# insurance_eda

December 27, 2024

# 1 Regression With an Insurance Dataset

## 1.1 Table of Contents



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# 2 1 Introduction

### 2.0.1 Project Description

**Goal/Purpose:**

This dataset is from the Kaggle competition 'Regression with an Insurance Dataset'. The goal of this competition is to build a model to predict insurance Premiums based on various factors.

### 2.0.2 Data Description

**Content:**

This dataset is a csv file of 1200000 records. It contains information about insurance policyholders, which can be used to analyze factors influencing insurance premiums. The data includes various attributes such as This information can be valuable for insurance companies to understand risk profiles, develop personalized pricing strategies, and improve customer segmentation.

**Description of Attributes:**

Here you can describe what each column represents. | Column | Description | | ——— | ———————————————————— | |id | Unique identifier for each policyholder | |Age | Age of the policyholder | |Gender | Gender of the policyholder | |Annual Income | Annual income of the policyholder | |Marital Status | Marital status of the policyholder | |Number of Dependents | Number of dependents of the policyholder | |Education Level | Education level of the policyholder | |Occupation | Occupation of the policyholder| |Health Score | Health score of the policyholder | |Location | Location of the policyholder | |Policy Type | Type of insurance policy | |Previous Claims | Number of previous claims made by the policyholder | |Vehicle Age | Age of the vehicle | |Credit Score | Credit score of the policyholder | |Insurance Duration | Duration of the insurance policy | |Policy Start Date | Start date of the insurance policy | |Customer Feedback | Customer feedback on the insurance company | |Smoking Status | whether the policyholder smokes or not | |Exercise Frequency | Frequency of exercise of the policyholder | |Property Type | Type of property owned by the policyholder | |Premium Amount | Amount of the insurance premium |

**Acknowledgements:**

This dataset is provided by Kaggle and the original source can be found on kaggle.

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# 3 2

## 3.1 Acquiring and Loading Data

the data was acquired via manual download from the kaggle link provided above ### Importing Libraries and Notebook Setup

[ ]:
```
# Data manipulation
import datetime
import numpy as np
import pandas as pd
import pandas.api.types as ptypes
# Visualizations
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# Pandas settings
pd.options.display.max_columns = None
pd.options.display.max_colwidth = 60
pd.options.display.float_format = '{:,.3f}'.format
```

```python
# Visualization settings
from matplotlib import rcParams
rcParams['font.size'] = 12
%matplotlib inline
```

### 3.1.1 Loading Data

[3]:
```python
# # Load DataFrame
df = pd.read_csv('data/raw/train.csv', parse_dates=['Policy Start Date'])
```

### 3.1.2 Basic Data Exploration

[4]:
```python
# # Show rows and columns count
print(f"Rows count: {df.shape[0]}\nColumns count: {df.shape[1]}")
```

```
Rows count: 1200000
Columns count: 21
```

[5]:
```python
df.head(10)
```

[5]:
```
   id    Age  Gender  Annual Income Marital Status  Number of Dependents  \
0   0 19.000  Female     10,049.000        Married                 1.000
1   1 39.000  Female     31,678.000       Divorced                 3.000
2   2 23.000    Male     25,602.000       Divorced                 3.000
3   3 21.000    Male    141,855.000        Married                 2.000
4   4 21.000    Male     39,651.000         Single                 1.000
5   5 29.000    Male     45,963.000        Married                 1.000
6   6 41.000    Male     40,336.000        Married                 0.000
7   7 48.000  Female    127,237.000       Divorced                 2.000
8   8 21.000    Male      1,733.000       Divorced                 3.000
9   9 44.000    Male     52,447.000        Married                 2.000

  Education Level     Occupation  Health Score  Location    Policy Type  \
0      Bachelor's  Self-Employed        22.599     Urban        Premium
1        Master's            NaN        15.570     Rural  Comprehensive
2     High School  Self-Employed        47.178  Suburban        Premium
3      Bachelor's            NaN        10.938     Rural          Basic
4      Bachelor's  Self-Employed        20.376     Rural        Premium
5      Bachelor's            NaN        33.053     Urban        Premium
6             PhD            NaN           NaN     Rural          Basic
7     High School       Employed         5.770  Suburban  Comprehensive
8      Bachelor's            NaN        17.870     Urban        Premium
9        Master's       Employed        20.474     Urban  Comprehensive

   Previous Claims  Vehicle Age  Credit Score  Insurance Duration  \
0            2.000       17.000       372.000               5.000
1            1.000       12.000       694.000               2.000
```

```
2             1.000        14.000          NaN               3.000
3             1.000         0.000      367.000               1.000
4             0.000         8.000      598.000               4.000
5             2.000         4.000      614.000               5.000
6             2.000         8.000      807.000               6.000
7             1.000        11.000      398.000               5.000
8             1.000        10.000      685.000               8.000
9             1.000         9.000      635.000               3.000

           Policy Start Date Customer Feedback Smoking Status  \
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
5 2022-05-20 15:21:39.207847           Average             No
6 2020-02-21 15:21:39.219432              Poor             No
7 2022-08-08 15:21:39.181605           Average             No
8 2020-12-14 15:21:39.198406           Average             No
9 2020-08-02 15:21:39.144722              Poor             No

  Exercise Frequency Property Type  Premium Amount
0             Weekly         House       2,869.000
1            Monthly         House       1,483.000
2             Weekly         House         567.000
3              Daily     Apartment         765.000
4             Weekly         House       2,022.000
5             Weekly         House       3,202.000
6             Weekly         House         439.000
7             Rarely         Condo         111.000
8            Monthly         Condo         213.000
9              Daily         Condo          64.000
```

[6]:
```
df.tail(10)
```

[6]:
```
              id    Age  Gender  Annual Income Marital Status  \
1199990  1199990 55.000  Female     72,384.000         Single
1199991  1199991 59.000  Female     23,706.000       Divorced
1199992  1199992 53.000  Female      6,837.000        Married
1199993  1199993 38.000    Male      1,607.000        Married
1199994  1199994 34.000    Male     23,456.000         Single
1199995  1199995 36.000  Female     27,316.000        Married
1199996  1199996 54.000    Male     35,786.000       Divorced
1199997  1199997 19.000    Male     51,884.000       Divorced
1199998  1199998 55.000    Male            NaN         Single
1199999  1199999 21.000  Female            NaN       Divorced
```

| | Number of Dependents | Education Level | Occupation | Health Score | \ |
|---|---|---|---|---|---|
| 1199990 | 0.000 | High School | Unemployed | 13.662 | |
| 1199991 | 4.000 | High School | Self-Employed | 24.913 | |
| 1199992 | 2.000 | High School | Self-Employed | 17.844 | |
| 1199993 | 1.000 | High School | NaN | 18.552 | |
| 1199994 | 4.000 | Master's | Self-Employed | 14.783 | |
| 1199995 | 0.000 | Master's | Unemployed | 13.773 | |
| 1199996 | NaN | Master's | Self-Employed | 11.483 | |
| 1199997 | 0.000 | Master's | NaN | 14.724 | |
| 1199998 | 1.000 | PhD | NaN | 18.547 | |
| 1199999 | 0.000 | PhD | NaN | 10.125 | |

| | Location | Policy Type | Previous Claims | Vehicle Age | Credit Score | \ |
|---|---|---|---|---|---|---|
| 1199990 | Urban | Basic | 1.000 | 3.000 | 789.000 | |
| 1199991 | Suburban | Comprehensive | NaN | 17.000 | NaN | |
| 1199992 | Urban | Comprehensive | NaN | 15.000 | 406.000 | |
| 1199993 | Suburban | Comprehensive | 0.000 | 12.000 | 469.000 | |
| 1199994 | Rural | Basic | NaN | 12.000 | 548.000 | |
| 1199995 | Urban | Premium | NaN | 5.000 | 372.000 | |
| 1199996 | Rural | Comprehensive | NaN | 10.000 | 597.000 | |
| 1199997 | Suburban | Basic | 0.000 | 19.000 | NaN | |
| 1199998 | Suburban | Premium | 1.000 | 7.000 | 407.000 | |
| 1199999 | Rural | Premium | 0.000 | 18.000 | 502.000 | |

| | Insurance Duration | Policy Start Date | Customer Feedback | \ |
|---|---|---|---|---|
| 1199990 | 5.000 | 2020-01-10 15:21:39.155231 | Average | |
| 1199991 | 1.000 | 2021-06-22 15:21:39.188220 | Good | |
| 1199992 | 4.000 | 2021-01-09 15:21:39.281787 | Good | |
| 1199993 | 2.000 | 2022-08-10 15:21:39.132191 | Good | |
| 1199994 | 9.000 | 2023-06-09 15:21:39.134960 | Good | |
| 1199995 | 3.000 | 2023-05-03 15:21:39.257696 | Poor | |
| 1199996 | 4.000 | 2022-09-10 15:21:39.134960 | Poor | |
| 1199997 | 6.000 | 2021-05-25 15:21:39.106582 | Good | |
| 1199998 | 4.000 | 2021-09-19 15:21:39.190215 | Poor | |
| 1199999 | 6.000 | 2020-08-26 15:21:39.155231 | Good | |

| | Smoking Status | Exercise Frequency | Property Type | Premium Amount |
|---|---|---|---|---|
| 1199990 | Yes | Monthly | Apartment | 231.000 |
| 1199991 | Yes | Monthly | Apartment | 3,381.000 |
| 1199992 | No | Rarely | House | 1,251.000 |
| 1199993 | No | Rarely | House | 1,027.000 |
| 1199994 | No | Monthly | Apartment | 1,584.000 |
| 1199995 | No | Daily | Apartment | 1,303.000 |
| 1199996 | No | Weekly | Apartment | 821.000 |
| 1199997 | No | Monthly | Condo | 371.000 |
| 1199998 | No | Daily | Apartment | 596.000 |
| 1199999 | Yes | Monthly | House | 2,480.000 |

