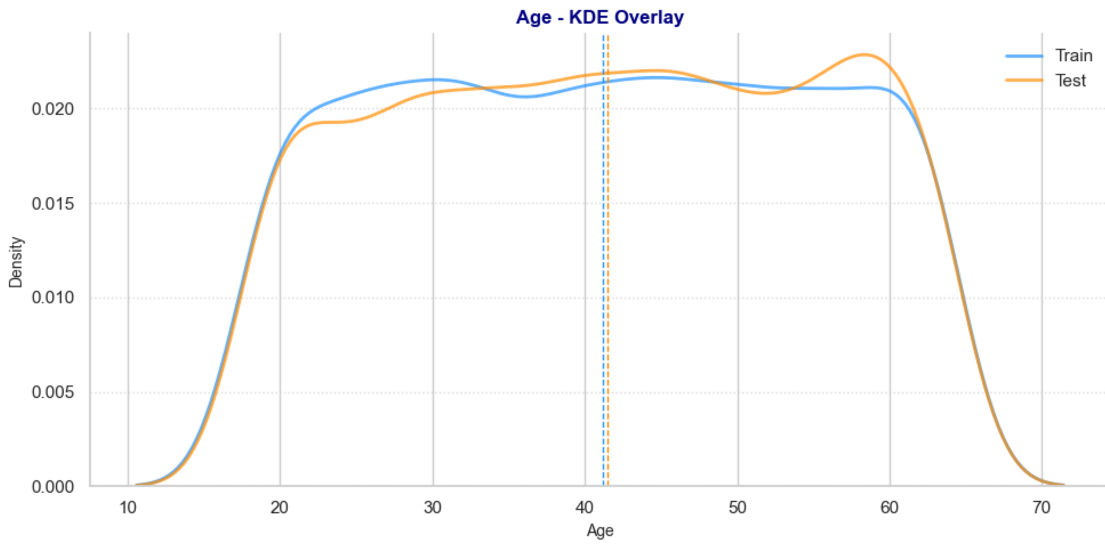
[2206]:
```
df_numerical = df_train.select_dtypes(include=['number'])
correlation_matrix = df_numerical.corr()

plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, linewidths=0.5)
plt.title("Correlation Matrix Heatmap")
plt.show()
```

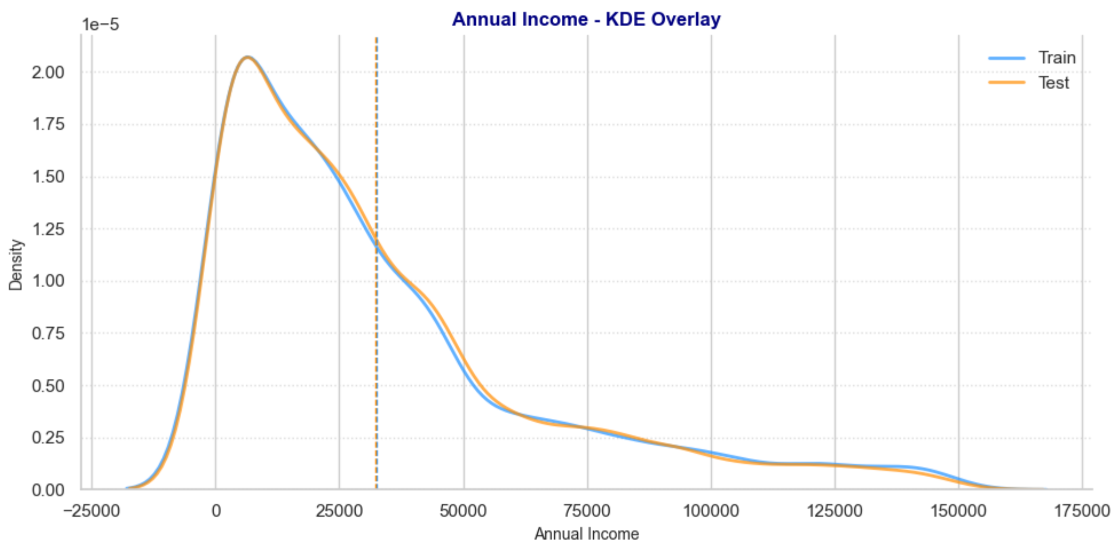


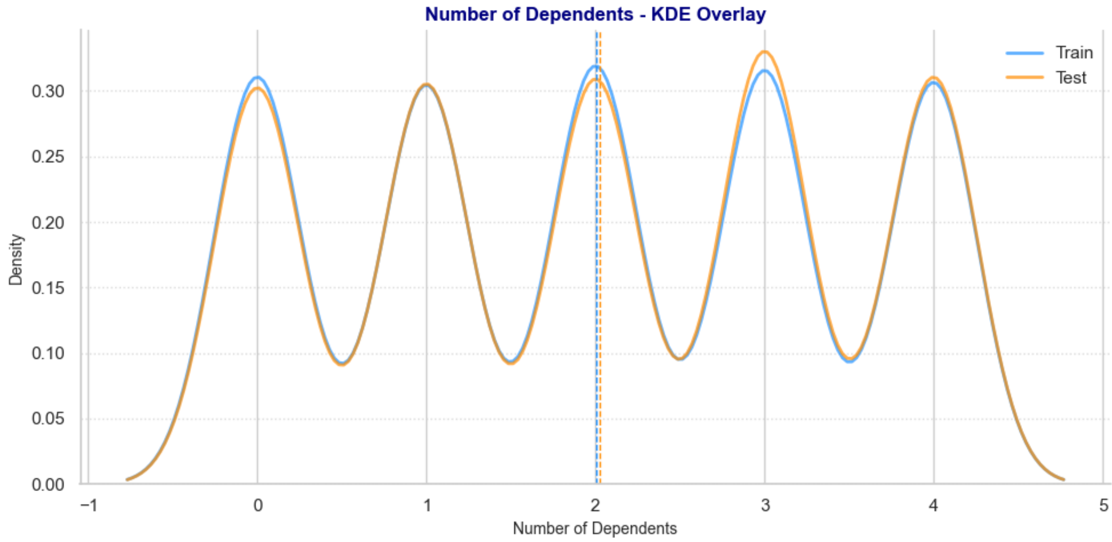
3 Train vs Test set comparison

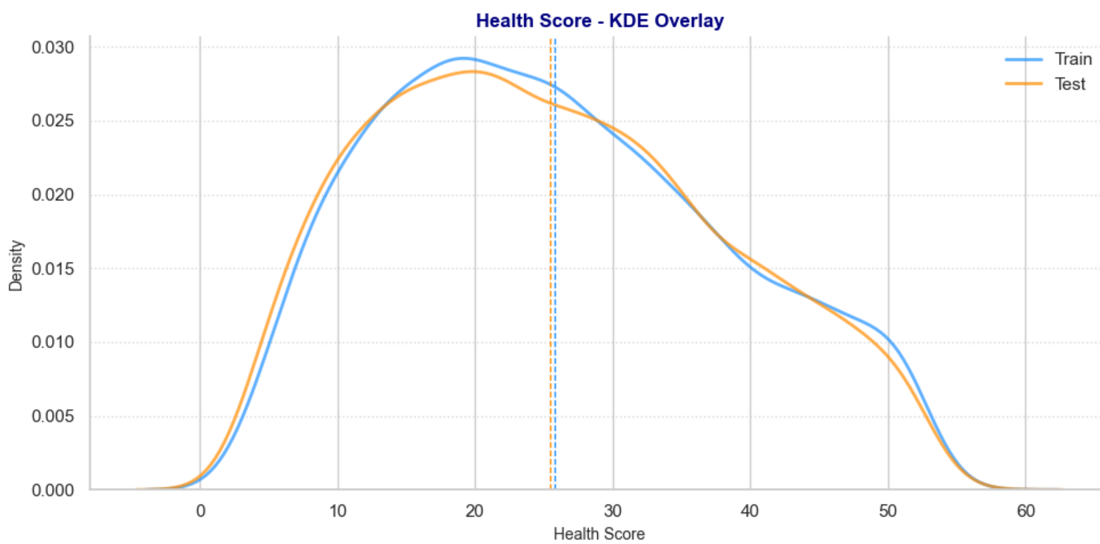
[2207]:
```python
from scipy.stats import ks_2samp

palette = {"Train": "dodgerblue", "Test": "darkorange"}

for col in columns_numerical_values.columns:
    plt.figure(figsize=(10, 5))

    sample_size = min(5000, len(df_train), len(df_test))
    train_sample = df_train[col].dropna().sample(sample_size, random_state=42)
    test_sample = df_test[col].dropna().sample(sample_size, random_state=42)

    # Overlay KDEs
    sns.kdeplot(train_sample, color=palette["Train"], label='Train',␣
 ↪linewidth=2, alpha=0.7)
    sns.kdeplot(test_sample, color=palette["Test"], label='Test', linewidth=2,␣
 ↪alpha=0.7)
```

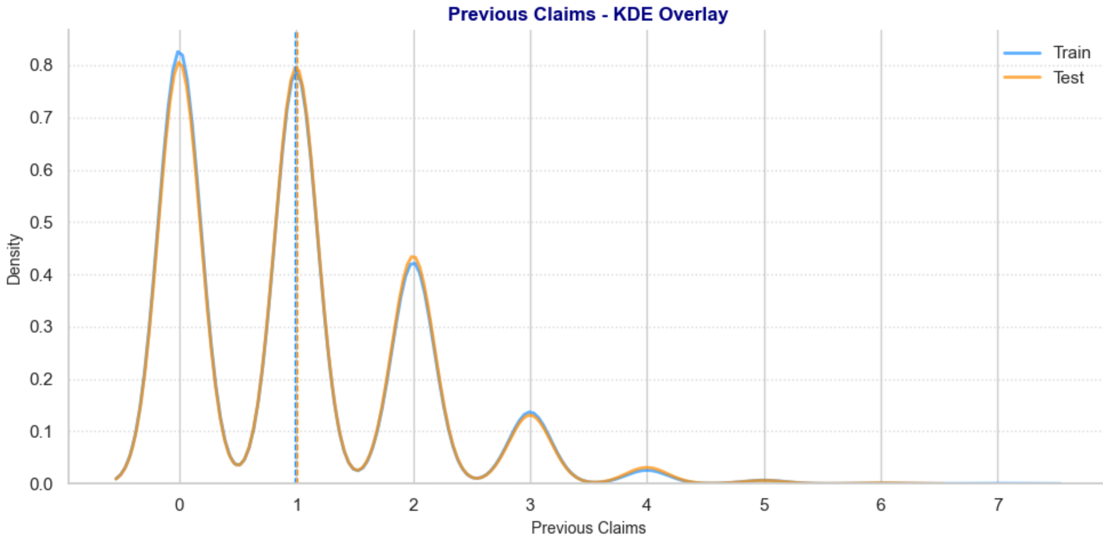
```
    # Add mean/median lines
    plt.axvline(train_sample.mean(), color=palette["Train"], linestyle='--',␣
↪linewidth=1)
    plt.axvline(test_sample.mean(), color=palette["Test"], linestyle='--',␣
↪linewidth=1)

    format_axes(plt.gca(), f'{col} - KDE Overlay', col, 'Density')
    plt.legend(frameon=False)
    plt.tight_layout()
    plt.show()
    plt.close()
```

