Exploratory Data Analysis (EDA) Report of Import Export Dataest

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1. Introduction

- **Dataset Name**: Imports_Exports V23
- **Source**: https://www.kaggle.com/datasets/willianoliveiragibin/imports-exports-v23/data
- **Date of Analysis**: 2024/10/24
- **Objective** : The objective of this exploratory data analysis (EDA) is to gain insights into the import-export dataset by examining patterns, trends, and key factors that influence international trade. Specifically, this report aims to:
  - **Understand the structure of the dataset**: Analyze the overall composition of the dataset, including the number of records, types of variables, and data completeness.
  - **Identify key trade indicators**: Investigate key metrics such as trade volumes, value of imports and exports, major trade routes, and trading partners over time.
  - **Analyze product categories**: Examine the distribution of different product categories in terms of their import and export values to identify the most significant commodities.
  - **Explore geographical trends**: Analyze the countries or regions involved in the import-export activities to identify the top importing and exporting countries and any regional patterns.
  - **Detect seasonality or time-based trends**: Identify any trends or seasonal variations in trade activities over time (e.g., monthly, quarterly, or yearly trends).
  - **Evaluate data quality**: Detect and handle any missing values, outliers, or inconsistencies in the dataset to ensure reliable results.
  - **Uncover potential correlations**: Investigate relationships between different variables (e.g., country, product type, trade value) to uncover significant patterns that may impact trade dynamics.

2. Importing the Python Libraries

Follwoing python libraries are used for the analysis:

- `pandas`: For data manipulation and analysis.
- `numpy` : For numerical operations.
- `matplotlib.pyplot` : For data visualization.
- `seaborn` : For data visualization.

```
# Import the libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

Environment Setup

```
# set the environment to print all the columns
pd.set_option('display.max_columns', None)
```

Importing the data

The dataset is imported from the csv file named as data.csv which is stored in the data folder of the directory as this notebook.

```
# Import the dataset from the data folder of the is project folder , file name
is 'data.csv'
dataset = pd.read_csv('data/data.csv')
```

4. Composition of Dataset

4.1. Data Structure and Data Types

The Structure is examined and the Data types of the columns are checked.

4.1.1 Dataset Dimensions

```
# Print the dimensions of the dataset using the shape attribute
print("The      dataset      has      {}      rows      and      {}
columns".format(dataset.shape[0],dataset.shape[1]))
```

```
The dataset has 15000 rows and 12 columns
```

4.1.2. Inspection of Data Set

```
## Inspect the dataset
# the first 5 rows of the dataset using the head method
print(dataset.head())
```

```
                         Transaction_ID           Country    Product  \
0  e3e70682-c209-4cac-a29f-6fbed82c07cd          Colombia   describe
1  f728b4fa-4248-4e3a-8a5d-2f346baa9455             Chile  president
2  f7c1bd87-4da5-4709-9471-3d60c8a70639  Christmas Island     agency
3  e443df78-9558-467f-9ba9-1faf7a024204           Finland     policy
4  23a7711a-8133-4876-b7eb-dcd9e87a1613       New Zealand   positive
```

```
  Import_Export Shipping_Method         Port     Category  Quantity    Value  \
0        Export             Air    Robertbury    Machinery      1979  9506.57
1        Export             Air      Shahport     Clothing      5763  7100.91
2        Export             Air      Adamfort    Furniture      2592  7226.42
3        Export             Air     Juliebury  Electronics      2622  2817.29
4        Export             Sea  East Randall    Machinery      6975   657.80

         Date  Customs_Code   Weight
0  07-12-2023        620537  4248.65
1  04-04-2023        927600  4340.81
2  09-05-2022        996084  4886.14
3  03-04-2023        555981  4406.74
4  23-07-2021        741778  1497.16
```

4.1.3 Data Types

In this section, we will examine the data types of each column in the dataset to ensure that they are correctly interpreted by pandas.

```
# print the datatypes of the columns using the dtypes attribute in tabular form
print("Data types of the columns")
print("-----------------------------------")
print(dataset.dtypes)
```

```
Data types of the columns
-----------------------------------
Transaction_ID            object
Country                   object
Product                   object
Import_Export             object
Shipping_Method           object
Port                      object
Category                  object
Quantity                   int64
Value                    float64
Date              datetime64[ns]
Customs_Code               int64
Weight                   float64
dtype: object
```

4.2.4. The Metadata and Column Information

The data types are the kinds of values stored in each column of the import-export dataset. Here's an interpretation of each data type:

- **Transaction_ID (object)**: The column contains alphanumeric values, A unique identifier for each trade transaction, ensuring every entry can be tracked and referenced individually.

- **Country (object)**: The country of origin (for imports) or destination (for exports), represented as strings
- **Product (object)**: The specific product involved in the trade, which are also strings.
- **Import_Export (object)**: A clear indicator of whether the transaction is an import or export, stored as a string.
- **Shipping_Method (object)**: The mode of transportation (e.g., Air, Sea, Land) used to move the goods, stored as strings.
- **Port (object)**: The entry or departure port where the transaction was processed, stored as strings.
- **Category (object)**: The product category (e.g., Electronics, Clothing, Machinery), stored as strings.
- **Quantity (int64)**: The amount of the product traded, stored as integers (64-bit precision).
- **Value (float64)**: The monetary value of the trade, in U.S. dollars, stored as floating-point numbers (decimal values).
- **Date (object)**: The date when the transaction occurred. Dates are represented as strings in this column, and may need conversion to a proper datetime format for further analysis.
- **Customs_Code (int64)**: The Harmonized System (HS) or customs code for the product, stored as 64-bit integers.
- **Weight (float64)**: The product's weight in kilograms, stored as floating-point numbers (decimal values).

4.2.5. Handling of Incorrect Data Types

The Dates column is converted to datetime format for further analysis.

```
# convert the datatype of the 'Date' column to datetime using the to_datetime
method
dataset['Date'] = pd.to_datetime(dataset['Date'], dayfirst=True)
```

4.2.6. High Cardinality Columns

The high cardinality columns are identified and examined to determine if they need further processing.

```
# identify the high cardinality columns in the dataset using the nunique method
print("High cardinality columns")
print(dataset.nunique())
```

```
High cardinality columns
Transaction_ID     15000
```

```
Country              243
Product              971
Import_Export          2
Shipping_Method        3
Port               10657
Category               5
Quantity            7755
Value              14884
Date                1827
Customs_Code       14881
Weight             14775
dtype: int64
```

The following columns with their corresponding unique value counts:

- **Transaction_ID (15,000 unique values)**: This column has high cardinality, as it contains a unique ID for almost every transaction, which is typical in datasets where each row represents an individual transaction. This column might not be useful for modeling because it doesn't provide any meaningful pattern, just a unique identifier.
- **Country (243 unique values)**: With 243 unique values, the cardinality of this column is moderately high. This could be significant when analyzing data based on country-level trade patterns, but for certain machine learning models, this could require special handling (e.g., one-hot encoding or feature embedding).
- **Product (971 unique values)**: The Product column has relatively high cardinality, with 971 distinct products. This indicates a large variety of items being traded, which could impact modeling, especially if you want to analyze trends by product category.
- **Import_Export (2 unique values)**: This column has very low cardinality, as it only contains two distinct values, likely representing whether a transaction is an "Import" or "Export." It's simple and can be easily encoded.
- **Shipping_Method (3 unique values)**: Similarly, this column has low cardinality, likely indicating three different shipping methods. This won't cause any significant issue during modeling.
- **Port (10,657 unique values)**: The Port column has extremely high cardinality, with 10,657 unique entries. This represents a large number of different ports used in the transactions, which might complicate analysis. Handling high cardinality features like this might involve grouping ports by region or other characteristics to reduce complexity.
- **Category (5 unique values)**: The Category column has very low cardinality, which means only a few distinct categories are represented. This column is straightforward to encode.
- **Quantity (7,755 unique values)**: The Quantity column shows moderately high cardinality, with 7,755 unique values. This variation in quantities traded suggests a diverse range of product sizes/quantities being shipped, and this feature is likely numeric, so handling this in a model would be relatively easy.

- **Value (14,884 unique values)**: The Value column has very high cardinality, indicating a wide range of monetary transaction values. Since this is a continuous numeric feature, it may not require special handling beyond normalization or scaling.
- **Date (1,827 unique values)**: The Date column has moderately high cardinality, reflecting the number of distinct dates on which transactions occurred. Dates may need to be converted into a more useful format (e.g., extracting features like year, month, or day of the week).
- **Customs_Code (14,881 unique values)**: The Customs_Code column also has very high cardinality, with each transaction likely having a different customs classification. It may need special handling like grouping codes into broader categories.
- **Weight (14,775 unique values)**: This column, which likely represents the weight of the traded goods, has high cardinality. Like the Value column, it is a numeric feature, so standard scaling or transformation techniques would be sufficient.

4.2.7. Unit Consistency Check

The consistency of units in the dataset is checked to ensure that all values are in the same unit of measurement. The `Product` , `port` and `Date` columns had some inconsistencies , which will be handled at the appropriate time. While numerical columns like `Quantity`, `Value`, and `Weight` are expected to be in the same unit of measurement (e.g., kilograms, U.S. dollars), it is important to verify this assumption to avoid errors in analysis.

4.3. Missing Values