**Checking Data Types** we need to check the data types for the columns to see what needs to be fixed

[7]:
```
# # Show data types
df.dtypes
```

[7]:
```
id                          int64
Age                       float64
Gender                     object
Annual Income             float64
Marital Status             object
Number of Dependents      float64
Education Level            object
Occupation                 object
Health Score              float64
Location                   object
Policy Type                object
Previous Claims           float64
Vehicle Age               float64
Credit Score              float64
Insurance Duration        float64
Policy Start Date  datetime64[ns]
Customer Feedback          object
Smoking Status             object
Exercise Frequency         object
Property Type              object
Premium Amount            float64
dtype: object
```

- `age`, `Number of Dependents`, `Previous Claims`, `Vehicle Age` should be **integer**.
- `Gender` and `Marital Status`. `Education Level`, `Policy Type`, `Customer Feedback`, `Smoking Status`, `Exercise Frequency`, `Property Type` should be **category**.
- `Occupation`, `Location` might be better as a **category**.

**Check Missing Data**

[8]:
```
df.isna().sum()
```

[8]:
```
id                           0
Age                      18705
Gender                       0
Annual Income            44949
Marital Status           18529
Number of Dependents    109672
Education Level              0
Occupation              358075
Health Score             74076
Location                     0
Policy Type                  0
```

```
Previous Claims          364029
Vehicle Age                   6
Credit Score             137882
Insurance Duration            1
Policy Start Date             0
Customer Feedback         77824
Smoking Status                0
Exercise Frequency            0
Property Type                 0
Premium Amount                0
dtype: int64
```

we have a lot of missing data especially in the `Occupation` and `Previous Claims` columns.

### Check for Duplicate Rows

[9]:
```
df.duplicated().sum()
```

[9]:
```
np.int64(0)
```

Checking the number of duplicates via the id column.

[10]:
```
df.duplicated(subset=['id']).sum()
```

[10]:
```
np.int64(0)
```

We have no duplicated records in the dataset

### Check Uniqueness of Data

[11]:
```
print(f"Occuopation unique values: {df['Occupation'].nunique()}")
print(f"Location unique values: {df['Location'].nunique()}")
print(f"Credit Score unique values: {df['Credit Score'].nunique()}")
print(f"Customer Feedback unique values: {df['Customer Feedback'].nunique()}")
print("insurance duration unique values: ", df['Insurance Duration'].nunique())
```

```
Occuopation unique values: 3
Location unique values: 3
Credit Score unique values: 550
Customer Feedback unique values: 3
insurance duration unique values:  9
```

From these results `Occupation`, `Location`, `Customer Feedback`, `Insurance Duration` should be converted to **category**

### Check Data Range

[12]:
```
# # Print summary statistics
df.describe()
```

[12]:
```
                    id           Age  Annual Income  Number of Dependents  \
count 1,200,000.000 1,181,295.000  1,155,051.000         1,090,328.000
```

```
mean    599,999.500        41.146     32,745.218                 2.010
min           0.000        18.000          1.000                 0.000
25%     299,999.750        30.000      8,001.000                 1.000
50%     599,999.500        41.000     23,911.000                 2.000
75%     899,999.250        53.000     44,634.000                 3.000
max   1,199,999.000        64.000    149,997.000                 4.000
std     346,410.306        13.540     32,179.506                 1.417

       Health Score  Previous Claims   Vehicle Age  Credit Score  \
count 1,125,924.000      835,971.000 1,199,994.000 1,062,118.000
mean         25.614            1.003         9.570       592.924
min           2.012            0.000         0.000       300.000
25%          15.919            0.000         5.000       468.000
50%          24.579            1.000        10.000       595.000
75%          34.527            2.000        15.000       721.000
max          58.976            9.000        19.000       849.000
std          12.203            0.983         5.776       149.982

       Insurance Duration              Policy Start Date  Premium Amount
count       1,199,999.000                        1200000   1,200,000.000
mean                5.018  2022-02-13 05:06:30.972380672       1,102.545
min                 1.000     2019-08-17 15:21:39.080371          20.000
25%                 3.000  2020-11-20 15:21:39.121168896         514.000
50%                 5.000  2022-02-14 15:21:39.151731968         872.000
75%                 7.000  2023-05-06 15:21:39.182597120       1,509.000
max                 9.000     2024-08-15 15:21:39.287115       4,999.000
std                 2.594                            NaN         864.999
```

---

The data description shows no unexpected outliers or invalid data

# 4 3

## 4.1 Data Preprocessing

First step of the preprocessing is to create a copy of the df to preserve the original data.

[13]:
```
df_clean = df.copy()
```

Here you can add sections like:

- Renaming columns
- Drop Redundant Columns
- Changing Data Types
- Dropping Duplicates
- Handling Missing Values
- Handling Unreasonable Data Ranges
- Feature Engineering / Transformation

Use `assert` where possible to show that preprocessing is done.

#### 4.1.1 Rename Columns

[14]:
```
def clean_columns_names(df):
    df.columns = df.columns.str.lower().str.replace(' ', '_')
    return df
```

[15]:
```
# # Rename columns to snake_case
df_clean = clean_columns_names(df_clean)
```

[16]:
```
# # Verify columns are renamed
df_clean.columns
```

[16]:
```
Index(['id', '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'],
      dtype='object')
```

#### 4.1.2 Drop Redundant Columns

There are no redundant columns in the dataset

#### 4.1.3 Handle Missing Values

First, we need to handle the columns that have a large number of missing values which are `Occupation` and `Previous Claims`. the best way is to drop the Occupation column as it can't be predicted. And filling `Previous Claims` missing values with 0.

[17]:
```
#dropping the occupation column
df_clean.drop(columns=['occupation'], inplace=True, axis=1)
assert 'occupation' not in df_clean.columns
```

[18]:
```
#filling the missing values in the previous claims column with 0
df_clean['previous_claims'] =  df_clean['previous_claims'].fillna(0)
assert df_clean['previous_claims'].isna().sum() == 0
```

Now that we dealt with the columns that had huge numbers. We can drop the remaining null values.

[19]:
```
#dropping the null values in the dataset
df_clean = df_clean.dropna()
assert df_clean.isna().sum().sum() == 0
```

**now we have no missing values**

### 4.1.4 Changing Data Types

First in the conversion are the columns that need to be changed to int

[20]:
```
#convert the data type of the columns to integer
df_clean['age'] = df_clean['age'].astype(int)
df_clean['number_of_dependents'] = df_clean['number_of_dependents'].astype(int)
df_clean['credit_score'] = df_clean['credit_score'].astype(int)
df_clean['previous_claims'] = df_clean['previous_claims'].astype(int)
df_clean['insurance_duration'] = df_clean['insurance_duration'].astype(int)
df_clean['vehicle_age'] = df_clean['vehicle_age'].astype(int)

assert df_clean['age'].dtype == 'int64'
assert df_clean['number_of_dependents'].dtype == 'int64'
assert df_clean['credit_score'].dtype == 'int64'
assert df_clean['previous_claims'].dtype == 'int64'
assert df_clean['insurance_duration'].dtype == 'int64'
assert df_clean['vehicle_age'].dtype == 'int64'
```

Now, converting the columns that need to be converted to category type

[21]:
```
#converting columns to categorical
df_clean['gender'] = df_clean['gender'].astype('category')
df_clean['marital_status'] = df_clean['marital_status'].astype('category')
df_clean['education_level'] = df_clean['education_level'].astype('category')
df_clean['policy_type'] = df_clean['policy_type'].astype('category')
df_clean['customer_feedback'] = df_clean['customer_feedback'].astype('category')
df_clean['smoking_status'] = df_clean['smoking_status'].astype('category')
df_clean['exercise_frequency'] = df_clean['exercise_frequency'].
 ↪astype('category')
df_clean['property_type'] = df_clean['property_type'].astype('category')
df_clean['location'] = df_clean['location'].astype('category')
```

[96]:
```
#asserting the data types
assert df_clean['gender'].dtype == 'category'
assert df_clean['marital_status'].dtype == 'category'
assert df_clean['education_level'].dtype == 'category'
assert df_clean['policy_type'].dtype == 'category'
assert df_clean['customer_feedback'].dtype == 'category'
assert df_clean['smoking_status'].dtype == 'category'
assert df_clean['exercise_frequency'].dtype == 'category'
assert df_clean['property_type'].dtype == 'category'
assert df_clean['location'].dtype == 'category'
```

### 4.1.5 Dropping Duplicates

**there are no duplicates in the dataset**

### 4.1.6 Handling Unreasonable Data Ranges

**there are no unreasonable data ranges in the dataset**

### 4.1.7 Storing the clean data

[23]:
```
df_clean.to_csv('data/clean/train_cleaned.csv', index=False)
```

---

[ ]:
```
# # Verify columns are renamed
df_clean.columns
```

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

# 5 4

# 6 Data Analysis

Here is where your analysis begins. You can add different sections based on your project goals.