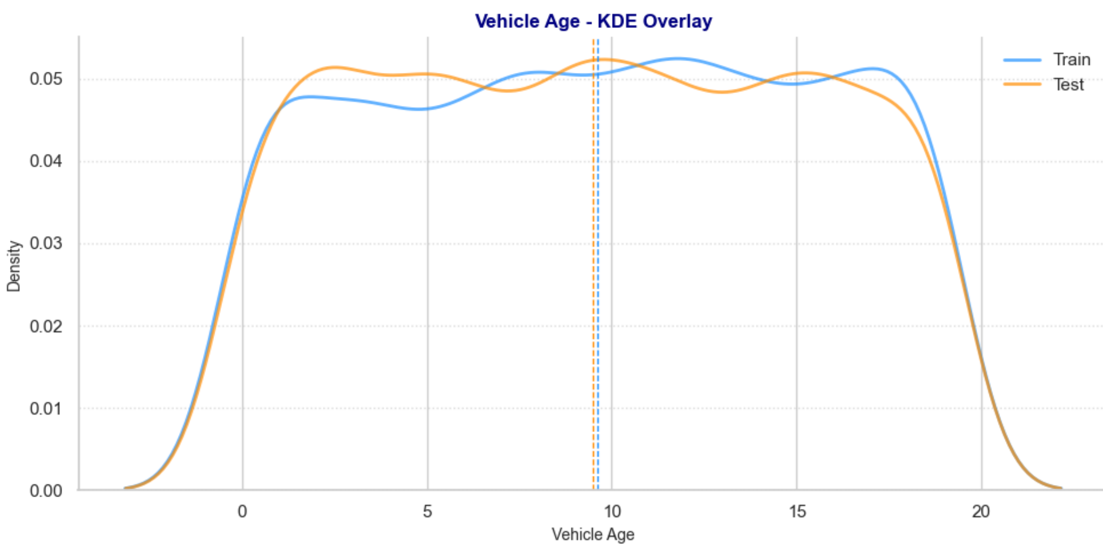


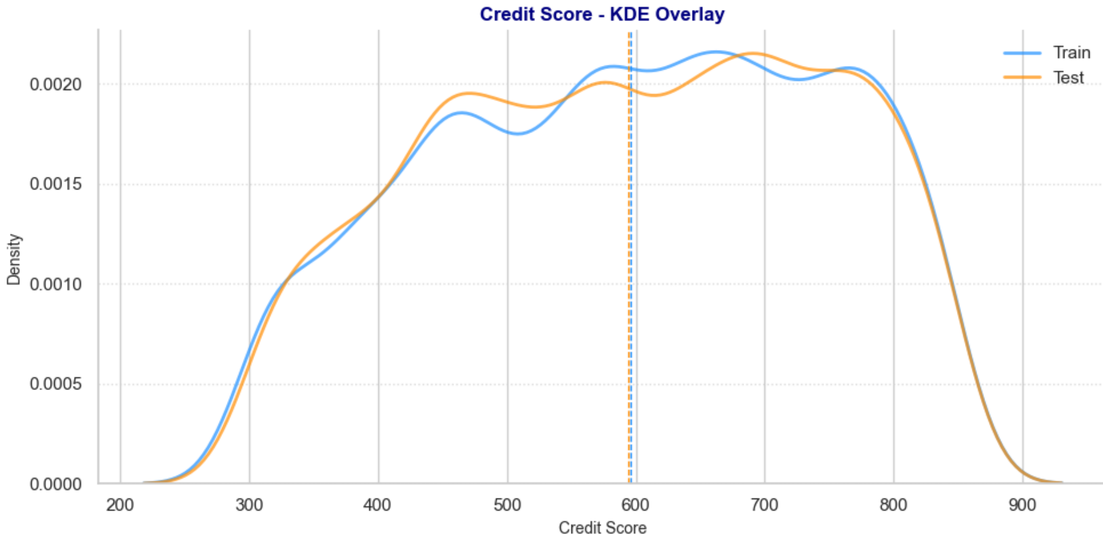


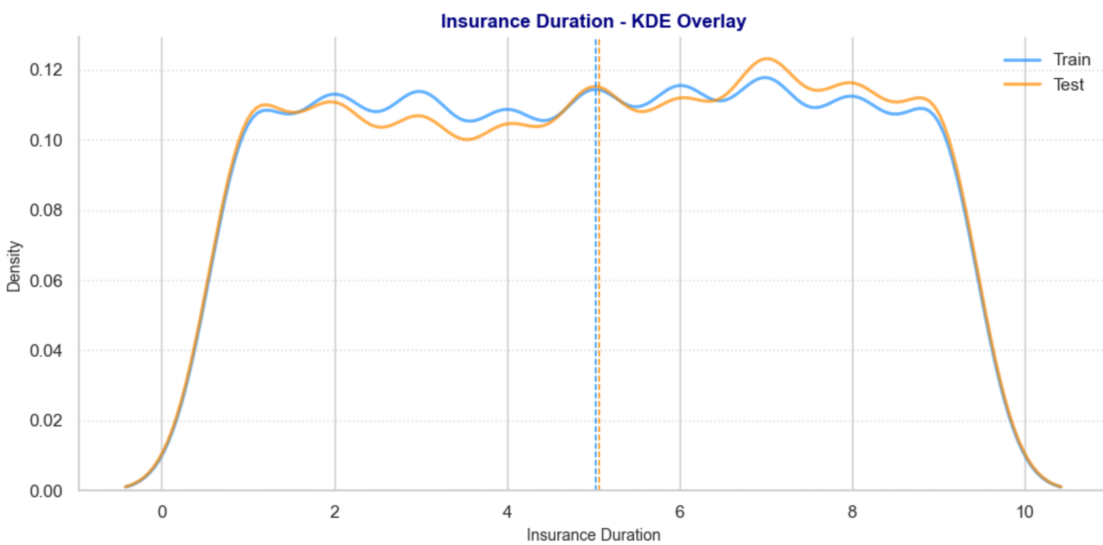

Number of Dependents - KDE Overlay
Train
Test
Density
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−1
0
1
2
3
4
5
Number of Dependents


Health Score - KDE Overlay
Train
Test
Density
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
10
20
30
40
50
60
Health Score


Previous Claims - KDE Overlay
Train
Test
Density
Previous Claims
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0
1
2
3
4
5
6
7


Vehicle Age - KDE Overlay
Train
Test
Density
Vehicle Age
0.00
0.01
0.02
0.03
0.04
0.05
0
5
10
15
20