```
The missing values in the dataset are checked.
```

```python
# Check the missing values in the dataset using the isnull method and also print
the percentage of missing values
# by rounding the number to 2 decimal places
missing_values = dataset.isnull().sum()
missing_values_percentage = round((missing_values/len(dataset))*100,2)
print("Missing values in the dataset")
print(pd.concat([missing_values,missing_values_percentage],axis=1,keys=['Missing
values','Percentage']))
```

```
Missing values in the dataset
                 Missing values  Percentage
Transaction_ID                0         0.0
Country                       0         0.0
Product                       0         0.0
Import_Export                 0         0.0
Shipping_Method               0         0.0
Port                          0         0.0
Category                      0         0.0
Quantity                      0         0.0
```

```
Value                          0         0.0
Date                           0         0.0
Customs_Code                   0         0.0
Weight                         0         0.0
```

As per the above table, there are no missing values in the dataset.

4.4. Duplicates

The duplicate rows in the dataset are checked.

```
# check ducplicates in the dataset using the duplicated method
duplicates = dataset.duplicated().sum()
print("Number of duplicates in the dataset: ",duplicates)
```

```
Number of duplicates in the dataset:  0
```

---

5 Distribution of Data

In this section , the distribution of the data is examined. The distribution of the data is important to understand the spread of the data and to identify any outliers or anomalies.

5.1. Summary Statistics

The descriptive statistics of the numerical columns are examined to understand the distribution of the data.

5.1.1 Measures of Central Tendency

The measures of central tendency (mean, median, and mode) are calculated for the numerical columns to understand the central values around which the data is distributed.

```
# print the summary statistics of the dataset using the describe method in
tabular form
print("Summary statistics of the dataset")
print(dataset.describe())
```

```
Summary statistics of the dataset
           Quantity         Value                        Date  Customs_Code  \
count  15000.000000  15000.000000                       15000   15000.00000
mean    4980.554733   5032.931120  2022-03-02 20:42:48.960000  549507.95920
min        1.000000    102.120000         2019-09-07 00:00:00  100041.00000
25%     2517.000000   2552.750000         2020-12-06 00:00:00  325635.50000
50%     4958.500000   5045.705000         2022-03-02 00:00:00  545432.00000
75%     7458.250000   7504.700000         2023-05-27 00:00:00  777988.00000
max    10000.000000   9999.130000         2024-09-06 00:00:00  999964.00000
std     2866.166690   2857.593897                         NaN  260886.91886
```

```
            Weight
count  15000.000000
mean    2492.118859
min        0.570000
25%     1243.482500
50%     2476.135000
75%     3747.392500
max     4999.930000
std     1451.378507
```

Interpretation of Summary Statistics: The summary statistics give a detailed overview of the key numeric columns in the dataset, including Quantity, Value, Customs_Code, and Weight, along with some other columns like Date (treated as an object here). Below is the interpretation for each column based on the summary statistics provided:

Quantity:

- **Count**: 15,000 entries (all rows have data for this field).
- **Mean**: The average quantity is around 4,980 units.
- **Min**: The minimum quantity is 1, indicating that some transactions involved just a single unit.
- **25% Quartile**: The bottom 25% of the transactions involve quantities up to 2,517 units.
- **50% (Median)**: Half of the transactions involve quantities of up to 4,958 units.
- **75% Quartile**: The top 25% of the transactions have quantities up to 7,458 units.
- **Max**: The largest quantity in a transaction is 10,000 units.
- **Std Dev (Standard Deviation)**: A standard deviation of 2,866 indicates moderate variability in the quantities of items traded.

Value:

- **Count**: 15,000 entries (all rows have data for this field).
- **Mean**: The average transaction value is approximately $5,023.
- **Min**: he smallest transaction value is $102.12, indicating a very small trade.
- **25% Quartile**: The bottom 25% of transactions are valued up to $2,552.
- **50% (Median)**: The middle transaction value is $5,045.
- **75% Quartile**: The top 25% of transactions are valued up to %7,504.
- **Max**: The highest transaction value is $9,999.
- **Std Dev (Standard Deviation)**: The standard deviation of $2,857 shows significant variability in transaction values, suggesting a wide range of transaction sizes.

Customs_Code:

- **Count**: 15,000 customs codes, meaning no missing data.
- **Mean**: The average customs code is approximately 549,507.95, but since this is likely a categorical or encoded numeric feature, its interpretation as a "mean" might not be meaningful.
- **Min**: The smallest customs code is 100,041.
- **25% Quartile**: The bottom 25% of customs codes are up to 325,635.

- **50% (Median)**: Half of the transactions have customs codes up to 545,432.
- **75% Quartile**: The top 25% of customs codes go up to 777,988.
- **Max**: The highest customs code is 999,964.
- **Std Dev**: The standard deviation of 260,886 indicates that the customs codes are widely spread, reinforcing the idea that this might represent distinct categories or groups.

Weight:

- **Count**: 15,000 entries (complete data).
- **Mean**: The average weight of the transactions is approximately 2,492.12 kg.
- **Min**: The smallest weight recorded is 0.57 kg, indicating small parcels or shipments.
- **25% Quartile**: 25% of the transactions weigh up to 1,243.48 kg.
- **50% (Median)**: Half of the transactions weigh up to 2,476.13 kg.
- **75% Quartile**: The top 25% of the transactions weigh up to 3,747.39 kg.
- **Max**: The largest transaction involves 4,999.93 kg of weight.
- **Std Dev**: The standard deviation of 1,451.37 kg shows that there is moderate variation in the weights of the transactions.

Date

- **Min**: The earliest transaction date is September 7, 2019.
- **25% Quartile**: By December 6, 2020, 25% of the transactions had already occurred.
- **50% (Median)**: By March 2, 2022, half of the transactions had occurred.
- **75% Quartile**: By May 27, 2023, 75% of the transactions had occurred.
- **Max**: The most recent transaction in the dataset occurred on September 6, 2024.
- **NaN Std Dev**: The standard deviation for the date is not provided, as it is not a numeric column.

5.1.2 Measures of Dispersion

The measures of dispersion (range, variance, standard deviation) are calculated for the numerical columns to understand the spread of the data.