[24]:
```
#creating a sample for analysis
random_state = 42
df_sample = df_clean.sample(frac=0.1, random_state=random_state)
```

## 6.1 4.1 Univariate Exploration

### 6.1.1 4.1.1 exploring premium_amount distribution

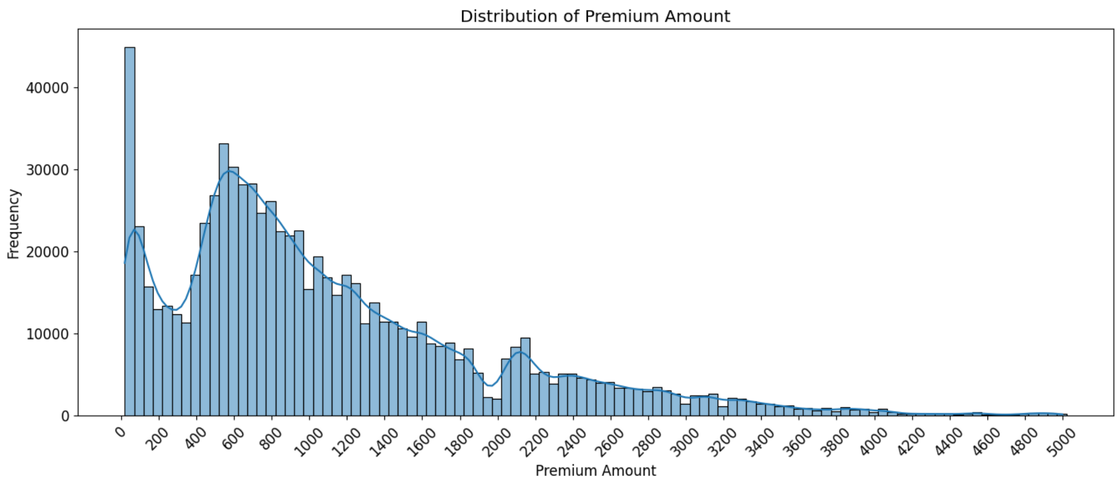
we need to look at the distribution of `premium_amount`, in order to do this we will print the descriptive statistics of `premium_amount` and plot its distribution. We will do that via a histogram plot.

[57]:
```
#printing the descriptive statistics for premium_amount
print('descriptive statistics for premium_amount')
print(df_sample['premium_amount'].describe())
```

```
descriptive statistics for premium_amount
count   79,033.000
mean     1,101.346
std        862.958
min         20.000
25%        514.000
50%        872.000
```

```
75%      1,502.000
max      4,996.000
Name: premium_amount, dtype: float64
```

[88]:
```
#plotting the distribution of the premium_amount
plt.figure(figsize=(16, 6))
sns.histplot(df_clean['premium_amount'], kde=True, bins=np.arange(20, 5050, 50))
plt.xticks(np.arange(0, 5200, 200), rotation=45)
plt.title('Distribution of Premium Amount')
plt.xlabel('Premium Amount')
plt.ylabel('Frequency')
plt.show()
```




#### Conclusion

- we can see that the distribution is heavily skewed to the left
- the interval with larges number of records is below 100
- very few policy holders have a premium amount larger that 2600

**4.1.1 exploring `Age`** to explore the Age variable we need to print the descriptive statistics. Moreover, we need to plot the distribution of the age column. we will do this through a histogram plot

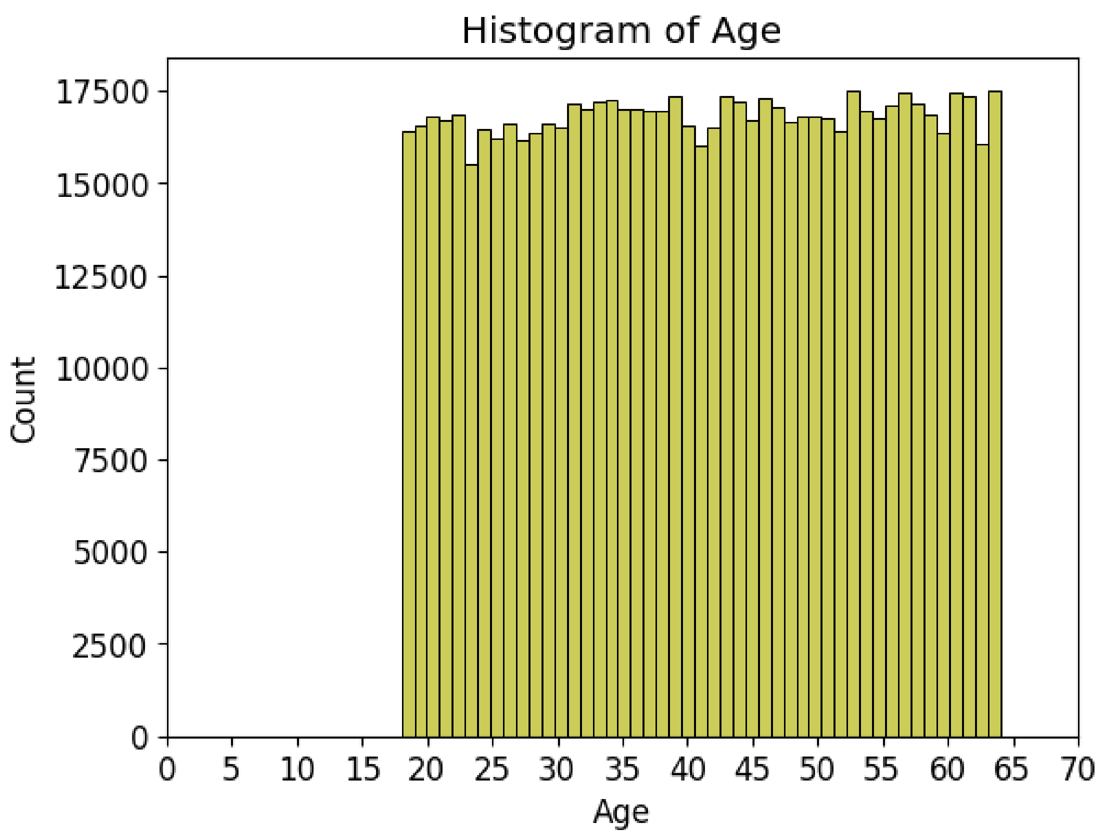
---

[25]:
```
# printing the descriptive statistics of the age column
print("Descriptive statistics of the age column")
df_clean['age'].describe()
```

```
Descriptive statistics of the age column
```

[25]:
```
count   790,332.000
mean         41.136
std          13.541
min          18.000
25%          30.000
50%          41.000
75%          53.000
max          64.000
Name: age, dtype: float64
```

[26]:
```
#plotting a histogram of the age column
sns.histplot(df_clean['age'], bins=47, color='tab:olive', edgecolor='black')
plt.xticks(np.arange(0, 75, 5))
plt.title('Histogram of Age')
plt.xlabel('Age')
plt.show()
```




**Observations** - the ages are between 18 and 64. - the data has an even distribution across the ages.

#### 4.1.2 exploring gender

to explore the gender variable we need to print the count of each gender value. Moreover, we need to plot the distribution of the gender column. we will do this through a bar chart