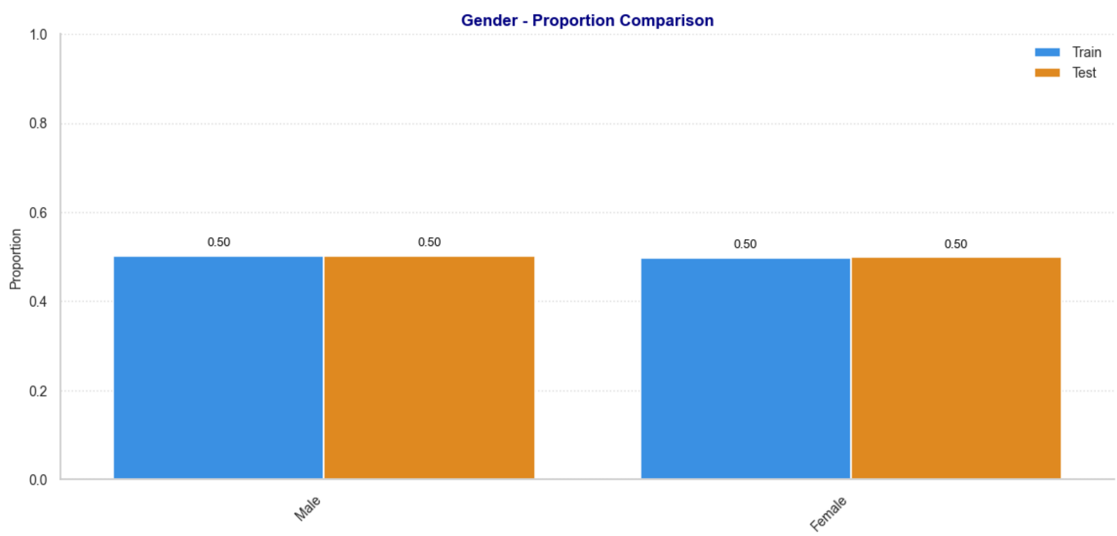


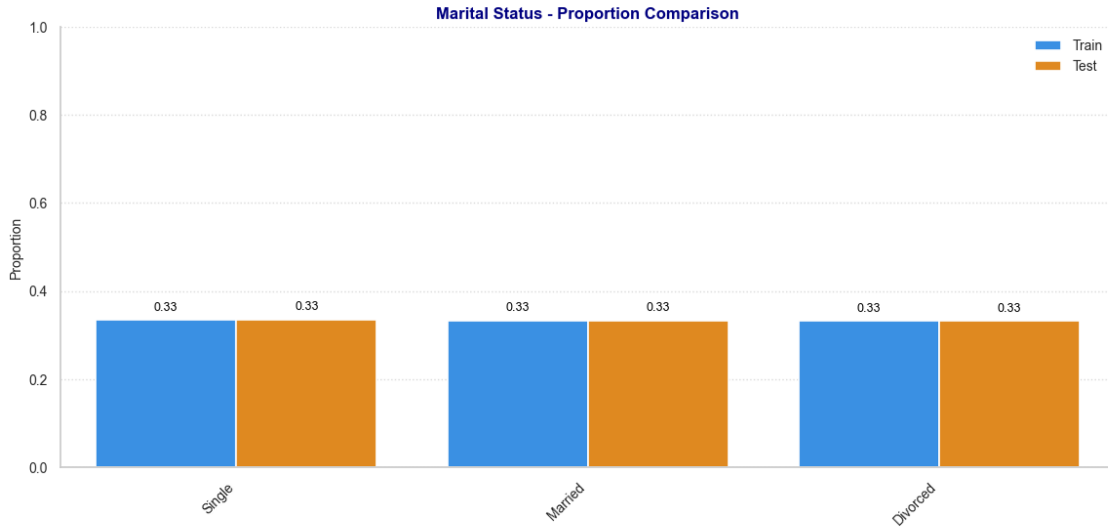


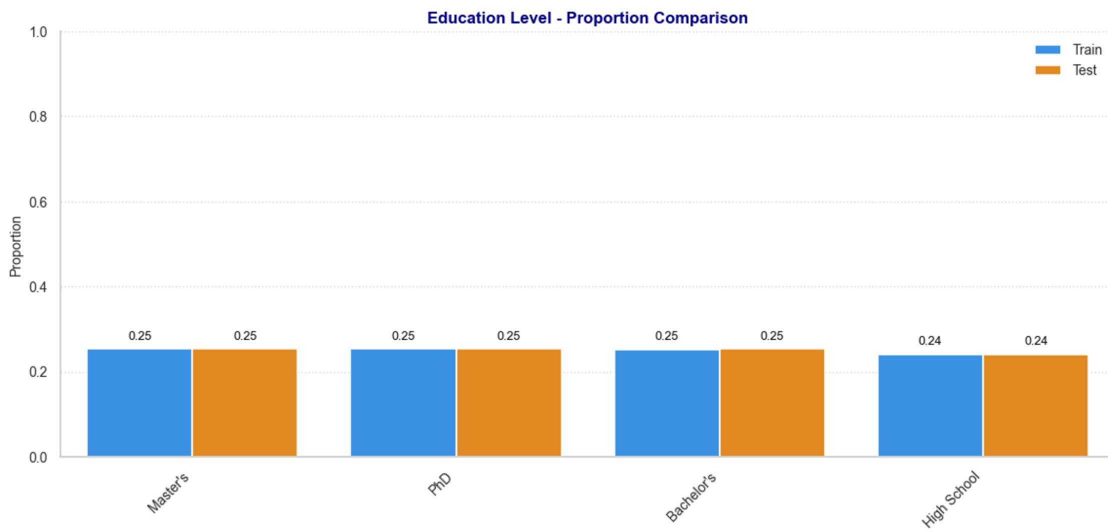
[2208]:

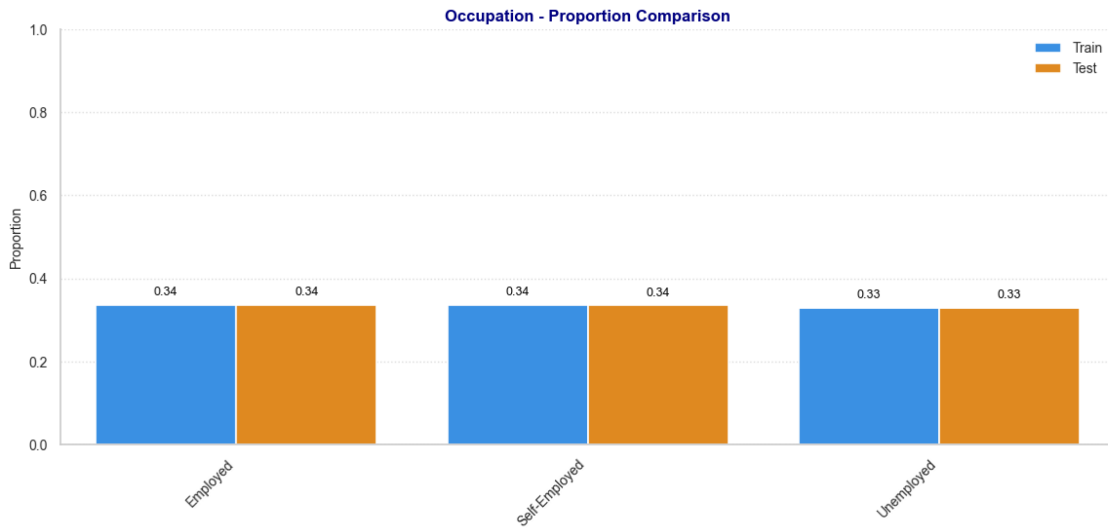
```
# Generate bar plots for categorical columns with proportions comparison
for col in columns_object_values.columns:
    plt.figure(figsize=(12, 6))

    train_prop = df_train[col].value_counts(normalize=True).reset_index()
    train_prop.columns = ['value', 'proportion']
    train_prop['dataset'] = 'Train'

    test_prop = df_test[col].value_counts(normalize=True).reset_index()
    test_prop.columns = ['value', 'proportion']
```

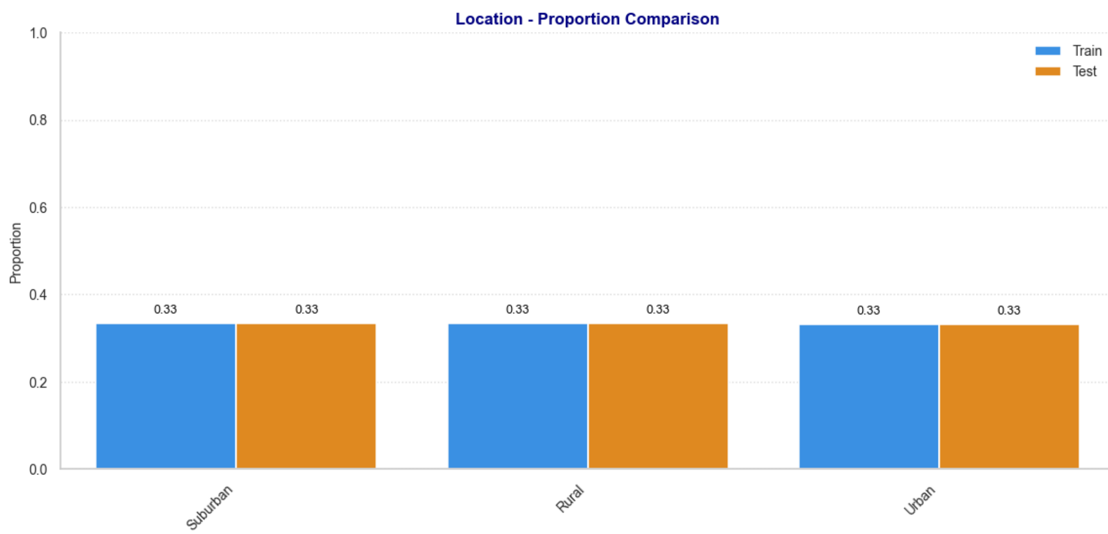
```
    test_prop['dataset'] = 'Test'

    temp_df = pd.concat([train_prop, test_prop], axis=0)

    ax = sns.barplot(
        data=temp_df,
        x='value',
        y='proportion',
        hue='dataset',
        palette=[MAIN_COLOR, TERTIARY_COLOR],
        edgecolor=EDGE_COLOR,
        linewidth=1.2
    )

    ax.set_ylim(0, 1)
    for p in ax.patches:
        height = p.get_height()
        if height > 0.05:
            ax.annotate(f'{height:.2f}', (p.get_x() + p.get_width() / 2.,␣
↪height),
                        ha='center', va='bottom', fontsize=9, color=TEXT_COLOR,
                        xytext=(0, 5), textcoords='offset points')

    format_axes(ax, f'{col} - Proportion Comparison', '', 'Proportion')
    plt.xticks(rotation=45, ha='right', fontsize=10)
    plt.yticks(fontsize=10)
    plt.legend(title='', frameon=False, fontsize=10)
    plt.tight_layout(pad=2.0)
    plt.show()
    plt.close()
```

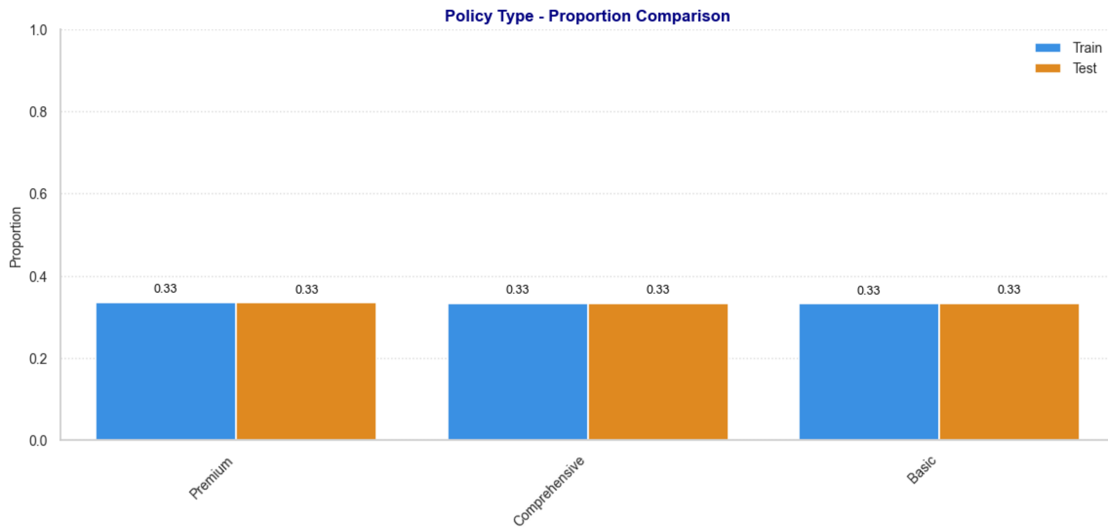


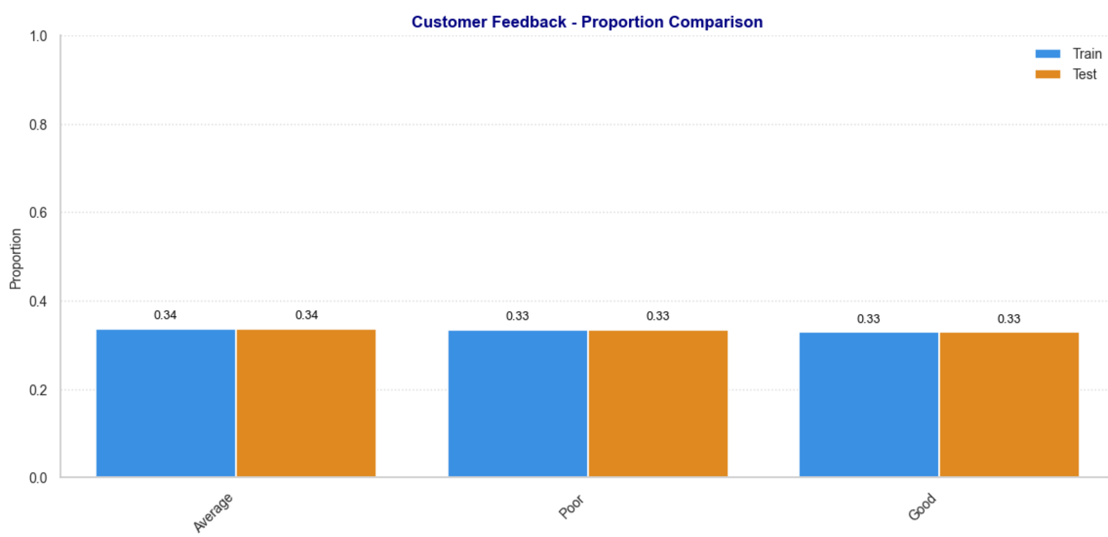

Marital Status - Proportion Comparison
Proportion
1.0
0.8
0.6
0.4
0.2
0.0
Train
Test
0.33
0.33
0.33
0.33
0.33
0.33
Single
Married
Divorced