```
# Measure the Variance, Standard Deviation, IQR and Range  of the numerical
columns in the dataset i.e. 'Quantity', 'Value' and 'Weight' columns
# Variance
variance = dataset[['Quantity','Value','Weight']].var()
print("Variance of the columns")
print(variance)
print ("------------------------------------")

# Standard Deviation
std_dev = dataset[['Quantity','Value','Weight']].std()
print("Standard Deviation of the columns")
print(std_dev)
print ("------------------------------------")

# IQR
IQR     =     dataset[['Quantity','Value','Weight']].quantile(0.75)     -
```

```
dataset[['Quantity','Value','Weight']].quantile(0.25)
print("IQR of the columns")
print(IQR)
print ("------------------------------------")

# Range
Range        =        dataset[['Quantity','Value','Weight']].max()        -
dataset[['Quantity','Value','Weight']].min()
print("Range of the columns")
print(Range)
print ("------------------------------------")
```

```
Variance of the columns
Quantity    8.214911e+06
Value       8.165843e+06
Weight      2.106500e+06
dtype: float64
------------------------------------
Standard Deviation of the columns
Quantity    2866.166690
Value       2857.593897
Weight      1451.378507
dtype: float64
------------------------------------
IQR of the columns
Quantity    4941.25
Value       4951.95
Weight      2503.91
dtype: float64
------------------------------------
Range of the columns
Quantity    9999.00
Value       9897.01
Weight      4999.36
dtype: float64
------------------------------------
```

Interpretation of Measures of Dispersion

Measures of dispersion tell us how spread out the data is within a dataset. The reuslts provide variance, standard deviation, interquartile range (IQR), and range for the columns Quantity, Value, and Weight. Let's interpret each measure:

- **Variance** Variance quantifies the spread of the data from the mean. A higher variance indicates that the data points are more dispersed.
  - **Quantity (8,214,911)**: The variance of quantity is high, showing that the number of items per transaction varies greatly.

  - **Value (8,165,843)**: The high variance indicates significant fluctuations in the monetary value of transactions.
  - **Weight (2,106,500)**: Though lower than the others, the variance of weight still shows substantial variability in shipment sizes.

- **Standard Deviation** Standard deviation is the square root of variance and is expressed in the same unit as the data. It's easier to interpret than variance as it directly reflects the data's spread.
  - **Quantity (2,866.17)**: The standard deviation suggests that the number of items traded typically deviates from the mean by around 2,866 units.
  - **Value (2,857.59)**: The monetary value of transactions tends to deviate from the mean by approximately $2,857.
  - **Weight (1,451.38)**: The weight of shipments deviates from the mean by about 1,451 kg. This indicates variability in shipment sizes, but not as extreme as the variation in quantity or value.

- **Interquartile Range (IQR)** The IQR measures the spread of the middle 50% of the data, and it's robust to outliers.
  - **Quantity (4,941.25)**: The middle 50% of transactions differ by approximately 4,941 units, which is a large range, again highlighting the diversity in the number of items traded.
  - **Value (4,951.95)**: The monetary value of the middle 50% of transactions differs by about $4,951.
  - **Weight (2,503.91)**: The middle 50% of shipments have a weight difference of around 2,504 kg, indicating moderate dispersion in the weight of traded items.

- Range The range is the difference between the maximum and minimum values, which provides the full spread of the data.
  - **Quantity (9,999.00)**: The range of 9,999 units shows the difference between the largest and smallest transactions in terms of quantity. This suggests some very large transactions.
  - **Value (9,897.01)**: The range of $9,897 in value suggests there are transactions that are quite small and others that are much larger.
  - **Weight (4,999.36)**: The range of weights (4,999.36 kg) shows a moderate spread in the size of shipments, from very small to quite large shipments.

5.1.3 Measures of Shape

The measures of shape (skewness, kurtosis) are calculated for the numerical columns to understand the distribution of the data.

```
# Visualize the measure of shape i.e. skewness and kurtosis of the numerical
columns in the dataset i.e. 'Quantity', 'Value' and 'Weight' columns
# Skewness
skewness = dataset[['Quantity','Value','Weight']].skew()
print("Skewness of the columns")
print(skewness)
print ("-----------------------------------")
```

```python
# Kurtosis
kurtosis = dataset[['Quantity','Value','Weight']].kurt()
print("Kurtosis of the columns")
print(kurtosis)
print ("-----------------------------------")
```

```
Skewness of the columns
Quantity    0.019183
Value       0.008283
Weight      0.025247
dtype: float64
------------------------------------
Kurtosis of the columns
Quantity   -1.182017
Value      -1.193535
Weight     -1.208368
dtype: float64
------------------------------------
```

Interpretation of Measures of Shape

The measures of shape, skewness and kurtosis, describe the distribution of the data in each column. Skewness indicates whether the data is symmetric or biased in one direction, while kurtosis measures the "tailedness" of the distribution, which helps in identifying outliers.

- **Skewness**
  - Skewness measures the asymmetry of the distribution.
    - A skewness of 0 indicates a perfectly symmetrical distribution.
    - Positive skewness (>0) indicates a distribution with a longer tail on the right (right-skewed).
    - Negative skewness (<0) indicates a distribution with a longer tail on the left (left-skewed).
  - Interpretation:
    - **Quantity (0.019183)**: The skewness is very close to zero, indicating that the distribution of quantity is nearly symmetrical, meaning the number of items traded doesn't have significant outliers or extreme skew in either direction.
    - **Value (0.008283)**: Similarly, the skewness of the value column (in $USD) is close to zero, showing a nearly symmetrical distribution. This suggests that the majority of transactions have values that are evenly spread, without extreme high or low outliers.
    - **Weight (0.025247)**: The skewness is also close to zero, meaning the distribution of shipment weight (in kg) is nearly symmetric, suggesting that small and large shipments occur with similar frequency and there are no extreme outliers on either end.
- **Kurtosis**

- Kurtosis measures the “tailedness” or the peak of the distribution.
  - A kurtosis of 3 indicates a normal distribution (mesokurtic).
  - A kurtosis < 3 indicates a flatter distribution with fewer extreme values (platykurtic).
  - A kurtosis > 3 indicates a distribution with heavier tails and more extreme outliers (leptokurtic).
- Interpretation:
  - **Quantity (-1.182017)**: The negative kurtosis suggests a platykurtic distribution, meaning the distribution of the number of items traded has fewer outliers and is relatively flatter compared to a normal distribution. The transactions are more centered around the mean, with fewer extreme quantities.
  - **Value (-1.193535)**: The value column (in $USD) also shows a platykurtic distribution. This indicates that most transaction values are clustered around the average value, with fewer extremely high or low-value transactions. The dataset does not have many extreme outliers in terms of transaction value.
  - **Weight (-1.208368)**: The negative kurtosis in the weight column (in kg) suggests that the distribution of weights is also platykurtic, meaning most shipments have weights close to the average. There are fewer extreme weights, indicating a more consistent range of shipment sizes.

- **General Insights**:
  - **Skewness**: All three columns (Quantity, Value, Weight) have very small positive skewness values, meaning that the distributions are nearly symmetrical with minimal skew in any direction. This suggests that the number of items traded, the transaction values, and the shipment weights are fairly balanced in the dataset, with no strong lean toward very high or very low values.
  - **Kurtosis**: All three columns have negative kurtosis, indicating that the distributions are flatter than a normal distribution (platykurtic). This means that the data is concentrated around the mean, with fewer outliers or extreme values in terms of quantity, value, and weight. The transactions are more consistently distributed, without large deviations from the average.
- **Conclusion**: The overall interpretation of skewness and kurtosis shows that the dataset is well-balanced with respect to the number of items traded, their value in dollars, and their weight in kilograms. The distributions are symmetric and exhibit a low likelihood of outliers, which indicates consistent and typical trading behavior across the dataset.

5.1.4 Advance Techniques for Relationships

The relationships between the numerical columns are examined using advanced techniques like covariance amd correlation matrices to identify any patterns or associations.