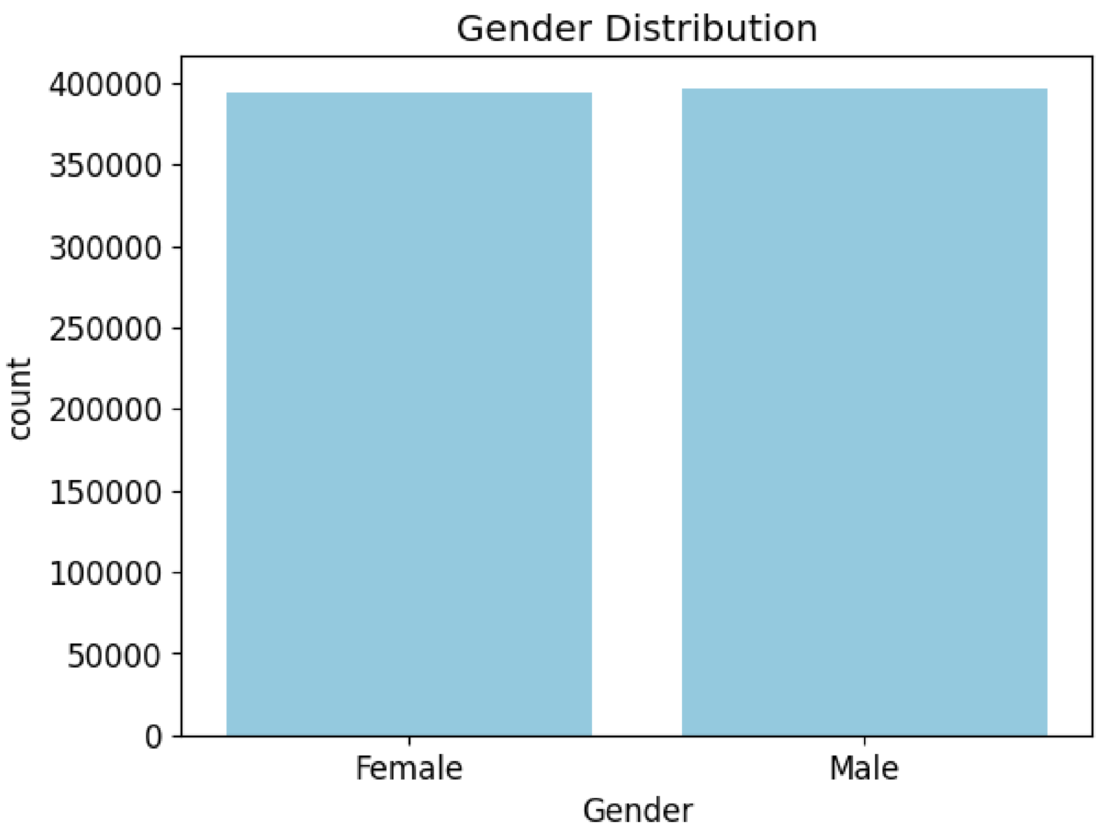
[27]:
```python
# printing the count and percentage for each gender
print("value count of the gender column")
print(df_clean['gender'].value_counts())
print("\n")
print("percentage value for each gender")
df_clean['gender'].value_counts(normalize=True) * 100
```

```
value count of the gender column
gender
Male      396702
Female    393630
Name: count, dtype: int64


percentage value for each gender
```

[27]:
```
gender
Male      50.194
Female    49.806
Name: proportion, dtype: float64
```

[28]:
```python
#plotting a bar chart of the gender column
sns.countplot(df_clean,x='gender', color='skyblue')
plt.title('Gender Distribution')
plt.xlabel('Gender')
plt.show()
```




**Observations** - the data has an even distribution across genders.

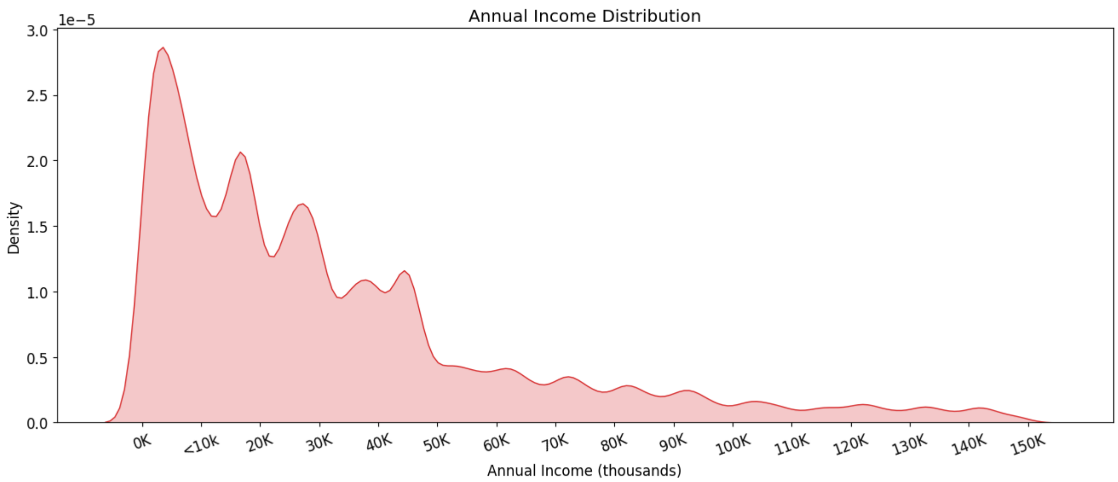
**4.1.3 exploring `annual_income`** to explore the annual_income variable we need to print the descriptive statistics for it. Moreover, we need to plot the distribution of the annual_income column. we will do this through a kde plot

[29]:
```python
# printing the descriptive statistics of the annual_income column
print("Descriptive statistics of the annual_income column")
df_clean['annual_income'].describe()
```

```
Descriptive statistics of the annual_income column
```

[29]:
```
count   790,332.000
mean     32,810.934
std      31,819.797
min           1.000
25%       8,791.000
50%      24,194.000
75%      44,393.000
max     149,997.000
Name: annual_income, dtype: float64
```

[30]:
```
#plotting a bar chart of the gender column
plt.figure(figsize=(16, 6))
sns.kdeplot(df_clean['annual_income'], color='tab:red', fill=True)
plt.title('Annual Income Distribution')
plt.xlabel('Annual Income (thousands)')
xticks = np.arange(0, 160000, 10000)
labels = [f'{int(x/1000)}K' for x in xticks]
labels[1] = '<10k'
plt.xticks(xticks, labels=labels, rotation=20)
plt.show()
```




**Observations** - the data is heavily skewed to the left - the peak point is under 10k - few records have annual_income above 50k

**4.1.4 exploring `marital_status`** to explore the marital_status variable we need to print the count of each marital_status value. Moreover, we need to plot the distribution of the marital_status column. we will do this through a bar chart

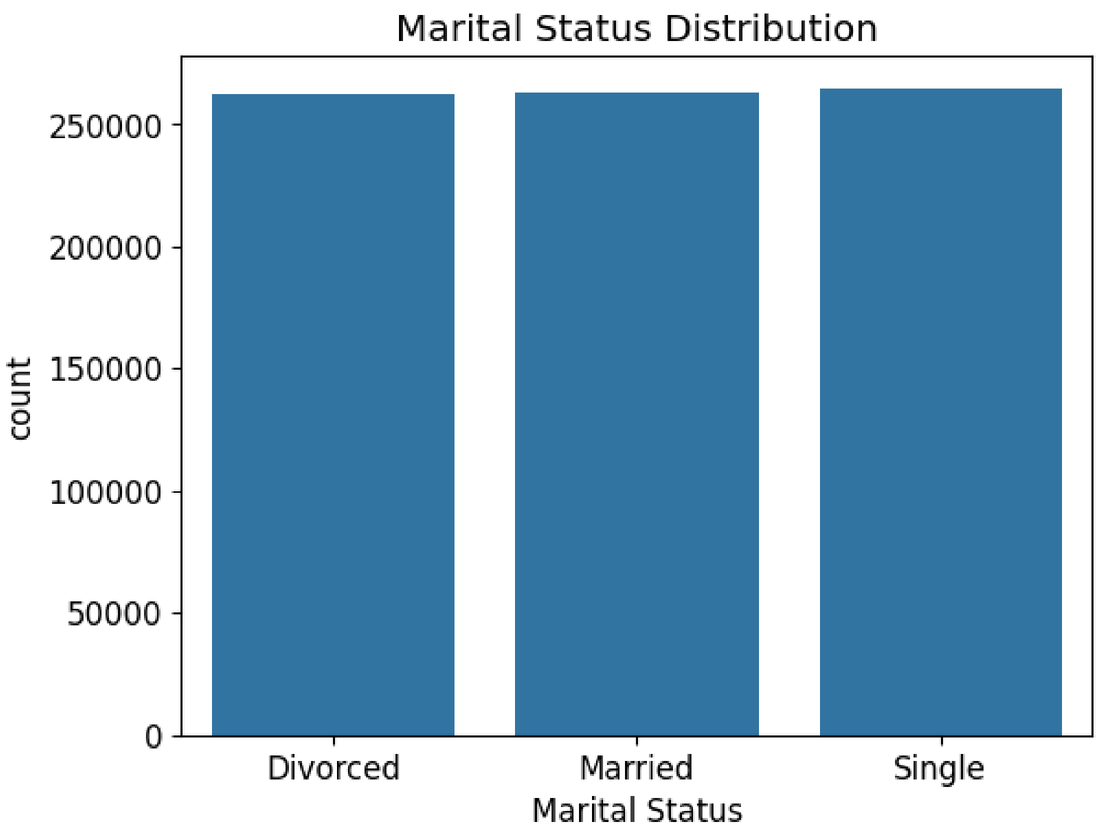
[31]:
```
# printing the count and percentage for each marital status
print("value count of the marital_status column")
print(df_clean['marital_status'].value_counts())
print("\n")
print("percentage value for each marital status")
df_clean['marital_status'].value_counts(normalize=True) * 100
```

```
value count of the marital_status column
marital_status
Single      264746
Married     263401
Divorced    262185
Name: count, dtype: int64
```

percentage value for each marital status

[31]:
```
marital_status
Single      33.498
Married     33.328
Divorced    33.174
Name: proportion, dtype: float64
```

[32]:
```
#plotting a bar chart of the marital status column
sns.countplot(df_clean,x='marital_status', color='tab:blue')
plt.title('Marital Status Distribution')
plt.xlabel('Marital Status')
plt.show()
```




**Observations** - the data has an even distribution across marital statuses.

---

### 6.1.2 4.1.6 Group analysis

printing the counts and statistics for the rest to see if there is something that needs farther investigation.