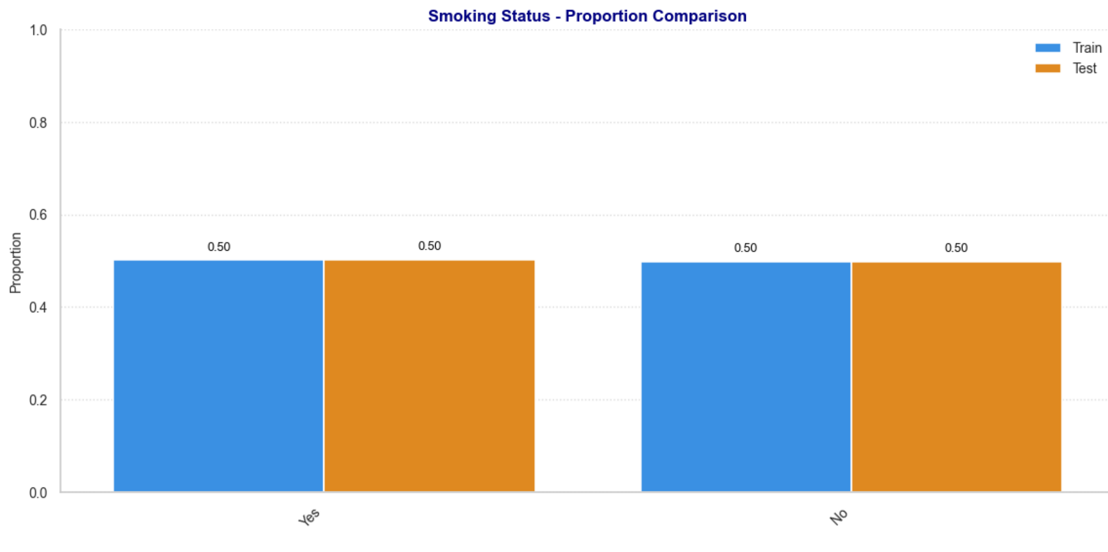

Education Level - Proportion Comparison
Proportion
1.0
0.8
0.6
0.4
0.2
0.0
Train
Test
0.25
0.25
0.25
0.25
0.25
0.25
0.24
0.24
Master's
PhD
Bachelor's
High School

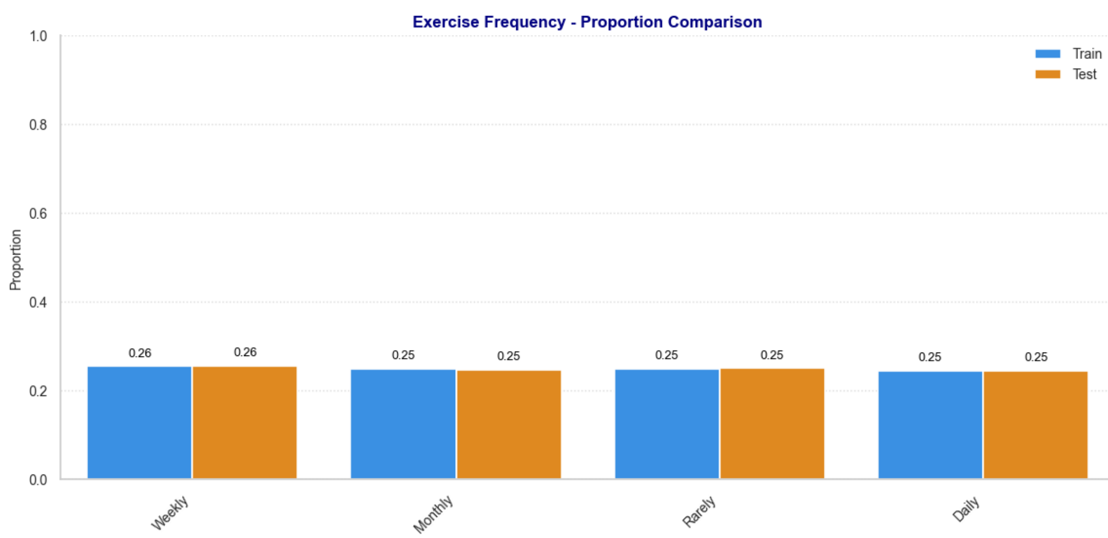

Occupation - Proportion Comparison
Proportion
1.0
0.8
0.6
0.4
0.2
0.0
Train
Test
0.34
0.34
0.34
0.34
0.33
0.33
Employed
Self-Employed
Unemployed

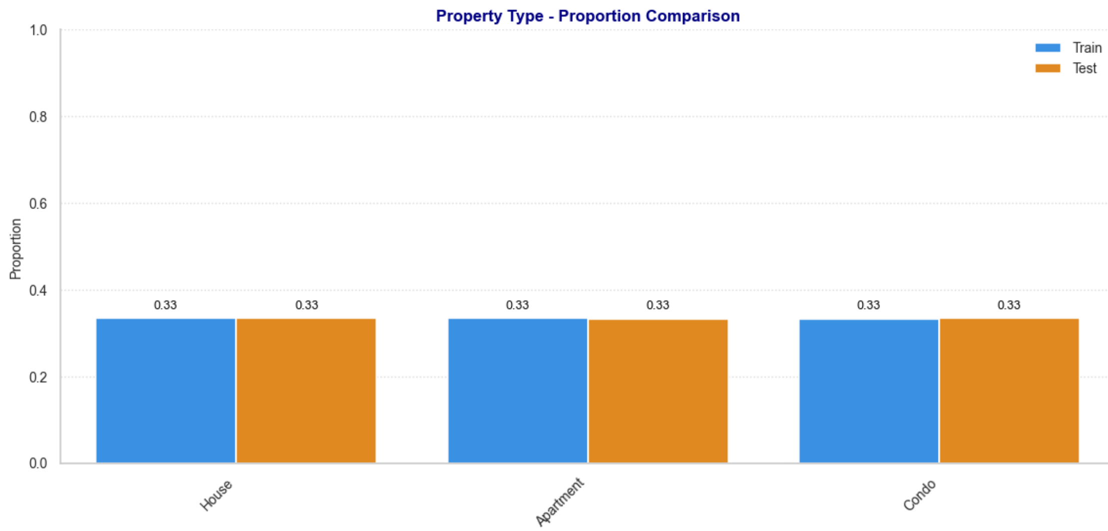

Location - Proportion Comparison
Proportion
1.0
0.8
0.6
0.4
0.2
0.0
Train
Test
0.33
0.33
0.33
0.33
0.33
0.33
Suburban
Rural
Urban


Policy Type - Proportion Comparison
1.0
0.8
0.6
0.4
0.2
0.0
Proportion
Train
Test
0.33
0.33
0.33
0.33
0.33
0.33
Premium
Comprehensive
Basic


Customer Feedback - Proportion Comparison
1.0
0.8
0.6
0.4
0.2
0.0
Proportion
Train
Test
0.34
0.34
0.33
0.33
0.33
0.33
Average
Poor
Good


Smoking Status - Proportion Comparison
Train
Test
Proportion
1.0
0.8
0.6
0.4
0.2
0.0
0.50
0.50
0.50
0.50
Yes
No


Exercise Frequency - Proportion Comparison
Train
Test
Proportion
1.0
0.8
0.6
0.4
0.2
0.0
0.26
0.26
0.25
0.25
0.25
0.25
0.25
0.25
Weekly
Monthly
Rarely
Daily



4 ML models

4.1 Feature engineering

[2209]:
```
df_train.columns
```

[2209]:
```
Index(['Age', 'Gender', 'Annual Income', 'Marital Status',
       'Number of Dependents', 'Education Level', 'Occupation', 'Health Score',
       'Location', 'Policy Type', 'Previous Claims', 'Vehicle Age',
       'Credit Score', 'Insurance Duration', 'Policy Start Date',
       'Customer Feedback', 'Smoking Status', 'Exercise Frequency',
       'Property Type', 'Premium Amount', 'Year', 'Month', 'day_of_week',
       'time_of_day_category'],
      dtype='object')
```

[2210]:
```
df_train['month_sin'] = np.sin(2 * np.pi * df_train['Month']   / 12)
df_train['month_cos'] = np.cos(2 * np.pi * df_train['Month']   / 12)
df_train['dow_sin'] = np.sin(2 * np.pi * df_train['day_of_week'] / 7)
df_train['dow_cos'] = np.cos(2 * np.pi * df_train['day_of_week'] / 7)
df_train['quarter'] = df_train['Policy Start Date'].dt.quarter
min_year = df_train['Year'].min()
max_year = df_train['Year'].max()
df_train['Year_sin'] = np.sin(2 * np.pi * (df_train['Year'] - min_year) /
 ↪(max_year - min_year))
df_train['Year_cos'] = np.cos(2 * np.pi * (df_train['Year'] - min_year) /
 ↪(max_year - min_year))
```