```
# Check the covariance and correlation of the numerical columns in the dataset
i.e. 'Quantity', 'Value' and 'Weight' columns
```

```
# Covariance
covariance = dataset[['Quantity','Value','Weight']].cov()
print("Covariance of the columns")
print(covariance)
print ("------------------------------------")

# Correlation
correlation = dataset[['Quantity','Value','Weight']].corr()
print("Correlation of the columns")
print(correlation)
print ("------------------------------------")
```

```
Covariance of the columns
              Quantity         Value        Weight
Quantity  8.214911e+06 -2.355745e+04  2.823106e+04
Value    -2.355745e+04  8.165843e+06  1.877632e+04
Weight    2.823106e+04  1.877632e+04  2.106500e+06
------------------------------------
Correlation of the columns
          Quantity     Value    Weight
Quantity  1.000000 -0.002876  0.006786
Value    -0.002876  1.000000  0.004527
Weight    0.006786  0.004527  1.000000
------------------------------------
```

Interpretation of Advanced Techniques of Relationships: Covariance and Correlation

This analysis focuses on the covariance and correlation between the columns Quantity, Value, and Weight. These measures help in understanding the relationships and dependencies between these numerical variables.

- **Covariance** Covariance measures how two variables change together. A positive covariance means the variables tend to increase together, while a negative covariance means that as one variable increases, the other tends to decrease. The magnitude of the covariance is influenced by the scale of the variables.
  - **Interpretation**:
    - **Quantity and Value (-2.355745e+04)**: The negative covariance indicates that there is a slight inverse relationship between the number of items traded and the value of the transaction. This means that as the quantity increases, the value tends to decrease slightly, although the magnitude of the covariance is small.
    - **Quantity and Weight (2.823106e+04)**: The positive covariance suggests that quantity and weight tend to increase together, meaning that larger quantities of items are usually associated with heavier shipments. The magnitude is moderate, indicating a reasonable relationship between these two variables.

    - **Value and Weight (1.877632e+04)**: The positive covariance indicates that value and weight increase together, although the relationship is relatively weak. This suggests that more expensive transactions tend to involve heavier shipments, but the relationship is not strong.
  - **Key Insight on Covariance**: The covariance values suggest that quantity and value move in opposite directions, while weight tends to move in the same direction as both quantity and value, although the relationships are weak or moderate.

- **Correlation** Correlation measures the strength and direction of a linear relationship between two variables. It is a standardized measure, ranging from -1 to 1:
  - 1 indicates a perfect positive correlation.
  - -1 indicates a perfect negative correlation.
  - 0 indicates no linear correlation.
  - **Interpretation**:
    - **Quantity and Value (-0.002876)**: The correlation between quantity and value is close to zero, meaning there is almost **no linear relationship** between the number of items traded and the value of the transaction. This suggests that large quantities do not necessarily correspond to higher or lower transaction values.
    - **Quantity and Weight (0.006786)**: The small positive correlation indicates that there is **a very weak positive relationship** between quantity and weight. While larger shipments tend to be heavier, the relationship is almost negligible.
    - **Value and Weight (0.004527)**: Similarly, the correlation between value and weight is close to zero, indicating almost **no linear relationship**. This suggests that the value of a transaction doesn't strongly depend on the weight of the shipment.
  - **Key Insight on Correlation**: The correlation values are close to zero for all pairs of variables, indicating that there is no strong linear relationship between quantity, value, and weight. This implies that these variables are largely independent of each other in terms of their linear relationship.

- **General Insights**:
  - **Covariance** provides a more general sense of how variables move together, with small relationships observed between quantity and weight and value and weight.
  - **Correlation** reveals that there is no strong linear dependency between the variables, as all correlation coefficients are close to zero, indicating very weak relationships.

- **Summary**:
  - The relationships between quantity, value, and weight are weak and almost negligible in terms of their linear correlation.

- While covariance shows a slight tendency for quantity and weight to increase together and a slight inverse relationship between quantity and value, these relationships are too weak to make significant conclusions about their dependencies.

5.1.5. Distribution of Categorical Data

The distribution of the categorical columns is examined to understand the spread of the data and identify any patterns or anomalies.

```
# Check the distribution of categorical columns in the dataset i.e. 'Country',
'Product' and 'Import_Export', 'Shipping_Method', 'Port' and 'Category' columns
# Country
print("Distribution of Country column")
print(dataset['Country'].value_counts())
print ("------------------------------------")

# Product
print("Distribution of Product column")
print(dataset['Product'].value_counts())
print ("------------------------------------")

# Import_Export
print("Distribution of Import_Export column")
print(dataset['Import_Export'].value_counts())
print ("------------------------------------")

# Shipping_Method
print("Distribution of Shipping_Method column")
print(dataset['Shipping_Method'].value_counts())
print ("------------------------------------")

# Port
print("Distribution of Port column")
print(dataset['Port'].value_counts())
print ("------------------------------------")

# Category
print("Distribution of Category column")
print(dataset['Category'].value_counts())
print ("------------------------------------")
```

```
Distribution of Country column
Country
Congo                   133
Korea                   113
Pakistan                 79
Pitcairn Islands         79
Israel                   79
```

```
                   ...
Myanmar              45
Reunion              44
Liechtenstein        44
Faroe Islands        43
Palau                41
Name: count, Length: 243, dtype: int64
------------------------------------
Distribution of Product column
Product
family     28
bank       27
music      27
address    27
card       27
           ..
science     7
state       7
energy      7
deep        6
rich        6
Name: count, Length: 971, dtype: int64
------------------------------------
Distribution of Import_Export column
Import_Export
Import    7569
Export    7431
Name: count, dtype: int64
------------------------------------
Distribution of Shipping_Method column
Shipping_Method
Sea     5054
Air     4995
Land    4951
Name: count, dtype: int64
------------------------------------
Distribution of Port column
Port
West Michael         20
Lake Michael         20
Port David           17
New Michael          14
East Michael         14
                     ..
Port Amandaton        1
Hillborough           1
Port Victoriatown     1
Camerontown           1
```

```
Shahport             1
Name: count, Length: 10657, dtype: int64
------------------------------------
Distribution of Category column
Category
Clothing       3048
Furniture      3024
Electronics    3021
Machinery      3010
Toys           2897
Name: count, dtype: int64
------------------------------------
```

Interpretation of the Distribution of Categorical Columns:

The results provide the distribution of several categorical columns: Country, Product, Import_Export, Shipping_Method, and Port. Here's the interpretation for each:

- **Country**
  - There are 243 unique countries in the dataset.
  - The highest number of transactions come from Congo (133), followed by Korea (113).
  - Other countries like Pakistan, Pitcairn Islands, and Israel have around 79 transactions each.
  - Smaller countries like Palau have much fewer transactions, around 41.
  - The spread across countries suggests some concentration in a few countries (like Congo and Korea), while many other countries have a smaller presence in the dataset.
  - **Insight:** The dataset seems to have more transactions concentrated in a few key countries, with the rest having much smaller involvement in trade.
- **Product**
  - There are 971 unique products in the dataset.
  - The most frequent products are family (28 transactions), followed by bank, music, address, and card (27 transactions each).
  - Other products like science, state, and energy have fewer occurrences (7 transactions).
  - The least frequent products include deep and rich (6 transactions).
  - **Insight**: The product distribution is wide, but most products appear only a few times, with a handful of products occurring more frequently. This suggests a diverse product portfolio, with a few products playing a central role in transactions.
- **Import_Export**
  - Import transactions (7,569) slightly outnumber Export transactions (7,431).
  - **Insight:** The import and export activities are almost evenly balanced, suggesting the dataset represents both sides of international trade with nearly equal emphasis.
- **Shipping_Method Column**
  - There are three shipping methods: Sea (5,054 transactions), Air (4,995 transactions), and Land (4,951 transactions).
  - The distribution is relatively even across all shipping methods.

    - **Insight**: The use of different shipping methods is balanced, indicating that sea, air, and land transport all play a significant role in trade operations.
- **Port**
    - There are 10,657 unique ports in the dataset, indicating a large geographical spread.
    - The most frequent ports include West Michael and Lake Michael (20 transactions each), followed by Port David (17), New Michael (14), and East Michael (14).
    - Many ports have only 1 transaction each, such as Port Amandaton, Hillborough, and Shahport.
    - **Insight**: The port distribution shows that while a few ports handle a significant number of transactions, the majority of the ports are used very infrequently, which reflects the diversity in the shipping routes used in trade.
    - Port names like Michael, David, and Amandaton suggest a mix of real and fictional port names, which may require further investigation for accuracy.
    - **The problem of port names are like spelling mistakes and the same port name with different spellings is also observed**.
- **General Insights**:
    - The Country and Product distributions indicate that a few key entities dominate trade, with many smaller contributors.
    - The balance between Import and Export, as well as the use of Shipping Methods, suggests an evenly distributed logistics operation.
    - The Port distribution suggests global shipping routes, but with a strong reliance on a few key ports.

This diversity in categorical data reflects the complexity and wide geographical range of the dataset's trade operations.

Use of Clustering for Correcting Inconsistent Port Names

Clustering is a good approach when there are many variations or when you don't have a predefined list of correct port names. It helps group similar names, allowing you to handle inconsistencies at scale.

1. **Import the necessary libraries for clustering**