[33]:
```
df_clean.describe()
```

[33]:
```
                 id         age  annual_income  number_of_dependents  \
count   790,332.000 790,332.000    790,332.000           790,332.000
mean    600,049.868      41.136     32,810.934                 2.012
min           0.000      18.000          1.000                 0.000
25%     300,275.750      30.000      8,791.000                 1.000
50%     600,243.000      41.000     24,194.000                 2.000
75%     899,674.250      53.000     44,393.000                 3.000
max   1,199,995.000      64.000    149,997.000                 4.000
std     346,263.596      13.541     31,819.797                 1.416

       health_score  previous_claims  vehicle_age  credit_score  \
count   790,332.000      790,332.000  790,332.000   790,332.000
mean         25.556            0.689        9.568       593.636
min           2.012            0.000        0.000       300.000
25%          15.899            0.000        5.000       469.000
50%          24.528            0.000       10.000       596.000
75%          34.405            1.000       15.000       721.000
max          58.976            8.000       19.000       849.000
std          12.163            0.933        5.776       149.667

       insurance_duration              policy_start_date  premium_amount
count         790,332.000                         790332     790,332.000
mean                5.023  2022-02-12 21:33:42.995619328       1,099.195
min                 1.000     2019-08-17 15:21:39.080371          20.000
25%                 3.000  2020-11-20 15:21:39.155230976         515.000
50%                 5.000  2022-02-13 15:21:39.167098880         871.000
75%                 7.000  2023-05-05 15:21:39.206099456       1,498.000
max                 9.000     2024-08-15 15:21:39.287115       4,999.000
std                 2.595                            NaN         860.546
```

[34]:
```
def print_column_stats(df, column):
    print(f"Value count of the {column} column")
    print(df[column].value_counts())
    print("\n")
    print(f"Percentage value for each {column}")
    print(df[column].value_counts(normalize=True) * 100)
```

[35]:
```
print_column_stats(df_clean, 'education_level')
```

```
Value count of the education_level column
education_level
PhD            200343
```

```
Bachelor's     200137
Master's       199294
High School    190558
Name: count, dtype: int64


Percentage value for each education_level
education_level
PhD            25.349
Bachelor's     25.323
Master's       25.216
High School    24.111
Name: proportion, dtype: float64
```

[36]:
```
print_column_stats(df_clean, 'policy_type')
```

```
Value count of the policy_type column
policy_type
Premium          264469
Comprehensive    263287
Basic            262576
Name: count, dtype: int64


Percentage value for each policy_type
policy_type
Premium          33.463
Comprehensive    33.313
Basic            33.224
Name: proportion, dtype: float64
```

[37]:
```
print_column_stats(df_clean, 'customer_feedback')
```

```
Value count of the customer_feedback column
customer_feedback
Average    266140
Poor       264196
Good       259996
Name: count, dtype: int64


Percentage value for each customer_feedback
customer_feedback
Average   33.674
Poor      33.428
Good      32.897
Name: proportion, dtype: float64
```

[38]:
```python
print_column_stats(df_clean, 'smoking_status')
```

```
Value count of the smoking_status column
smoking_status
Yes    395848
No     394484
Name: count, dtype: int64


Percentage value for each smoking_status
smoking_status
Yes   50.086
No    49.914
Name: proportion, dtype: float64
```

[39]:
```python
print_column_stats(df_clean, 'exercise_frequency')
```

```
Value count of the exercise_frequency column
exercise_frequency
Weekly     201861
Monthly    197489
Rarely     197406
Daily      193576
Name: count, dtype: int64


Percentage value for each exercise_frequency
exercise_frequency
Weekly    25.541
Monthly   24.988
Rarely    24.978
Daily     24.493
Name: proportion, dtype: float64
```

[40]:
```python
print_column_stats(df_clean, 'property_type')
```

```
Value count of the property_type column
property_type
House        263709
Apartment    263417
Condo        263206
Name: count, dtype: int64


Percentage value for each property_type
property_type
House       33.367
Apartment   33.330
Condo       33.303
```

```
Name: proportion, dtype: float64
```

[41]:
```
print_column_stats(df_clean, 'location')
```

```
Value count of the location column
location
Suburban    264597
Rural       264137
Urban       261598
Name: count, dtype: int64


Percentage value for each location
location
Suburban   33.479
Rural      33.421
Urban      33.100
Name: proportion, dtype: float64
```

**Observation:**

- All the Categorical data is evenly distributed between categories

## 6.2 4.2 Bivariate Analysis

### 6.2.1 4.2.1 correlation analysis

To start off the Bivariate analysis we will print the correlation matrix between the `premium_amount` and the other variables

[43]:
```
#printing correlation matrix for the premium_amount column
correlation = df_clean.corr(numeric_only=True)
correlation['premium_amount'].sort_values(ascending=False)
```

[43]:
```
premium_amount          1.000
previous_claims         0.042
health_score            0.014
vehicle_age             0.002
id                     -0.000
insurance_duration     -0.001
number_of_dependents   -0.001
age                    -0.003
credit_score           -0.030
annual_income          -0.031
Name: premium_amount, dtype: float64
```

From the Correlation analysis we see that the numerical variables don't have much correlation to premium amount

### 6.2.2 4.2.2 relation between gender and premium_amount

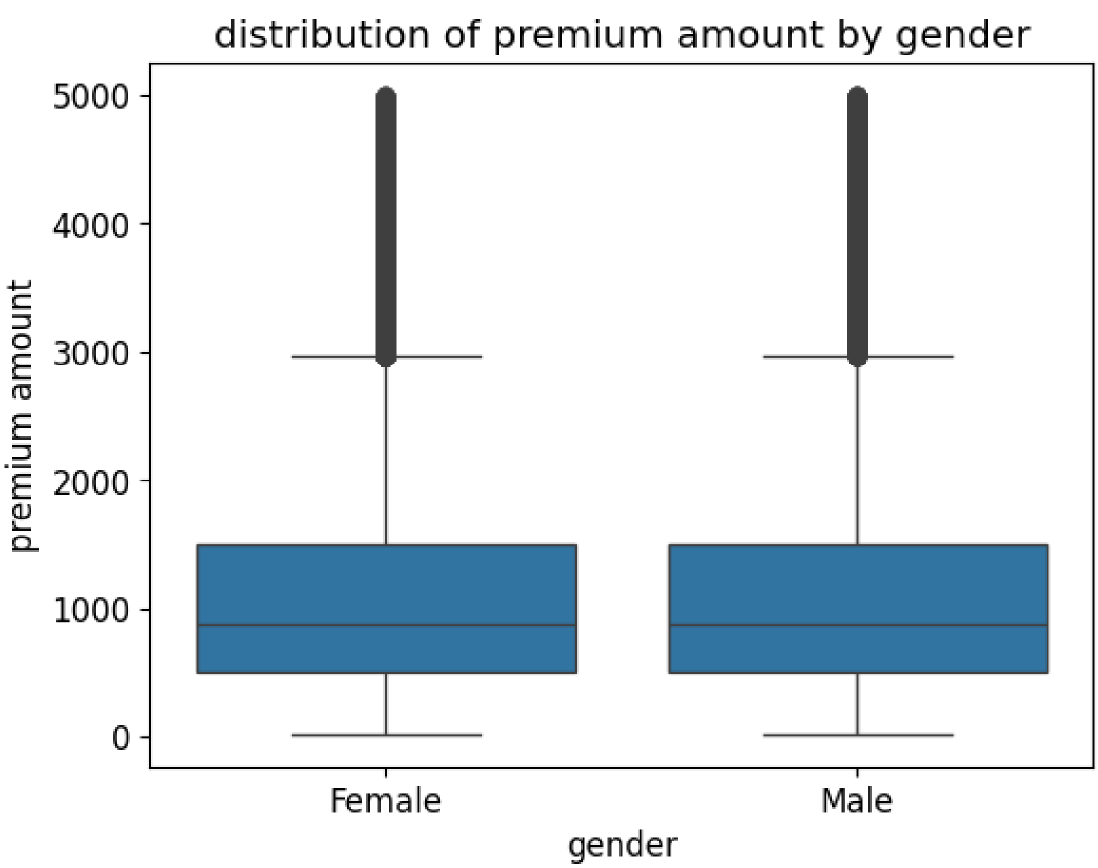
To study the relation between the gender and premium_amount columns we will print the descriptive statistics for each gender and plot the distribution of premium type by gender, we will do this via a box plot

[52]:
```
#printing the descriptive statistics of the premium_amount column by gender
df_clean.groupby('gender', observed=False).agg({'premium_amount': ['mean',␣
↪'median', 'std', 'min', 'max']})
```

[52]:

| | premium_amount | | | | |
|---|---|---|---|---|---|
| | mean | median | std | min | max |
| gender | | | | | |
| Female | 1,099.269 | 871.000 | 860.463 | 20.000 | 4,997.000 |
| Male | 1,099.122 | 871.000 | 860.631 | 20.000 | 4,999.000 |

[ ]:
```
#plotting a boxplot of the premium_amount by gender
sns.boxplot(data=df_clean, x='gender', y='premium_amount')
plt.title('distribution of premium amount by gender')
plt.xlabel('gender')
plt.ylabel('premium amount');
plt.show()
```



**Conclusion:**

- there is no difference between male and female in insurance premium.