[2211]:
```
df_train['Income_per_Dependent'] = df_train['Annual Income'] /␣
↪(df_train['Number of Dependents'] + 1)
df_train['Income_per_Year'] = df_train['Annual Income'] / (df_train['Age'] + 1)
df_train['Claims_per_Year'] = df_train['Previous Claims'] /␣
↪(df_train['Insurance Duration'] + 1)
```

[2212]:
```
means = df_train.groupby('Education Level')['Premium Amount'].mean()
df_train['Edu_target_enc'] = df_train['Education Level'].map(means)
```

[2213]:
```
for col in columns_numerical_values:
    df_train[col] = df_train[col].fillna(df_train[col].median())
```

[2214]:
```
object_types_input = {'Marital Status': 'Married', 'Customer Feedback':␣
↪'Average', 'Occupation':'Employed'}
df_train.fillna(object_types_input, inplace=True)
```

[2215]:
```
edu_order = {"High School": 0, "Bachelor's": 1, "Master's": 2, "PhD": 3}
df_train['Education Level'] = df_train['Education Level'].map(edu_order)
pol_type_order = {"Basic":0, "Comprehensive": 1, "Premium": 2}
df_train['Policy Type'] = df_train['Policy Type'].map(pol_type_order)
cust_order = {"Poor":0, "Average":1, "Good":2}
df_train['Customer Feedback'] = df_train['Customer Feedback'].map(cust_order)
exercise_order = {"Daily": 0, "Weekly":1, "Monthly":2, "Rarely":3}
df_train["Exercise Frequency"] = df_train["Exercise Frequency"].
↪map(exercise_order)
```

[2216]:
```
pd.set_option('display.max_columns', None)
df_train
```

[2216]:
```
          Age  Gender  Annual Income Marital Status  Number of Dependents  \
id
0        19.0  Female        10049.0        Married                   1.0
1        39.0  Female        31678.0       Divorced                   3.0
2        23.0    Male        25602.0       Divorced                   3.0
3        21.0    Male       141855.0        Married                   2.0
4        21.0    Male        39651.0         Single                   1.0
…         …      …              …              …                    …
1199995  36.0  Female        27316.0        Married                   0.0
1199996  54.0    Male        35786.0       Divorced                   2.0
1199997  19.0    Male        51884.0       Divorced                   0.0
1199998  55.0    Male        23911.0         Single                   1.0
1199999  21.0  Female        23911.0       Divorced                   0.0

         Education Level     Occupation  Health Score  Location  Policy Type  \
id
0                      1  Self-Employed     22.598761     Urban            2
1                      2       Employed     15.569731     Rural            1
```

```
2                      0  Self-Employed     47.177549  Suburban           2
3                      1       Employed     10.938144     Rural           0
4                      1  Self-Employed     20.376094     Rural           2
…                    …            …            …      …          …
1199995                2     Unemployed     13.772907     Urban           2
1199996                2  Self-Employed     11.483482     Rural           1
1199997                2       Employed     14.724469  Suburban           0
1199998                3       Employed     18.547381  Suburban           2
1199999                3       Employed     10.125323     Rural           2

         Previous Claims  Vehicle Age  Credit Score  Insurance Duration  \
id
0                    2.0         17.0         372.0                 5.0
1                    1.0         12.0         694.0                 2.0
2                    1.0         14.0         595.0                 3.0
3                    1.0          0.0         367.0                 1.0
4                    0.0          8.0         598.0                 4.0
…                    …           …            …                  …
1199995              1.0          5.0         372.0                 3.0
1199996              1.0         10.0         597.0                 4.0
1199997              0.0         19.0         595.0                 6.0
1199998              1.0          7.0         407.0                 4.0
1199999              0.0         18.0         502.0                 6.0

                 Policy Start Date  Customer Feedback Smoking Status  \
id
0       2023-12-23 15:21:39.134960                  0             No
1       2023-06-12 15:21:39.111551                  1            Yes
2       2023-09-30 15:21:39.221386                  2            Yes
3       2024-06-12 15:21:39.226954                  0            Yes
4       2021-12-01 15:21:39.252145                  0            Yes
…                              …                …            …
1199995 2023-05-03 15:21:39.257696                  0             No
1199996 2022-09-10 15:21:39.134960                  0             No
1199997 2021-05-25 15:21:39.106582                  2             No
1199998 2021-09-19 15:21:39.190215                  0             No
1199999 2020-08-26 15:21:39.155231                  2            Yes

         Exercise Frequency Property Type  Premium Amount  Year  Month  \
id
0                        1         House          2869.0  2023     12
1                        2         House          1483.0  2023      6
2                        1         House           567.0  2023      9
3                        0     Apartment           765.0  2024      6
4                        1         House          2022.0  2021     12
…                     …            …             …    …    …
1199995                  0     Apartment          1303.0  2023      5
```

```
1199996                    1     Apartment           821.0  2022      9
1199997                    2         Condo           371.0  2021      5
1199998                    0     Apartment           596.0  2021      9
1199999                    2         House          2480.0  2020      8

         day_of_week time_of_day_category     month_sin     month_cos  \
id
0                  5            Afternoon -2.449294e-16  1.000000e+00
1                  0            Afternoon  1.224647e-16 -1.000000e+00
2                  5            Afternoon -1.000000e+00 -1.836970e-16
3                  2            Afternoon  1.224647e-16 -1.000000e+00
4                  2            Afternoon -2.449294e-16  1.000000e+00
…               …                   …           …           …
1199995            2            Afternoon  5.000000e-01 -8.660254e-01
1199996            5            Afternoon -1.000000e+00 -1.836970e-16
1199997            1            Afternoon  5.000000e-01 -8.660254e-01
1199998            6            Afternoon -1.000000e+00 -1.836970e-16
1199999            2            Afternoon -8.660254e-01 -5.000000e-01

          dow_sin   dow_cos  quarter      Year_sin  Year_cos  \
id
0       -0.974928 -0.222521        4 -9.510565e-01  0.309017
1        0.000000  1.000000        2 -9.510565e-01  0.309017
2       -0.974928 -0.222521        3 -9.510565e-01  0.309017
3        0.974928 -0.222521        2 -2.449294e-16  1.000000
4        0.974928 -0.222521        4  5.877853e-01 -0.809017
…             …         …       …             …         …
1199995  0.974928 -0.222521        2 -9.510565e-01  0.309017
1199996 -0.974928 -0.222521        3 -5.877853e-01 -0.809017
1199997  0.781831  0.623490        2  5.877853e-01 -0.809017
1199998 -0.781831  0.623490        3  5.877853e-01 -0.809017
1199999  0.974928 -0.222521        3  9.510565e-01  0.309017

         Income_per_Dependent  Income_per_Year  Claims_per_Year  \
id
0                      5024.5       502.450000         0.333333
1                      7919.5       791.950000         0.333333
2                      6400.5      1066.750000         0.250000
3                     47285.0      6447.954545         0.500000
4                     19825.5      1802.318182         0.000000
…                        …              …                …
1199995               27316.0       738.270270              NaN
1199996                   NaN       650.654545              NaN
1199997               51884.0      2594.200000         0.000000
1199998                   NaN              NaN         0.200000
1199999                   NaN              NaN         0.000000
```

```
          Edu_target_enc
id
0            1102.698438
1            1102.113989
2            1104.787490
3            1102.698438
4            1102.698438
…                  …
1199995      1102.113989
1199996      1102.113989
1199997      1102.113989
1199998      1100.683885
1199999      1100.683885

[1200000 rows x 35 columns]
```

[2217]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1200000 entries, 0 to 1199999
Data columns (total 35 columns):
 #   Column                Non-Null Count    Dtype
---  ------                --------------    -----
 0   Age                   1200000 non-null  float64
 1   Gender                1200000 non-null  object
 2   Annual Income         1200000 non-null  float64
 3   Marital Status        1200000 non-null  object
 4   Number of Dependents  1200000 non-null  float64
 5   Education Level       1200000 non-null  int64
 6   Occupation            1200000 non-null  object
 7   Health Score          1200000 non-null  float64
 8   Location              1200000 non-null  object
 9   Policy Type           1200000 non-null  int64
 10  Previous Claims       1200000 non-null  float64
 11  Vehicle Age           1200000 non-null  float64
 12  Credit Score          1200000 non-null  float64
 13  Insurance Duration    1200000 non-null  float64
 14  Policy Start Date     1200000 non-null  datetime64[ns]
 15  Customer Feedback     1200000 non-null  int64
 16  Smoking Status        1200000 non-null  object
 17  Exercise Frequency    1200000 non-null  int64
 18  Property Type         1200000 non-null  object
 19  Premium Amount        1200000 non-null  float64
 20  Year                  1200000 non-null  int32
 21  Month                 1200000 non-null  int32
 22  day_of_week           1200000 non-null  int32
 23  time_of_day_category  1200000 non-null  object
 24  month_sin             1200000 non-null  float64
```

```
 25  month_cos              1200000 non-null  float64
 26  dow_sin                1200000 non-null  float64
 27  dow_cos                1200000 non-null  float64
 28  quarter                1200000 non-null  int32
 29  Year_sin               1200000 non-null  float64
 30  Year_cos               1200000 non-null  float64
 31  Income_per_Dependent   1049387 non-null  float64
 32  Income_per_Year        1137086 non-null  float64
 33  Claims_per_Year        835970 non-null   float64
 34  Edu_target_enc         1200000 non-null  float64
dtypes: datetime64[ns](1), float64(19), int32(4), int64(4), object(7)
memory usage: 311.3+ MB
```

[2218]:

```
df_train = df_train.drop(columns = 'Policy Start Date')
```

[2219]:

```
columns_object_values = columns_object_values.columns.tolist()  # This creates␣
↪a list
to_remove = ['Education Level', 'Policy Type', 'Customer Feedback', 'Exercise␣
↪Frequency']
columns_object_values = [col for col in columns_object_values if col not in␣
↪to_remove]
columns_object_values.append('time_of_day_category')

# Apply one-hot encoding
df_train = pd.get_dummies(df_train,
                          columns=columns_object_values,
                          drop_first=True,
                          dtype=int)
```

[2220]:

```
columns_object_values
```

[2220]:

```
['Gender',
 'Marital Status',
 'Occupation',
 'Location',
 'Smoking Status',
 'Property Type',
 'time_of_day_category']
```

[2221]:

```
X = df_train.drop(columns=['Premium Amount', 'Year', 'Month', 'day_of_week'])
y = df_train['Premium Amount']
```

[2222]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[2223]:

```
obj_cols = X_train.select_dtypes(include='object').columns
print(obj_cols)
```

```
Index([], dtype='object')
```

[2224]:
```python
from sklearn.preprocessing import QuantileTransformer

y_transformer = QuantileTransformer(output_distribution='normal')
y_transformer.fit(y_train.values.reshape(-1, 1))

y_train_trans = y_transformer.transform(y_train.values.reshape(-1, 1)).ravel()
y_test_trans = y_transformer.transform(y_test.values.reshape(-1, 1)).ravel()
```

[2225]:
```python
# import optuna
# import xgboost as xg
# import mlflow
# import numpy as np
# import pandas as pd
# from sklearn.metrics import mean_squared_log_error
# from sklearn.model_selection import KFold

# # MLflow setup
# mlflow.set_tracking_uri("http://127.0.0.1:8080")
# mlflow.set_experiment("optuna_xgb")
# def objective(trial):
#     params = {
#         'max_depth': trial.suggest_int('max_depth', 3, 10),
#         'eta': trial.suggest_float('eta', 0.01, 0.3, log=True),
#         'subsample': trial.suggest_float('subsample', 0.5, 1.0),
#         'colsample_bytree': trial.suggest_float('colsample_bytree', 0.5, 1.0),
#         'gamma': trial.suggest_float('gamma', 1e-8, 5.0, log=True),
#         'alpha': trial.suggest_float('alpha', 1e-8, 10.0, log=True),
#         'lambda': trial.suggest_float('lambda', 1e-8, 10.0, log=True),
#         'min_child_weight': trial.suggest_int('min_child_weight', 1, 10),
#         'objective': 'reg:squarederror',
#         'n_jobs': -1,
#     }

#     kf = KFold(n_splits=5, shuffle=True, random_state=42)
#     rmsle_scores = []
#     neg_rmsle_sum = 0.0

#     for train_idx, val_idx in kf.split(X_train):
#         X_tr, X_val = X_train.iloc[train_idx], X_train.iloc[val_idx]
#         y_tr_trans = y_train_trans[train_idx]
#         y_val_trans = y_train_trans[val_idx]
#         y_val = y_train.iloc[val_idx].values

#         dtrain = xg.DMatrix(X_tr, label=y_tr_trans)
#         dval = xg.DMatrix(X_val, label=y_val_trans)
```

```
#         model = xg.train(
#             params,
#             dtrain,
#             num_boost_round=1000,
#             early_stopping_rounds=50,
#             evals=[(dval, 'eval')],
#             verbose_eval=False
#         )

#         preds_trans = model.predict(xg.DMatrix(X_val))
#         preds = y_transformer.inverse_transform(preds_trans.reshape(-1, 1)).
↪ravel()
#         preds = np.maximum(preds, 0)

#         try:
#             rmsle = np.sqrt(mean_squared_log_error(y_val, preds))
#         except ValueError:
#             rmsle = float('inf')

#         if rmsle < 0:
#             neg_rmsle_sum += rmsle

#         rmsle_scores.append(rmsle)

#     final_score = np.mean(rmsle_scores)
#     trial.set_user_attr("neg_rmsle_sum", neg_rmsle_sum)
#     return final_score


# if __name__ == '__main__':
#     with mlflow.start_run(run_name="Optuna_Study"):
#         study = optuna.create_study(direction='minimize')
#         study.optimize(objective, n_trials=50)

#         best_params = study.best_params
#         best_value = study.best_value
#         mlflow.log_params(best_params)
#         mlflow.log_metric('best_rmsle', best_value)

#         # Sum of all negative RMSLEs across trials
#         total_neg_rmsle = sum(
#             t.user_attrs.get("neg_rmsle_sum", 0.0) for t in study.trials
#         )
#         mlflow.log_metric("sum_negative_rmsle", total_neg_rmsle)

#         print("Best RMSLE: {:.4f}".format(best_value))
```

```
#         print("Best parameters:")
#         for key, value in best_params.items():
#             print(f"  {key}: {value}")
```

[2226]:
```
from sklearn.metrics import mean_squared_log_error
import xgboost as xg
dtrain_full = xg.DMatrix(X_train, label=y_train_trans)
best_params = {
    "max_depth": 9,
    "eta": 0.010210644111991293,
    "subsample": 0.9590370210705078,
    "colsample_bytree": 0.9550080187777964,
    "gamma": 3.0685315773707374e-08,
    "alpha": 1.0457292034153025e-08,
    "lambda": 1.6174048282694194e-08,
    "min_child_weight": 2,
    'objective': 'reg:squarederror',
    'n_jobs': -1,
}

final_model = xg.train(
    params=best_params,
    dtrain=dtrain_full,
    num_boost_round=1000,
    early_stopping_rounds=50,
    evals=[(dtrain_full, 'train')],
    verbose_eval=10
)

preds_trans = final_model.predict(dtrain_full)
preds = y_transformer.inverse_transform(preds_trans.reshape(-1, 1)).ravel()

# TRAIN RMSLE
rmsle = np.sqrt(mean_squared_log_error(y_train, preds))
print(f"Train RMSLE: {rmsle}")

# TEST RMSLE
dtest = xg.DMatrix(X_test)  # <--- Konwersja DataFrame na DMatrix
preds_trans_test = final_model.predict(dtest)  # <--- Użyj dtest zamiast X_test
preds_test = y_transformer.inverse_transform(preds_trans_test.reshape(-1, 1)).
 ↪ravel()
preds_test = np.maximum(preds_test, 0)  # Zapobieganie wartościom ujemnym
test_rmsle = np.sqrt(mean_squared_log_error(y_test, preds_test))
print(f"Test RMSLE: {test_rmsle}")
```

```
[0]     train-rmse:1.03070
[10]    train-rmse:1.02565
[20]    train-rmse:1.02131
```

```
[30]	train-rmse:1.01727
[40]	train-rmse:1.01407
[50]	train-rmse:1.01155
[60]	train-rmse:1.00944
[70]	train-rmse:1.00729
[80]	train-rmse:1.00555
[90]	train-rmse:1.00404
[100]	train-rmse:1.00271
[110]	train-rmse:1.00150
[120]	train-rmse:1.00043
[130]	train-rmse:0.99958
[140]	train-rmse:0.99874
[150]	train-rmse:0.99797
[160]	train-rmse:0.99732
[170]	train-rmse:0.99667
[180]	train-rmse:0.99607
[190]	train-rmse:0.99552
[200]	train-rmse:0.99498
[210]	train-rmse:0.99450
[220]	train-rmse:0.99403
[230]	train-rmse:0.99355
[240]	train-rmse:0.99310
[250]	train-rmse:0.99266
[260]	train-rmse:0.99224
[270]	train-rmse:0.99185
[280]	train-rmse:0.99144
[290]	train-rmse:0.99102
[300]	train-rmse:0.99065
[310]	train-rmse:0.99024
[320]	train-rmse:0.98987
[330]	train-rmse:0.98950
[340]	train-rmse:0.98914
[350]	train-rmse:0.98877
[360]	train-rmse:0.98841
[370]	train-rmse:0.98805
[380]	train-rmse:0.98769
[390]	train-rmse:0.98735
[400]	train-rmse:0.98701
[410]	train-rmse:0.98664
[420]	train-rmse:0.98631
[430]	train-rmse:0.98598
[440]	train-rmse:0.98566
[450]	train-rmse:0.98531
[460]	train-rmse:0.98501
[470]	train-rmse:0.98471
[480]	train-rmse:0.98441
[490]	train-rmse:0.98409
[500]	train-rmse:0.98380
```

```
[510]	train-rmse:0.98349
[520]	train-rmse:0.98323
[530]	train-rmse:0.98295
[540]	train-rmse:0.98266
[550]	train-rmse:0.98234
[560]	train-rmse:0.98207
[570]	train-rmse:0.98176
[580]	train-rmse:0.98148
[590]	train-rmse:0.98117
[600]	train-rmse:0.98089
[610]	train-rmse:0.98062
[620]	train-rmse:0.98034
[630]	train-rmse:0.98010
[640]	train-rmse:0.97982
[650]	train-rmse:0.97951
[660]	train-rmse:0.97921
[670]	train-rmse:0.97895
[680]	train-rmse:0.97865
[690]	train-rmse:0.97840
[700]	train-rmse:0.97813
[710]	train-rmse:0.97786
[720]	train-rmse:0.97754
[730]	train-rmse:0.97724
[740]	train-rmse:0.97700
[750]	train-rmse:0.97675
[760]	train-rmse:0.97650
[770]	train-rmse:0.97620
[780]	train-rmse:0.97593
[790]	train-rmse:0.97563
[800]	train-rmse:0.97537
[810]	train-rmse:0.97513
[820]	train-rmse:0.97484
[830]	train-rmse:0.97460
[840]	train-rmse:0.97430
[850]	train-rmse:0.97401
[860]	train-rmse:0.97375
[870]	train-rmse:0.97348
[880]	train-rmse:0.97325
[890]	train-rmse:0.97298
[900]	train-rmse:0.97271
[910]	train-rmse:0.97242
[920]	train-rmse:0.97212
[930]	train-rmse:0.97184
[940]	train-rmse:0.97157
[950]	train-rmse:0.97130
[960]	train-rmse:0.97101
[970]	train-rmse:0.97072
[980]	train-rmse:0.97046
```

```
[990]	train-rmse:0.97016
[999]	train-rmse:0.96994
Train RMSLE: 1.0457759505530262
Test RMSLE: 1.0725665172382386
```

[2227]:

```python
importance_dict = final_model.get_score(importance_type='gain')
importance_series = pd.Series(importance_dict).sort_values(ascending=False)
print(importance_series)
```

```
Previous Claims              65.995369
Year_cos                     24.532572
Health Score                 21.141071
Year_sin                     17.777683
Credit Score                 17.657919
Annual Income                17.159927
Customer Feedback            15.610570
Income_per_Year              12.390729
Income_per_Dependent         10.497802
Claims_per_Year               8.392055
Marital Status_Married        7.555318
month_sin                     7.218613
quarter                       6.955407
month_cos                     6.791186
Insurance Duration            6.694890
Edu_target_enc                6.650929
dow_sin                       6.638108
Occupation_Unemployed         6.605708
Marital Status_Single         6.577114
Vehicle Age                   6.575997
Age                           6.567995
Occupation_Self-Employed      6.559406
dow_cos                       6.474607
Location_Urban                6.464523
Location_Suburban             6.375484
Gender_Male                   6.371581
Property Type_Condo           6.344994
Exercise Frequency            6.344084
Smoking Status_Yes            6.289271
Property Type_House           6.177646
Number of Dependents          5.971280
Education Level               5.845872
Policy Type                   5.753743
dtype: float64
```

4.2 Choose the most importance features

[2228]:
```
selected_features = [
    "Previous Claims",
    "Year_cos",
    "Health Score",
    "Annual Income",
    "Year_sin",
    "Credit Score",
    "Customer Feedback",
    "Income_per_Year",
    "Income_per_Dependent",
    "Claims_per_Year",
    "Marital Status_Married"
]