```
# import scikit-learn and nltk libraries
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.cluster import DBSCAN
```

2. **Prepare the data**

```
# Show number of unique values in the 'port' column
print("Number of unique values in the 'Port' column: ",
dataset['Port'].nunique())
```

```
Number of unique values in the 'Port' column:  10657
```

3. **Text Vectorization (TF-IDF)** TF-IDF (Term Frequency-Inverse Document Frequency) to convert port names into numerical vectors that can be used for clustering. TF-IDF works well for text data as it captures the importance of words relative to the entire dataset.

```
# Initialize the TF-IDF vectorizer
vectorizer = TfidfVectorizer(analyzer='char', ngram_range=(2, 3))
X = vectorizer.fit_transform(dataset['Port'])
```

4. **Clustering the Port Names with DBSCAN** DBSCAN (Density-Based Spatial Clustering of Applications with Noise) automatically determines the number of clusters and is good for datasets where the number of clusters isn't known.

```
# Initialize DBSCAN with a small epsilon for short text distances
dbscan = DBSCAN(eps=0.2, min_samples=1, metric='cosine')
dataset['Cluster'] = dbscan.fit_predict(X.toarray())

# Check which cluster each port belongs to
print(dataset)
```

```
                             Transaction_ID              Country    Product  \
0      e3e70682-c209-4cac-a29f-6fbed82c07cd             Colombia   describe
1      f728b4fa-4248-4e3a-8a5d-2f346baa9455                Chile  president
2      f7c1bd87-4da5-4709-9471-3d60c8a70639     Christmas Island     agency
3      e443df78-9558-467f-9ba9-1faf7a024204              Finland     policy
4      23a7711a-8133-4876-b7eb-dcd9e87a1613          New Zealand   positive
...                                     ...                  ...        ...
14995  8535daa3-1da5-4b80-9a0c-955e5aad1f2e             Anguilla      stuff
14996  f101ae45-9529-46fb-93b5-ae5c81cd7706  Antigua and Barbuda    feeling
14997  171f03fc-52ac-4e21-b976-45a8fb03879c           Luxembourg  beautiful
14998  fdf88f9d-94f0-451f-a21d-ca24b95f199b                Congo      watch
14999  5cc039d0-a052-41fd-bfbb-c9f60c4565ac      North Macedonia       year

      Import_Export Shipping_Method                Port     Category  \
0            Export             Air          Robertbury    Machinery
1            Export             Air            Shahport     Clothing
2            Export             Air            Adamfort    Furniture
3            Export             Air           Juliebury  Electronics
4            Export             Sea        East Randall    Machinery
...             ...             ...                 ...          ...
14995        Import            Land           Henryberg  Electronics
14996        Import             Air           Tracyview    Furniture
14997        Import             Sea      North Juliatown  Electronics
14998        Import            Land  North Kathleentown     Clothing
14999        Import             Air           West Gary     Clothing

       Quantity    Value       Date  Customs_Code   Weight  Cluster
```

```
0          1979  9506.57 2023-12-07        620537  4248.65        0
1          5763  7100.91 2023-04-04        927600  4340.81        1
2          2592  7226.42 2022-05-09        996084  4886.14        2
3          2622  2817.29 2023-04-03        555981  4406.74        3
4          6975   657.80 2021-07-23        741778  1497.16        4
...         ...      ...        ...           ...      ...      ...
14995      3115  9263.96 2022-05-07        570345   541.97     3231
14996      2885  4114.55 2023-02-20        946363  2147.70     3370
14997      7090  9043.26 2020-06-01        282403  3300.82     6277
14998      2016  4572.23 2020-11-07        855213  2559.71       71
14999      5635   561.33 2019-12-25        766709  2913.82     1356

[15000 rows x 13 columns]
```

5. **Analyze the Clusters** The clusters are analyzed to identify patterns and inconsistencies in the port names.

```
# Display the ports in each cluster
# for cluster in dataset['Cluster'].unique():
#     print(f"\nCluster {cluster}:")
#     print(dataset[dataset['Cluster'] == cluster]['Port'].values)

# save the output in a text file in the data folder
with open('data/ports_clusters.txt', 'w') as f:
    for cluster in dataset['Cluster'].unique():
        f.write(f"\nCluster {cluster}:\n")
          f.write(str(dataset[dataset['Cluster'] == cluster]['Port'].values)
+ '\n')
```

6. **Mapping of Corrected Port Names** The corrected port names are mapped back to the original dataset to replace the inconsistent port names.

```
# Load the data from the csv and add it to the dataset as a new column
data = pd.read_csv('data/corrected_ports_clusters.csv')
dataset['Corrected_Port'] = data['Corrected_Port']

# Save the dataset to a new csv file
dataset.to_csv('data/data.csv', index=False)

# Print the first 5 rows of the dataset
print(dataset.head())
```

```
                         Transaction_ID           Country    Product  \
0  e3e70682-c209-4cac-a29f-6fbed82c07cd          Colombia   describe
1  f728b4fa-4248-4e3a-8a5d-2f346baa9455             Chile  president
2  f7c1bd87-4da5-4709-9471-3d60c8a70639  Christmas Island     agency
```

```
3  e443df78-9558-467f-9ba9-1faf7a024204          Finland     policy
4  23a7711a-8133-4876-b7eb-dcd9e87a1613      New Zealand   positive

  Import_Export Shipping_Method          Port     Category  Quantity    Value  \
0        Export             Air    Robertbury    Machinery      1979  9506.57
1        Export             Air      Shahport     Clothing      5763  7100.91
2        Export             Air      Adamfort    Furniture      2592  7226.42
3        Export             Air     Juliebury  Electronics      2622  2817.29
4        Export             Sea  East Randall    Machinery      6975   657.80

        Date  Customs_Code   Weight       Cluster Corrected_Port
0 2023-12-07        620537  4248.65    Robertbury     Robertbury
1 2023-04-04        927600  4340.81      Shahport       Shahport
2 2022-05-09        996084  4886.14      Adamfort       Adamfort
3 2023-04-03        555981  4406.74   South Julie    South Julie
4 2021-07-23        741778  1497.16  East Randall   East Randall
```