### 6.2.3 4.2.3 relation between marital_status and premium_amount

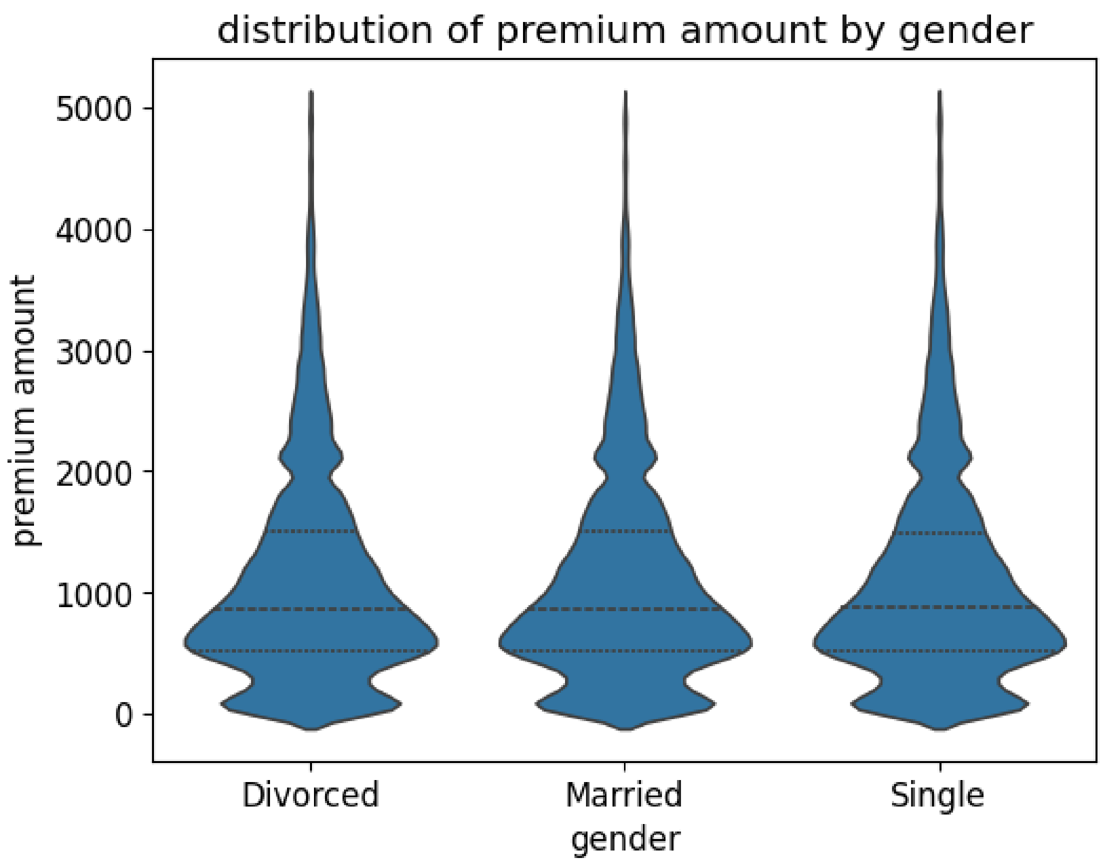
To study the relation between the marital_status and premium_amount columns we will print the descriptive statistics for each gender and plot the distribution of premium type by gender, we will do this via a violin chart

[ ]:
```
#printing the descriptive statistics of the premium_amount column by␣
↪marital_status
df_clean.groupby('marital_status', observed=False).agg({'premium_amount':␣
↪['mean', 'median', 'std', 'min', 'max']})
```

[ ]:

| | premium_amount | | | | |
|---|---|---|---|---|---|
| | mean | median | std | min | max |
| marital_status | | | | | |
| Divorced | 1,098.472 | 870.000 | 860.837 | 20.000 | 4,997.000 |
| Married | 1,098.565 | 871.000 | 859.074 | 20.000 | 4,996.000 |
| Single | 1,100.538 | 872.000 | 861.723 | 20.000 | 4,999.000 |

[89]:
```
#plotting a boxplot of the premium_amount by marital_status
sns.violinplot(data=df_clean, x='marital_status', y='premium_amount',␣
↪inner='quartile')
plt.title('distribution of premium amount by gender')
plt.xlabel('gender')
plt.ylabel('premium amount');
plt.show()
```




**Conclusion:**

- there is no difference between marital statuses in insurance premium.

#### 6.2.4 4.2.4 relation between `education_level` and `premium_amount`

To study the relation between the `education_level` and `premium_amount` columns we will print the descriptive statistics for each gender and plot the distribution of premium type by gender, we will do this via a box plot

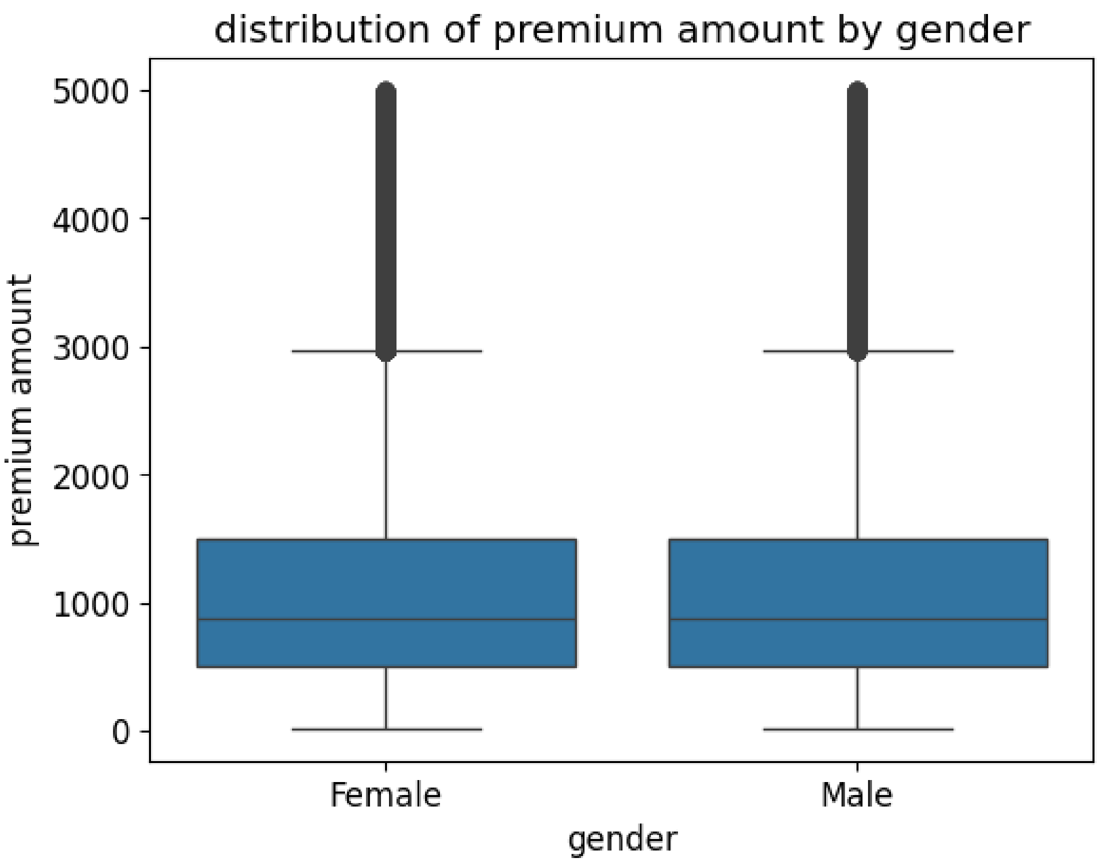
[56]:
```
#printing the descriptive statistics of the premium_amount column by␣
↪education_level
df_clean.groupby('education_level', observed=False).agg({'premium_amount':␣
↪['mean', 'median', 'std', 'min', 'max']})
```

[56]:

| | premium_amount | | | | |
|---|---|---|---|---|---|
| | mean | median | std | min | max |
| education_level | | | | | |
| Bachelor's | 1,100.187 | 872.000 | 860.945 | 20.000 | 4,988.000 |
| High School | 1,099.398 | 872.000 | 860.226 | 20.000 | 4,999.000 |

```
Master's            1,099.740 870.000 862.058 20.000 4,997.000
PhD                 1,097.468 867.000 858.950 20.000 4,991.000
```

[55]:
```
#plotting a boxplot of the premium_amount by education_level
sns.boxplot(data=df_clean, x='gender', y='premium_amount')
plt.title('distribution of premium amount by gender')
plt.xlabel('gender')
plt.ylabel('premium amount');
plt.show()
```




**Conclusion:**

- there is no difference between education levels in premium amount.