X_train_selected = X_train[selected_features]
dtrain_full = xg.DMatrix(X_train_selected, label=y_train_trans)

final_model = xg.train(
    params=best_params,
    dtrain=dtrain_full,
    num_boost_round=1000,
    early_stopping_rounds=50,
    evals=[(dtrain_full, 'train')],
    verbose_eval=10
)

preds_trans = final_model.predict(dtrain_full)
preds = y_transformer.inverse_transform(preds_trans.reshape(-1, 1)).ravel()
# preds = np.maximum(preds, 0)

# TRAIN RMSLE
rmsle = np.sqrt(mean_squared_log_error(y_train, preds))
print(f"Train RMSLE: {rmsle}")

# TEST RMSLE
dtest = xg.DMatrix(X_test[selected_features])  # <--- Konwersja DataFrame na␣
↪DMatrix
preds_trans_test = final_model.predict(dtest)  # <--- Użyj dtest zamiast X_test
preds_test = y_transformer.inverse_transform(preds_trans_test.reshape(-1, 1)).
↪ravel()
preds_test = np.maximum(preds_test, 0)  # Zapobieganie wartościom ujemnym
test_rmsle = np.sqrt(mean_squared_log_error(y_test, preds_test))
print(f"Test RMSLE: {test_rmsle}")
```

```
[0]	train-rmse:1.03077
```

```
[10]	train-rmse:1.02558
[20]	train-rmse:1.02151
[30]	train-rmse:1.01779
[40]	train-rmse:1.01461
[50]	train-rmse:1.01195
[60]	train-rmse:1.00978
[70]	train-rmse:1.00790
[80]	train-rmse:1.00638
[90]	train-rmse:1.00492
[100]	train-rmse:1.00368
[110]	train-rmse:1.00259
[120]	train-rmse:1.00165
[130]	train-rmse:1.00078
[140]	train-rmse:1.00001
[150]	train-rmse:0.99931
[160]	train-rmse:0.99865
[170]	train-rmse:0.99809
[180]	train-rmse:0.99757
[190]	train-rmse:0.99707
[200]	train-rmse:0.99661
[210]	train-rmse:0.99617
[220]	train-rmse:0.99575
[230]	train-rmse:0.99534
[240]	train-rmse:0.99494
[250]	train-rmse:0.99456
[260]	train-rmse:0.99420
[270]	train-rmse:0.99386
[280]	train-rmse:0.99352
[290]	train-rmse:0.99318
[300]	train-rmse:0.99286
[310]	train-rmse:0.99254
[320]	train-rmse:0.99221
[330]	train-rmse:0.99191
[340]	train-rmse:0.99160
[350]	train-rmse:0.99130
[360]	train-rmse:0.99101
[370]	train-rmse:0.99072
[380]	train-rmse:0.99045
[390]	train-rmse:0.99017
[400]	train-rmse:0.98988
[410]	train-rmse:0.98961
[420]	train-rmse:0.98935
[430]	train-rmse:0.98911
[440]	train-rmse:0.98883
[450]	train-rmse:0.98859
[460]	train-rmse:0.98835
[470]	train-rmse:0.98809
[480]	train-rmse:0.98785
```

```
[490]	train-rmse:0.98760
[500]	train-rmse:0.98736
[510]	train-rmse:0.98712
[520]	train-rmse:0.98692
[530]	train-rmse:0.98668
[540]	train-rmse:0.98645
[550]	train-rmse:0.98620
[560]	train-rmse:0.98597
[570]	train-rmse:0.98575
[580]	train-rmse:0.98555
[590]	train-rmse:0.98533
[600]	train-rmse:0.98512
[610]	train-rmse:0.98491
[620]	train-rmse:0.98471
[630]	train-rmse:0.98451
[640]	train-rmse:0.98433
[650]	train-rmse:0.98412
[660]	train-rmse:0.98388
[670]	train-rmse:0.98367
[680]	train-rmse:0.98346
[690]	train-rmse:0.98324
[700]	train-rmse:0.98302
[710]	train-rmse:0.98282
[720]	train-rmse:0.98255
[730]	train-rmse:0.98233
[740]	train-rmse:0.98215
[750]	train-rmse:0.98196
[760]	train-rmse:0.98175
[770]	train-rmse:0.98155
[780]	train-rmse:0.98135
[790]	train-rmse:0.98113
[800]	train-rmse:0.98094
[810]	train-rmse:0.98075
[820]	train-rmse:0.98056
[830]	train-rmse:0.98038
[840]	train-rmse:0.98015
[850]	train-rmse:0.97994
[860]	train-rmse:0.97972
[870]	train-rmse:0.97950
[880]	train-rmse:0.97933
[890]	train-rmse:0.97913
[900]	train-rmse:0.97894
[910]	train-rmse:0.97874
[920]	train-rmse:0.97851
[930]	train-rmse:0.97831
[940]	train-rmse:0.97811
[950]	train-rmse:0.97791
[960]	train-rmse:0.97772
```

```
[970]	train-rmse:0.97751
[980]	train-rmse:0.97734
[990]	train-rmse:0.97711
[999]	train-rmse:0.97694
Train RMSLE: 1.051219727539931
Test RMSLE: 1.0723566140681724
```

[2234]:

```python
df_test = pd.read_csv('test.csv')
df_test.set_index('id', inplace=True)
df_test['Policy Start Date'] = pd.to_datetime(df_test['Policy Start Date'])

df_test['Year'] = df_test['Policy Start Date'].dt.year
min_year = df_test['Year'].min()
max_year = df_test['Year'].max()
df_test['Year_sin'] = np.sin(2 * np.pi * (df_test['Year'] - min_year) / (max_year - min_year))
df_test['Year_cos'] = np.cos(2 * np.pi * (df_test['Year'] - min_year) / (max_year - min_year))

cust_order = {"Poor":0, "Average":1, "Good":2}
df_test['Customer Feedback'] = df_test['Customer Feedback'].map(cust_order)
df_test['Income_per_Dependent'] = df_test['Annual Income'] / (df_test['Number of Dependents'] + 1)
df_test['Income_per_Year'] = df_test['Annual Income'] / (df_test['Age'] + 1)
df_test['Claims_per_Year'] = df_test['Previous Claims'] / (df_test['Insurance Duration'] + 1)

columns_numerical_values_test = df_test.select_dtypes("number")
for col in columns_numerical_values_test:
    df_test[col] = df_test[col].fillna(df_test[col].median())
object_types_input = {'Marital Status': 'Married', 'Customer Feedback': 'Average', 'Occupation':'Employed'}
df_test.fillna(object_types_input, inplace=True)
columns_object_values_test = df_test.select_dtypes("object")
df_test = df_test.drop(columns = 'Policy Start Date')

columns_object_values_test = columns_object_values_test.columns.tolist()

df_test = pd.get_dummies(df_test,
                          columns=columns_object_values_test,
                          drop_first=True,  # Unikaj multikolinearności
                          dtype=int)       # Typ danych dla kolumn 0/1

selected_features = [
    "Previous Claims",
    "Year_cos",
    "Health Score",
```

```python
    "Annual Income",
    "Year_sin",
    "Credit Score",
    "Customer Feedback",
    "Income_per_Year",
    "Income_per_Dependent",
    "Claims_per_Year",
    "Marital Status_Married"
]

df_test_selected = df_test[selected_features]
dtest_full = xg.DMatrix(df_test_selected)

# Predykcja w przestrzeni przekształconej
y_pred_trans = final_model.predict(dtest_full)

# Odwrócenie transformacji
y_pred = y_transformer.inverse_transform(y_pred_trans.reshape(-1, 1)).ravel()
y_pred = np.maximum(y_pred, 0)  # Zapobieganie wartościom ujemnym

df_test = pd.read_csv('test.csv')
df_test['Premium Amount'] = y_pred
df_test[['id', 'Premium Amount']].to_csv('submission.csv', index = False)
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 800000 entries, 1200000 to 1999999
Data columns (total 19 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   Age                   787511 non-null  float64
 1   Gender                800000 non-null  object
 2   Annual Income         770140 non-null  float64
 3   Marital Status        787664 non-null  object
 4   Number of Dependents  726870 non-null  float64
 5   Education Level       800000 non-null  object
 6   Occupation            560875 non-null  object
 7   Health Score          750551 non-null  float64
 8   Location              800000 non-null  object
 9   Policy Type           800000 non-null  object
 10  Previous Claims       557198 non-null  float64
 11  Vehicle Age           799997 non-null  float64
 12  Credit Score          708549 non-null  float64
 13  Insurance Duration    799998 non-null  float64
 14  Policy Start Date     800000 non-null  object
 15  Customer Feedback     747724 non-null  object
 16  Smoking Status        800000 non-null  object
 17  Exercise Frequency    800000 non-null  object
 18  Property Type         800000 non-null  object
```

```
dtypes: float64(8), object(11)
memory usage: 122.1+ MB
```

[ ]:
```
# import xgboost as xg
# import mlflow
# import numpy as np
# from sklearn.metrics import root_mean_squared_log_error
# from sklearn.model_selection import KFold
# from mlflow.models import infer_signature

# # MLflow configuration
# mlflow.set_tracking_uri("http://127.0.0.1:8080")
# mlflow.set_experiment("optimized_xgb_scaled")

# # Enhanced configurations with cross-validation
# param_configs = [
#     {
#         'max_depth': 7,
#         'eta': 0.06,  # Native API uses 'eta' instead of 'learning_rate'
#         'subsample': 0.8,
#         'colsample_bytree': 0.8,
#         'gamma': 0.5,
#         'alpha': 10,   # Native API uses 'alpha' for reg_alpha
#         'lambda': 10,  # Native API uses 'lambda' for reg_lambda
#         'objective': 'reg:squaredlogerror',
#         'n_jobs': -1
#     },
#     {
#         'max_depth': 7,
#         'eta': 0.08,
#         'subsample': 0.75,
#         'colsample_bytree': 0.75,
#         'gamma': 0.3,
#         'alpha': 8,
#         'lambda': 8,
#         'min_child_weight': 3,
#         'objective': 'reg:squaredlogerror',
#         'n_jobs': -1
#     }
# ]