```python
# Print the number of unique values in the 'Corrected_Port' column and the 'Port'
column
print("Number    of    unique    values    in    the    'Port'    column:    ",
dataset['Port'].nunique())
print("Number   of   unique   values   in   the   'Corrected_Port'   column:   ",
dataset['Corrected_Port'].nunique())
```

```
Number of unique values in the 'Port' column:  10657
Number of unique values in the 'Corrected_Port' column:  6278
```

The correction process reduced the number of unique values in the Port column from 10,657 to 6,278 unique values in the Corrected_Port column. Here's what this reduction signifies:

- **Consolidation of Variants**:
  - Initially, the Port column had many variations of the same port name due to spelling differences, prefixes (like "East," "West," "New"), and minor inconsistencies.
  - By grouping these similar names into clusters and assigning a single corrected name for each cluster, we consolidated these variations. This led to a more standardized dataset, reducing redundant or duplicate representations of the same port.
- **Data Quality Improvement**:
  - The reduction from 10,657 to 6,278 unique values reflects improved data quality and consistency. Each port is now represented by a single, standardized name, making analysis easier and more reliable.
  - This correction minimizes errors in analysis that could arise from treating variations of the same port as distinct entities.
- **Streamlined Analysis**:

- With fewer unique names, analyses such as grouping, counting, or mapping trade routes by port are more straightforward and accurate. The consolidated names enable a clearer view of trade activity at each distinct port.

In summary, the correction has transformed a dataset with significant inconsistencies into a more streamlined and manageable form, improving the reliability and interpretability of future analyses.

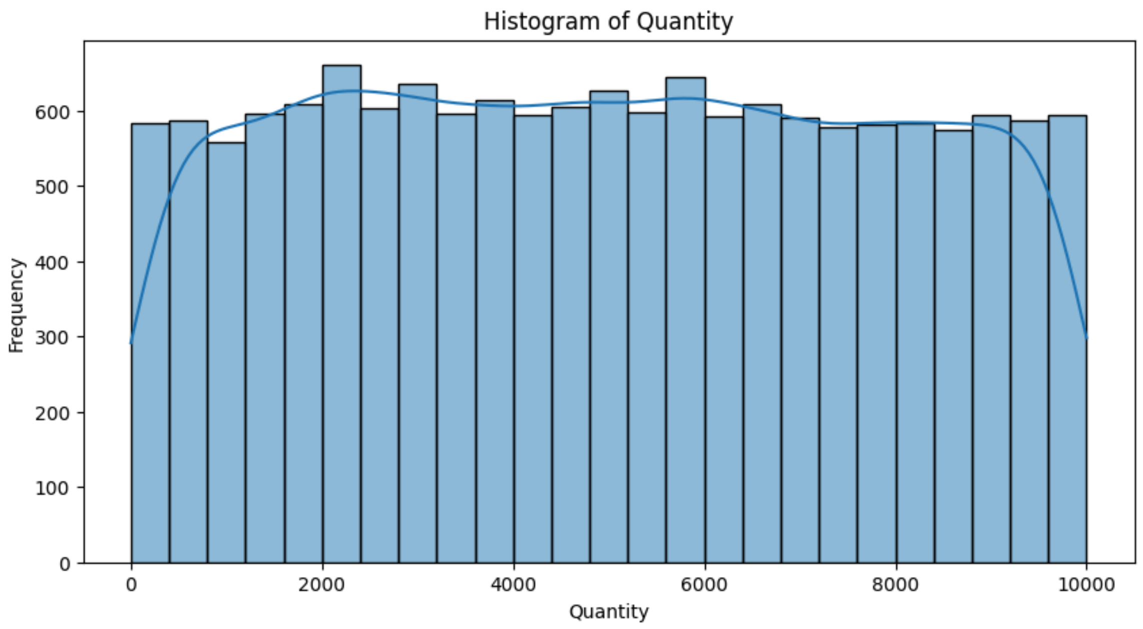
5.2. Visualisation

The data is visualized using various plots to identify patterns, trends, and relationships in the dataset.

5.2.1. Histogram

The histograms of the numerical columns are plotted to visualize the distribution of the data.

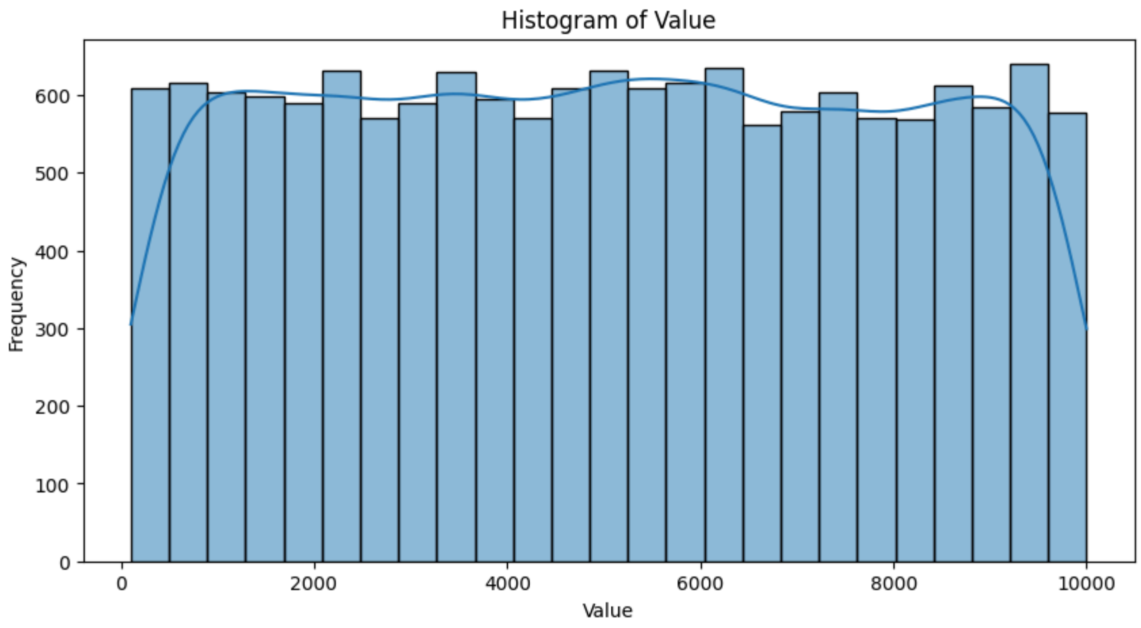
```
# plot the histogram of the numerical columns in the dataset i.e. 'Quantity',
'Value' and 'Weight' columns also label the x and y axis
# Quantity
plt.figure(figsize=(10,5))
sns.histplot(dataset['Quantity'], kde=True)
plt.xlabel('Quantity')
plt.ylabel('Frequency')
plt.title('Histogram of Quantity')
plt.show()
```



- The distribution of **Quantity** is mostly uniform, with some fluctuations across different quantity ranges.

- The KDE curve shows a slight rise around 1,000 and 7,000 units, indicating a small preference for these quantity levels in the dataset.
- There is a minor dip at the start of the range (close to 0) and at the higher end (close to 10,000).
- The overall shape suggests that transactions involve a wide range of item quantities with no strong concentration in any specific range, but there are slightly more transactions in the middle ranges (1,000 - 7,000 units).

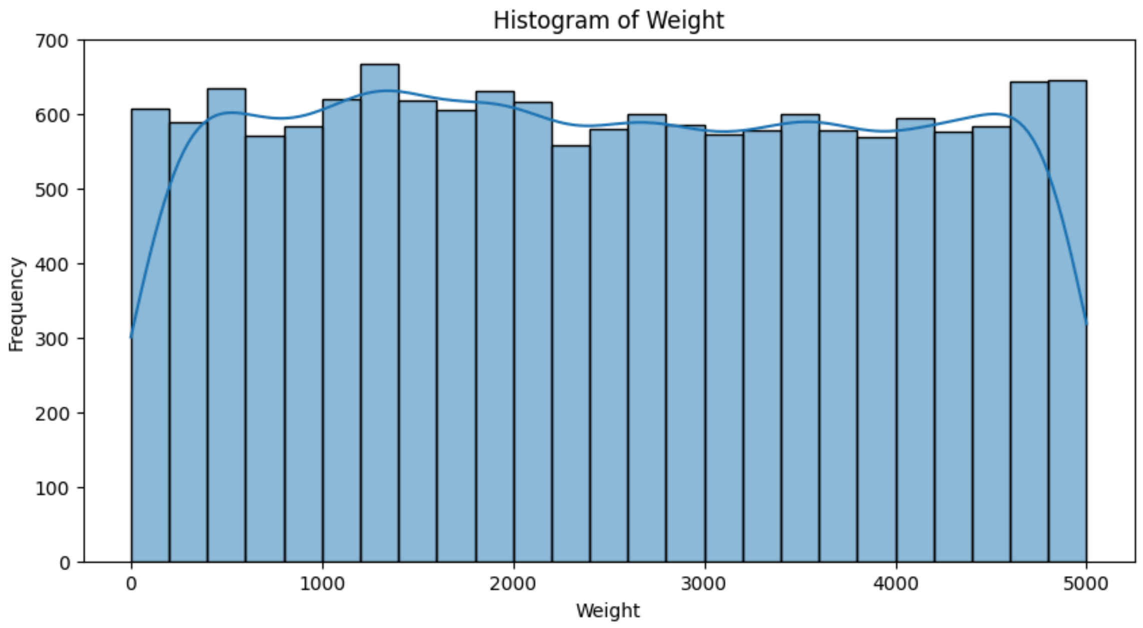
```python
# Value
plt.figure(figsize=(10,5))
sns.histplot(dataset['Value'], kde=True)
plt.xlabel('Value')
plt.ylabel('Frequency')
plt.title('Histogram of Value')
plt.show()
```



- The **Value** (in USD) is also relatively uniformly distributed, similar to the quantity.
- The KDE curve shows that there is a higher frequency of transactions with values between 1,000 and 7,000 USD.
- There are slight dips near 0 and 10,000 USD, meaning that fewer transactions involve extreme low or high values.
- The uniformity, with some concentration in the middle, suggests that the dataset has a balanced spread of transaction values, without strong bias toward very expensive or very inexpensive transactions.