#### 6.2.5 4.2.5 relation between `location` and `premium_amount`

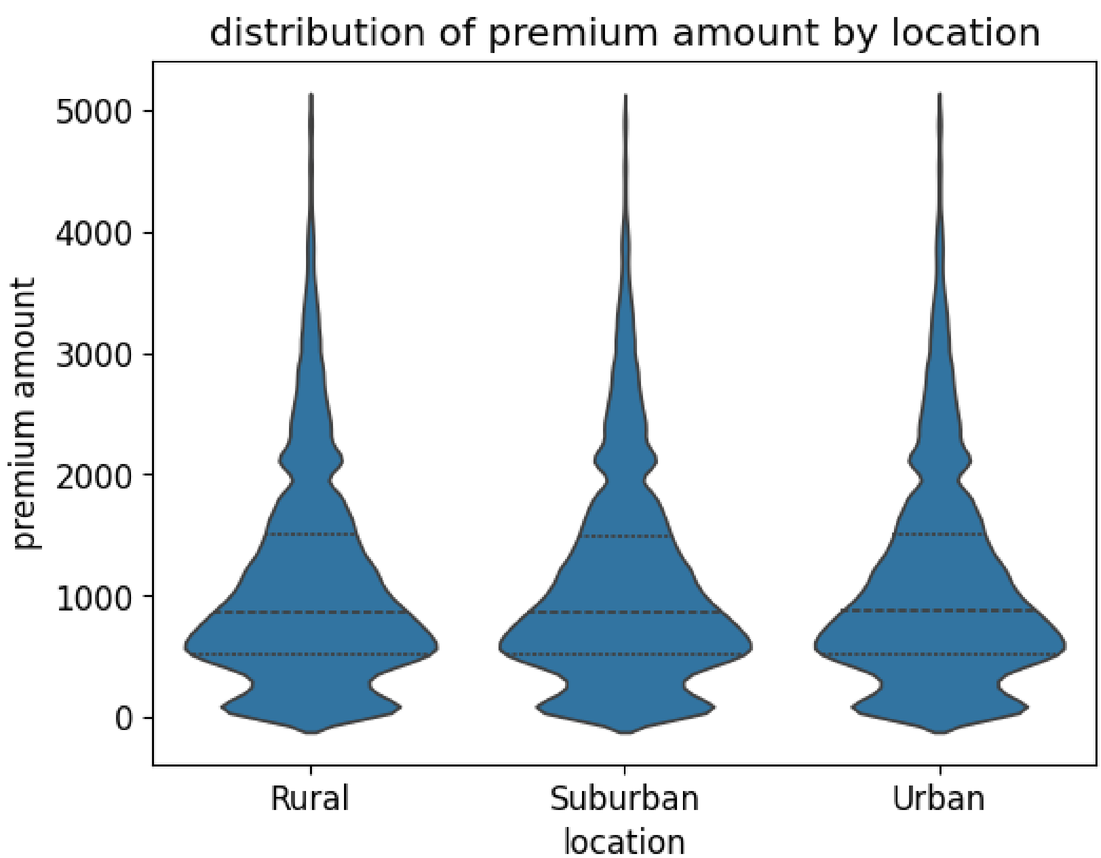
To study the relation between the `location` and `premium_amount` columns we will print the descriptive statistics for each gender and plot the distribution of premium type by gender, we will do this via a violin chart

[91]:
```
#printing the descriptive statistics of the premium_amount column by location
df_clean.groupby('location', observed=False).agg({'premium_amount': ['mean',
↪'median', 'std', 'min', 'max']})
```

[91]:

| | premium_amount | | | | |
|---|---|---|---|---|---|
| | mean | median | std | min | max |
| location | | | | | |
| Rural | 1,097.429 | 870.000 | 860.399 | 20.000 | 4,997.000 |
| Suburban | 1,099.163 | 870.000 | 860.999 | 20.000 | 4,988.000 |
| Urban | 1,101.011 | 873.000 | 860.237 | 20.000 | 4,999.000 |

[90]:
```
#plotting a boxplot of the premium_amount by location
sns.violinplot(data=df_clean, x='location', y='premium_amount',
↪inner='quartile')
plt.title('distribution of premium amount by location')
plt.xlabel('location')
plt.ylabel('premium amount');
plt.show()
```



**Conclusion:**

- there is no difference between location in insurance premium.

### 6.2.6 4.2.6 relation between `policy_type` and `premium_amount`

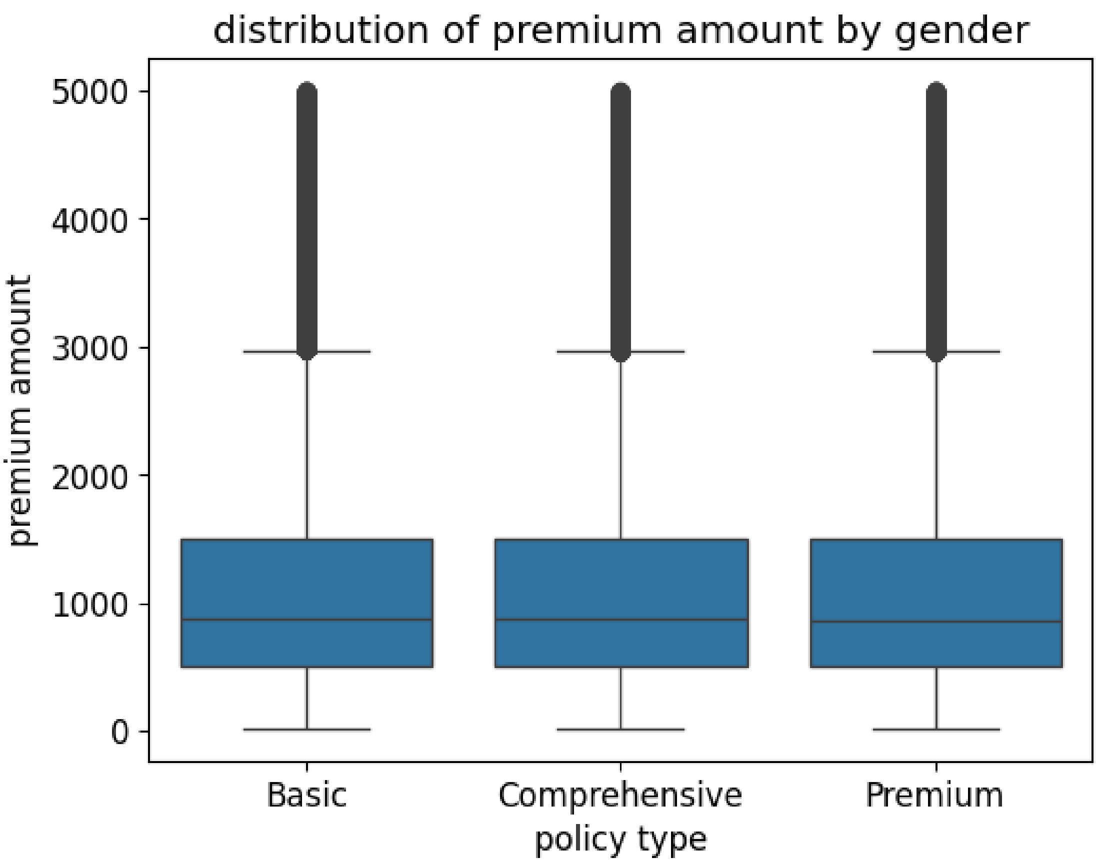
To study the relation between the `policy_type` and `premium_amount` columns we will print the descriptive statistics for each gender and plot the distribution of premium type by gender, we will do this via a box plot

[93]:
```
#printing the descriptive statistics of the premium_amount column by policy_type
df_clean.groupby('policy_type', observed=False).agg({'premium_amount': ['mean',␣
↪'median', 'std', 'min', 'max']})
```

[93]:

| | premium_amount | | | | |
|---|---|---|---|---|---|
| | mean | median | std | min | max |
| policy_type | | | | | |
| Basic | 1,099.689 | 872.000 | 860.550 | 20.000 | 4,999.000 |
| Comprehensive | 1,099.406 | 872.000 | 859.755 | 20.000 | 4,992.000 |
| Premium | 1,098.495 | 867.000 | 861.333 | 20.000 | 4,997.000 |

[95]:
```
#plotting a boxplot of the premium_amount by education_level
sns.boxplot(data=df_clean, x='policy_type', y='premium_amount')
plt.title('distribution of premium amount by gender')
plt.xlabel('policy type')
plt.ylabel('premium amount');
plt.show()
```




**Conclusion:**

- there is no difference between policy types in premium amount.