# for i, params in enumerate(param_configs):
#     with mlflow.start_run(run_name=f"optimized_run_{i+1}") as run:
#         kf = KFold(n_splits=5, shuffle=True, random_state=42)
#         cv_scores = []

#         for fold, (train_idx, val_idx) in enumerate(kf.split(X_train)):
```

```
#             X_fold_train = X_train.iloc[train_idx]
#             X_fold_val = X_train.iloc[val_idx]
#             y_fold_train = y_train.iloc[train_idx]
#             y_fold_val = y_train.iloc[val_idx]

#             # Convert to DMatrix for native API
#             dtrain = xg.DMatrix(X_fold_train, label=y_fold_train)
#             dval = xg.DMatrix(X_fold_val, label=y_fold_val)

#             # Train with early stopping
#             model = xg.train(
#                 params,
#                 dtrain,
#                 num_boost_round=2000,  # Set to your desired n_estimators
#                 early_stopping_rounds=50,
#                 evals=[(dval, 'eval')],
#                 verbose_eval=False
#             )

#             val_pred = model.predict(dval)
#             fold_rmsle = root_mean_squared_log_error(y_fold_val, val_pred)
#             cv_scores.append(fold_rmsle)

#             mlflow.log_metric(f"fold_{fold}_rmsle", fold_rmsle)

#         avg_cv_rmsle = np.mean(cv_scores)
#         mlflow.log_params(params)
#         mlflow.log_metrics({
#             "avg_cv_rmsle": avg_cv_rmsle,
#             "cv_rmsle_std": np.std(cv_scores)
#         })

#         # Train final model on full data
#         dtrain_full = xg.DMatrix(X_train, label=y_train)
#         dtest = xg.DMatrix(X_test, label=y_test)

#         final_model = xg.train(
#             params,
#             dtrain_full,
#             num_boost_round=2000,
#             early_stopping_rounds=50,
#             evals=[(dtest, 'test')],
#             verbose_eval=False
#         )

#         test_pred = final_model.predict(dtest)
#         test_rmsle = root_mean_squared_log_error(y_test, test_pred)
```

```
#         mlflow.log_metric("final_test_rmsle", test_rmsle)

#         # Log model
#         signature = infer_signature(X_train, test_pred)
#         mlflow.xgboost.log_model(
#             final_model,
#             artifact_path="optimized_model",
#             signature=signature,
#             registered_model_name="OptimizedXGBoost",
#             input_example=X_train.iloc[:1]
#         )

#         print(f"Run {i+1} - Test RMSLE: {test_rmsle:.4f}")
```

[ ]:

```
# import xgboost as xg
# from sklearn.metrics import root_mean_squared_log_error
# import mlflow
# import mlflow.xgboost
# from mlflow.models import infer_signature
# from sklearn.model_selection import ParameterGrid
# import numpy as np

# mlflow.set_tracking_uri("http://127.0.0.1:8080")
# mlflow.set_experiment("max_depth_n_est_hyperparameters")

# # Pełna siatka parametrów (8 wartości każdy)
# param_grid_full = {
#     'max_depth':       [4,5,6],
#     'n_estimators':    [100,3000],
#     'learning_rate':   [0.75,1],
#     'subsample':       [1],
#     'colsample_bytree':[1.0],
#     'gamma':           [0],
#     'reg_alpha':       [0],
#     'reg_lambda':      [0],
# }

# # Z każdego parametru bierzemy 2 pierwsze i 2 ostatnie wartości
# param_grid_subset = param_grid_full
# # Stałe parametry
# fixed_params = {'n_jobs': -1}

# # Generowanie pełnej siatki (4 wartości na parametr --> 4**8 = 65 536␣
 ↪kombinacji)
# grid = list(ParameterGrid(param_grid_subset))
# print(f"Liczba kombinacji: {len(grid)}")  # -> 65536
```

```python
# # Pętla po wszystkich kombinacjach
# for i, params in enumerate(grid, start=1):
#     with mlflow.start_run(run_name=f"run_{i}"):
#         full_params = {**params, **fixed_params}
#         mlflow.log_params(full_params)

#         try:
#             # Trenowanie modelu
#             model = xg.XGBRegressor(**full_params)
#             model.fit(X_train, y_train_trans)

#             # Predykcje i odtransformowanie
#             y_train_pred = y_transformer.inverse_transform(
#                 model.predict(X_train).reshape(-1, 1)
#             ).ravel()
#             y_test_pred = y_transformer.inverse_transform(
#                 model.predict(X_test).reshape(-1, 1)
#             ).ravel()

#             train_neg_count = (y_train_pred < 0).sum()
#             test_neg_count = (y_test_pred < 0).sum()

#             y_train_pred = np.where(y_train_pred < 0, 0, y_train_pred)
#             y_test_pred = np.where(y_test_pred < 0, 0, y_test_pred)


#             # Obliczenie metryk
#             train_rmsle = root_mean_squared_log_error(y_train, y_train_pred)
#             test_rmsle  = root_mean_squared_log_error(y_test,  y_test_pred)
#             mlflow.log_metrics({
#                 "train_rmsle": train_rmsle,
#                 "test_rmsle":  test_rmsle,
#                 "train_negatives_count": train_neg_count,
#                 "test_negatives_count": test_neg_count
#             })

#             # Logowanie modelu
#             signature = infer_signature(X_train, y_train_pred)
#             mlflow.xgboost.log_model(
#                 model,
#                 artifact_path="model",
#                 signature=signature,
#                 registered_model_name="XGBoost_Optimized"
#             )

#         except Exception as e:
```

```
#             # Zaloguj błąd i kontynuuj
#             mlflow.set_tag("run_status", "FAILED")
#             mlflow.log_param("error_message", str(e))
#             print(f"[run_{i}] POMINIĘTO: {e}")
#             continue
```

4.3 XGBoost Regresssor

4.3.1 Preparing submission

[ ]:
```
# df_test = pd.read_csv('test.csv')
# df_test.set_index('id', inplace=True)
# df_test['Policy Start Date'] = pd.to_datetime(df_test['Policy Start Date'])

# df_test['year'] = df_test['Policy Start Date'].dt.year
# df_test['month'] = df_test['Policy Start Date'].dt.month
# df_test['day_of_week'] = df_test['Policy Start Date'].dt.dayofweek  # 0 -␣
↪Poniedziałek, 6 - Niedziela
# # Function to assign time of day category
# def get_time_of_day_category(time):
#     hour = time.hour
#     if 20 <= hour < 24 or 0 <= hour < 6:
#         return 'Night'
#     elif 6 <= hour < 12:
#         return 'Morning'
#     elif 12 <= hour < 14:
#         return 'Noon'
#     elif 14 <= hour < 20:
#         return 'Afternoon'

# # Create a new column for time of day category
# df_test['time_of_day_category'] = df_test['Policy Start Date'].
↪apply(get_time_of_day_category)
# columns_numerical_values_test = df_test.select_dtypes("number")
# for col in columns_numerical_values_test:
#     df_test[col] = df_test[col].fillna(df_test[col].median())
# object_types_input = {'Marital Status': 'Married', 'Customer Feedback':␣
↪'Average', 'Occupation':'Employed'}
# df_test.fillna(object_types_input, inplace=True)
# columns_object_values_test = df_test.select_dtypes("object")
# df_test = df_test.drop(columns = 'Policy Start Date')
# columns_object_values_test = columns_object_values_test.columns.tolist()
# columns_object_values_test.append('time_of_day_category')
# df_test = pd.get_dummies(df_test,
#                             columns=columns_object_values_test,
#                             drop_first=True,  # Unikaj multikolinearności
#                             dtype=int)       # Typ danych dla kolumn 0/1
```

[ ]:
```
# df_test= X_scaler.transform(df_test)
# y_pred = final_model.predict(df_test)
```

[ ]:
```
# df_test = pd.read_csv('test.csv')
# df_test['Premium Amount'] = y_pred
# df_test[['id', 'Premium Amount']].to_csv('submission.csv', index = False)
```

4.4 Decision Tree Regressor

[ ]:
```
# from sklearn.tree import DecisionTreeRegressor
# from sklearn.model_selection import GridSearchCV

# param_grid = {
#     'max_depth':  [20, 30, 50],
#     'min_samples_split': [10, 15, 20],
#     'min_samples_leaf': [5, 8, 10],
#     'max_leaf_nodes': [100,200,300, 500, 1000]
# }

# grid_search = GridSearchCV(DecisionTreeRegressor(), param_grid, cv=5)
# grid_search.fit(X_train, y_train)

# dt = grid_search.best_estimator_
# print(dt)
# dt.fit(X_train, y_train)
```

[ ]:
```
# from sklearn.metrics import mean_absolute_error,r2_score

# y_pred = dt.predict(X)

# # Calcul des métriques
# rmse = np.sqrt(mean_squared_error(y, y_pred))
# mae = mean_absolute_error(y, y_pred)
# r2 = r2_score(y, y_pred)
# mape = np.mean(np.abs((y - y_pred) / y)) * 100

# # Display performance metrics
# print(f"\nPerformance Metrics:\n{'-'*30}")
# print(f"RMSE: {rmse:.4f}")
# print(f"MAE: {mae:.4f}")
# print(f"R²: {r2:.4f}")
# print(f"MAPE: {mape:.2f}%")
```

[ ]:
```
# from sklearn.ensemble import RandomForestRegressor
# rf = RandomForestRegressor()
# rf.fit(X_train, y_train)
```

[ ]:
```
# rf.score(X_train, y_train)
```

[ ]:
```
# rf.score(X_test, y_test)
```

[ ]:
```
# from sklearn.metrics import mean_absolute_error,r2_score

# y_pred = rf.predict(X)

# # Calcul des métriques
# rmse = np.sqrt(mean_squared_error(y, y_pred))
# mae = mean_absolute_error(y, y_pred)
# r2 = r2_score(y, y_pred)
# mape = np.mean(np.abs((y - y_pred) / y)) * 100

# # Display performance metrics
# print(f"\nPerformance Metrics:\n{'-'*30}")
# print(f"RMSE: {rmse:.4f}")
# print(f"MAE: {mae:.4f}")
# print(f"R²: {r2:.4f}")
# print(f"MAPE: {mape:.2f}%")
```