```python
# Weight
plt.figure(figsize=(10,5))
```

```python
sns.histplot(dataset['Weight'], kde=True)
plt.xlabel('Weight')
plt.ylabel('Frequency')
plt.title('Histogram of Weight')
plt.show()
```



- The **Weight** (in kg) distribution shows similar patterns to the other variables, with a near-uniform spread across the range from 0 to 5,000 kg.
- The KDE curve shows slight peaks around the 1,000 - 2,000 kg and 4,000 - 5,000 kg ranges, meaning that some shipments tend to cluster in these weight ranges.
- Like the other variables, the frequency drops at the extremes (close to 0 kg and near 5,000 kg), with most transactions falling somewhere in the middle.
- This distribution indicates a broad range of shipment sizes, with a slight preference for medium to larger shipments.

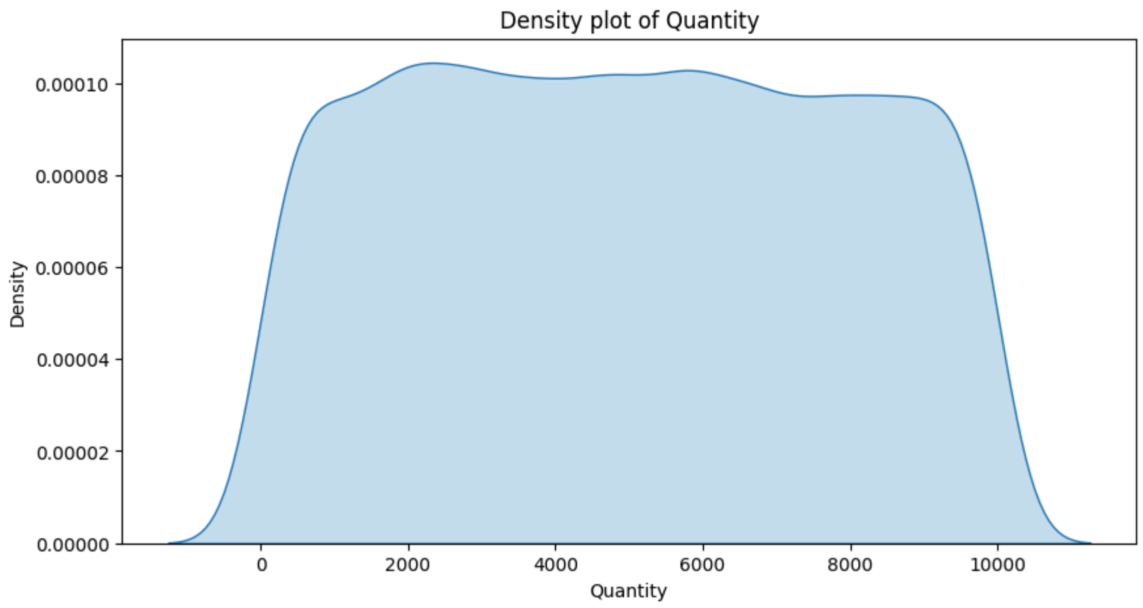
General Insights: - All three histograms show relatively uniform distributions with some minor fluctuations, indicating that the dataset has a wide range of values for quantity, value, and weight. - The slight concentration in the middle ranges (1,000 - 7,000 for Quantity and Value, and 1,000 - 5,000 for Weight) suggests that most transactions are of medium size in terms of quantity, value, and shipment weight, with fewer extreme small or large transactions. - The KDE curves further reinforce the idea that the distributions are relatively balanced, with no extreme skewness or concentration in any one area.

These visualizations suggest that the dataset is well-rounded and diverse in terms of the size, value, and weight of transactions.

5.3. Density Plots

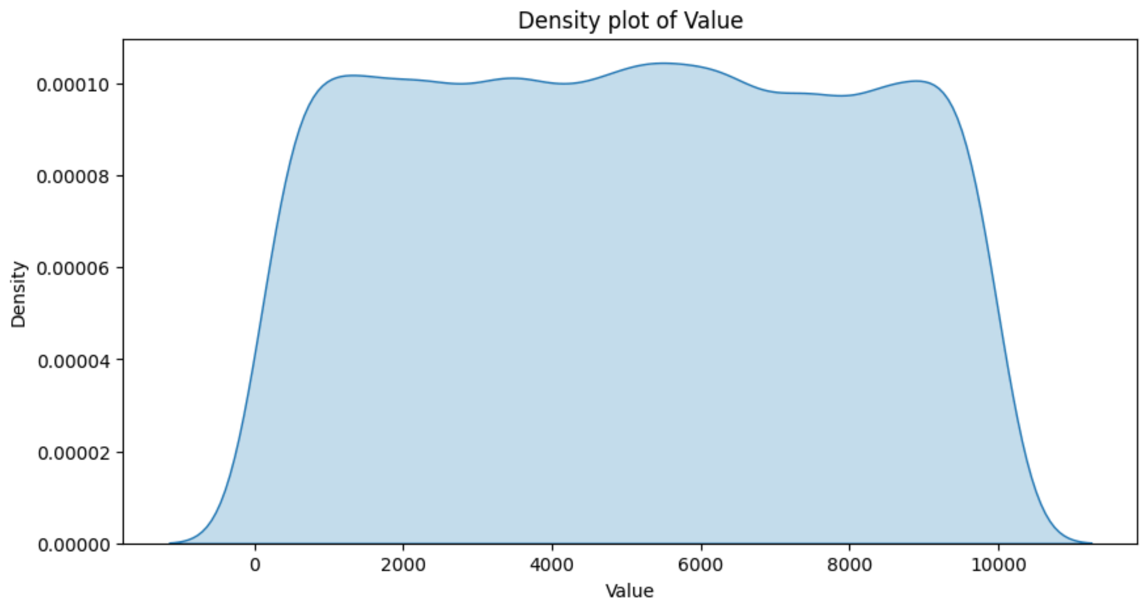
The density plots of the numerical columns are plotted to estimate the probability density function of variance in the data.