### 6.2.7 4.2.7 relation between `property_type` and `premium_amount`

To study the relation between the `property_type` and `premium_amount` columns we will print the descriptive statistics for each gender and plot the distribution of premium type by gender, we will do this via a violin chart

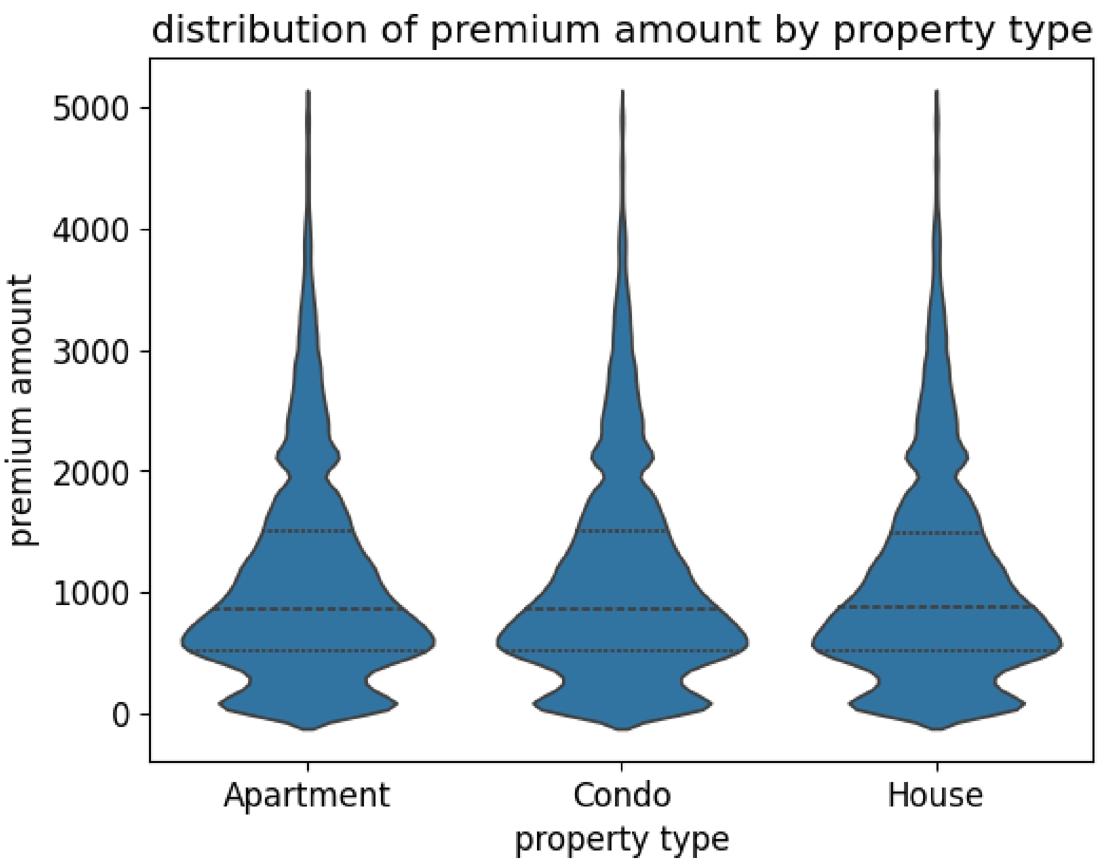
[98]:
```
#printing the descriptive statistics of the premium_amount column by␣
↪property_type
df_clean.groupby('property_type', observed=False).agg({'premium_amount':␣
↪['mean', 'median', 'std', 'min', 'max']})
```

[98]:

| | premium_amount | | | | |
|---|---|---|---|---|---|
| | mean | median | std | min | max |
| property_type | | | | | |
| Apartment | 1,100.277 | 870.000 | 862.531 | 20.000 | 4,997.000 |
| Condo | 1,098.845 | 869.000 | 862.406 | 20.000 | 4,997.000 |

```
House               1,098.464 873.000 856.697 20.000 4,999.000
```

[97]:
```
#plotting a boxplot of the premium_amount by property_type
sns.violinplot(data=df_clean, x='property_type', y='premium_amount',␣
 ↪inner='quartile')
plt.title('distribution of premium amount by property type')
plt.xlabel('property type')
plt.ylabel('premium amount');
plt.show()
```




**Conclusion:**

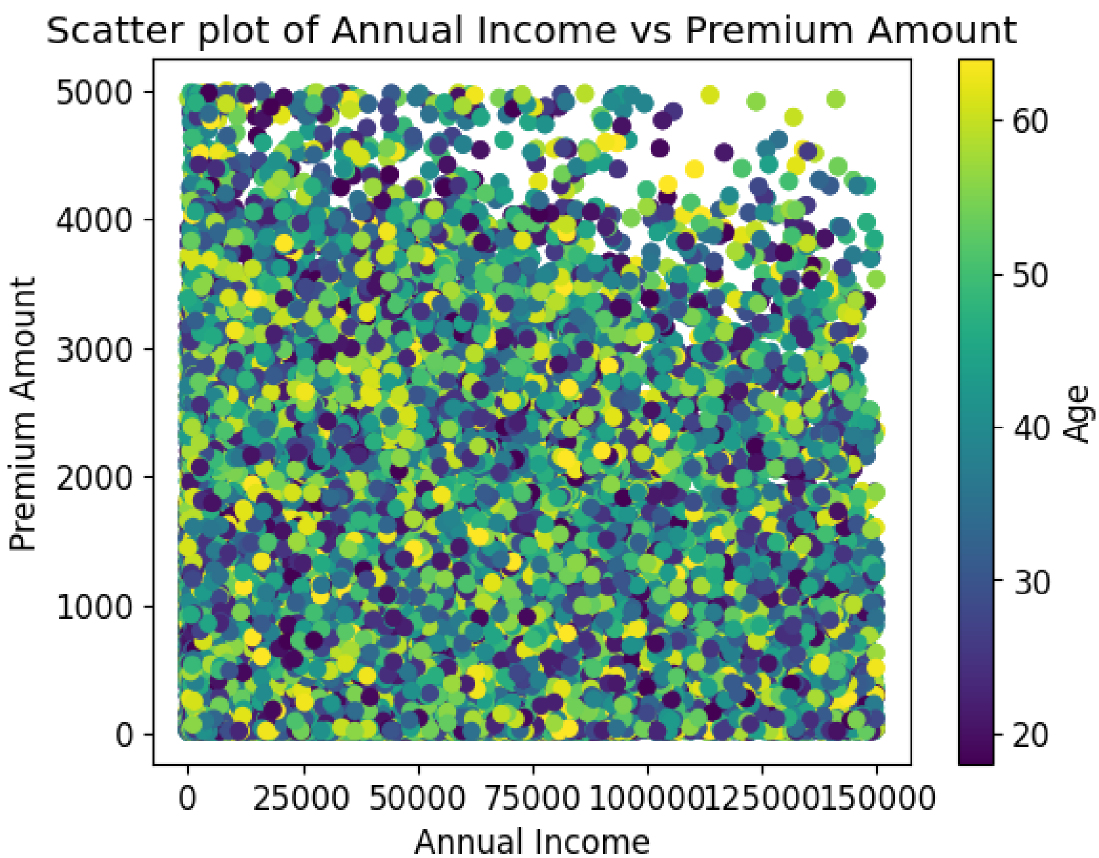
- there is no difference between property type in insurance premium.

## 6.3 4.3 Multivariate Analysis

### 6.3.1 4.3.1 relation between `annual_income` and `premium_amount` by `age`

in order to investigate this relation we will plot a colored scatter plot to visualize the relation

[118]:
```
plt.scatter(data=df_sample, x='annual_income', y='premium_amount', c='age',␣
  ↪cmap='viridis')
plt.title('Scatter plot of Annual Income vs Premium Amount')
plt.colorbar(label='Age')
plt.xlabel('Annual Income')
plt.ylabel('Premium Amount')
plt.show()
```




**Conclusion**

- there is no strong correlation between the variables

# 7 5

## 7.1 Conclusion

### 7.1.1 Insights

After the analysis we found no strong relation we could rely on in the prediction, it is most likely a distribution of small weights of all the columns in the prediction

### 7.1.2 Suggestions

the prediction process should rely on all the columns,

---

### 7.1.3 Versioning

Notebook and insights by Momen Ghulmi. - Version: 1.0.0 - Date: 2024-12-25