```
# plot the Density plot of the numerical columns in the dataset i.e. 'Quantity',
'Value' and 'Weight'  to estimate the probability
# density function of the variable
# Quantity
plt.figure(figsize=(10,5))
sns.kdeplot(dataset['Quantity'], fill=True)
plt.xlabel('Quantity')
plt.ylabel('Density')
plt.title('Density plot of Quantity')
plt.show()
```



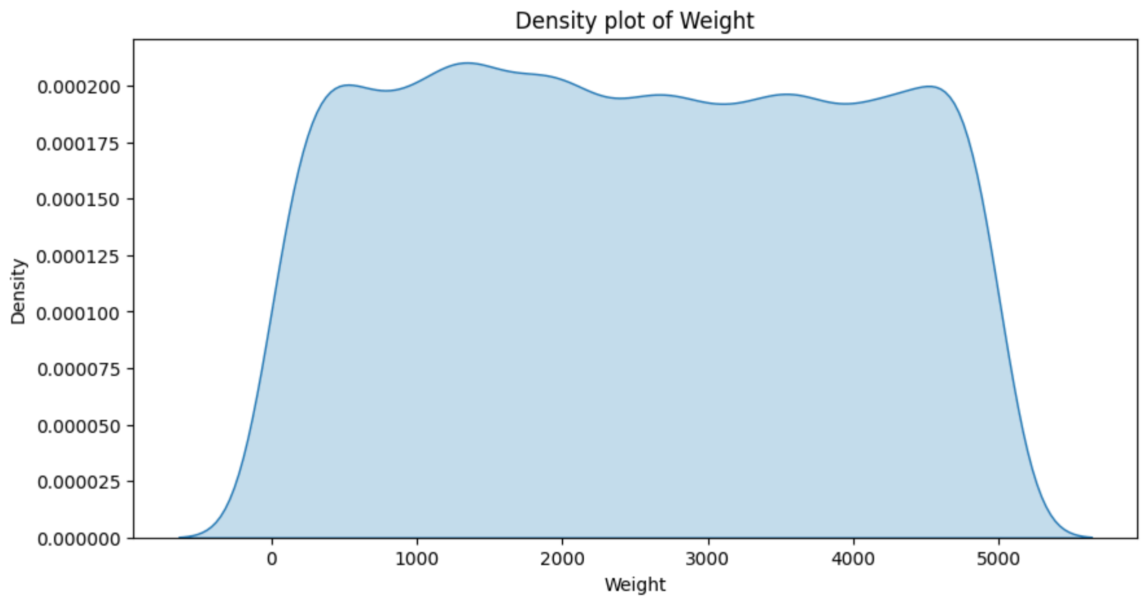
- The plot shows a flat density across the range from 0 to 10,000 units. This suggests a uniform distribution, where all quantity levels have almost equal likelihood of occurring.
- There are small fluctuations around 2,000 and 6,000 units, indicating that transactions involving these quantities might occur slightly more frequently, but overall, the density is evenly spread.
- The variance in the quantity data is consistent across the range, with no significant peaks or drops, indicating that different quantities are equally probable.

```
# Value
plt.figure(figsize=(10,5))
sns.kdeplot(dataset['Value'], fill=True)
plt.xlabel('Value')
plt.ylabel('Density')
plt.title('Density plot of Value')
plt.show()
```



- The Value (in USD) also shows a relatively flat density, indicating that transactions across the full range of values (from 0 to 10,000 USD) have almost equal likelihood.
- Small fluctuations around 2,000 and 9,000 USD suggest that there may be slightly more transactions involving values in these ranges, but overall, the distribution remains uniform.
- The density plot shows a uniform spread of transaction values, meaning the dataset contains a wide range of transaction amounts without significant variance in specific value ranges.

```
# Weight
plt.figure(figsize=(10,5))
sns.kdeplot(dataset['Weight'], fill=True)
plt.xlabel('Weight')
plt.ylabel('Density')
plt.title('Density plot of Weight')
plt.show()
```

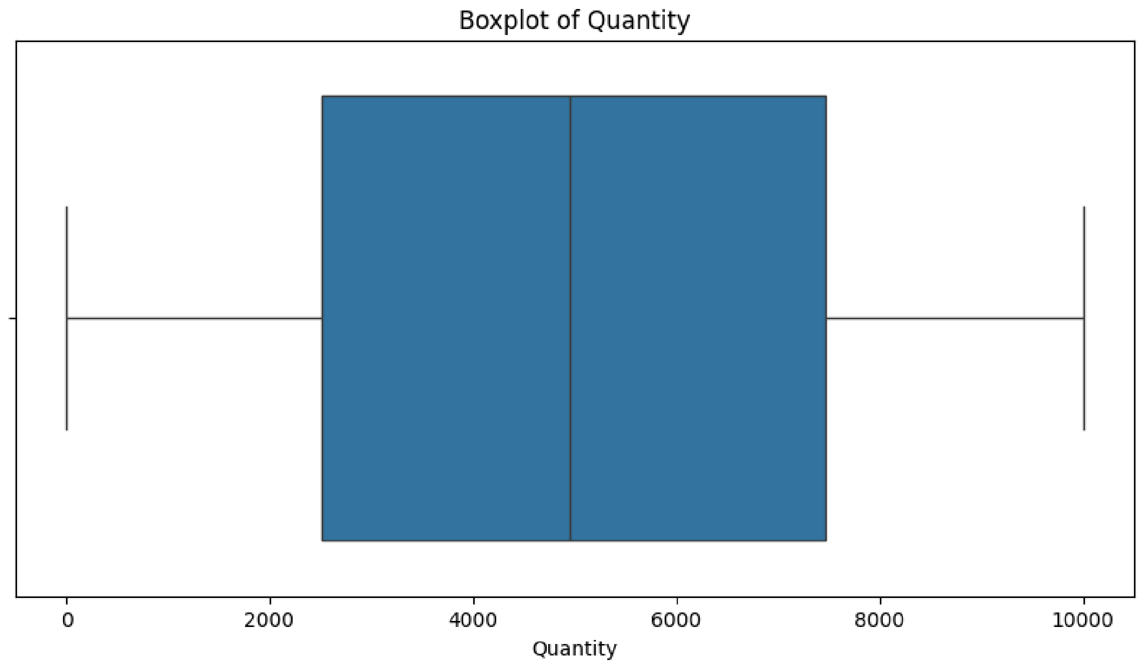


- The Weight (in kg) distribution follows a similar pattern, with a flat density across the range from 0 to 5,000 kg.
- Slight fluctuations can be seen around 1,000 and 4,000 kg, suggesting these weight ranges might occur slightly more often, but overall, the distribution remains even.
- The uniform shape of the density plot indicates that the variance in weights is consistent across different shipment sizes, with no strong bias toward small or large weights.

5.4. Box Plots

The box plots of the numerical columns are plotted to visualize the spread of the data and identify any outliers, quartiles, and median values.

```
# plot the boxplot of the numerical columns in the dataset i.e. 'Quantity',
'Value' and 'Weight' columns
# Quantity
plt.figure(figsize=(10,5))
sns.boxplot(x=dataset['Quantity'])
plt.xlabel('Quantity')
plt.title('Boxplot of Quantity')
plt.show()
```



Interpretation of the Box Plot for Quantity

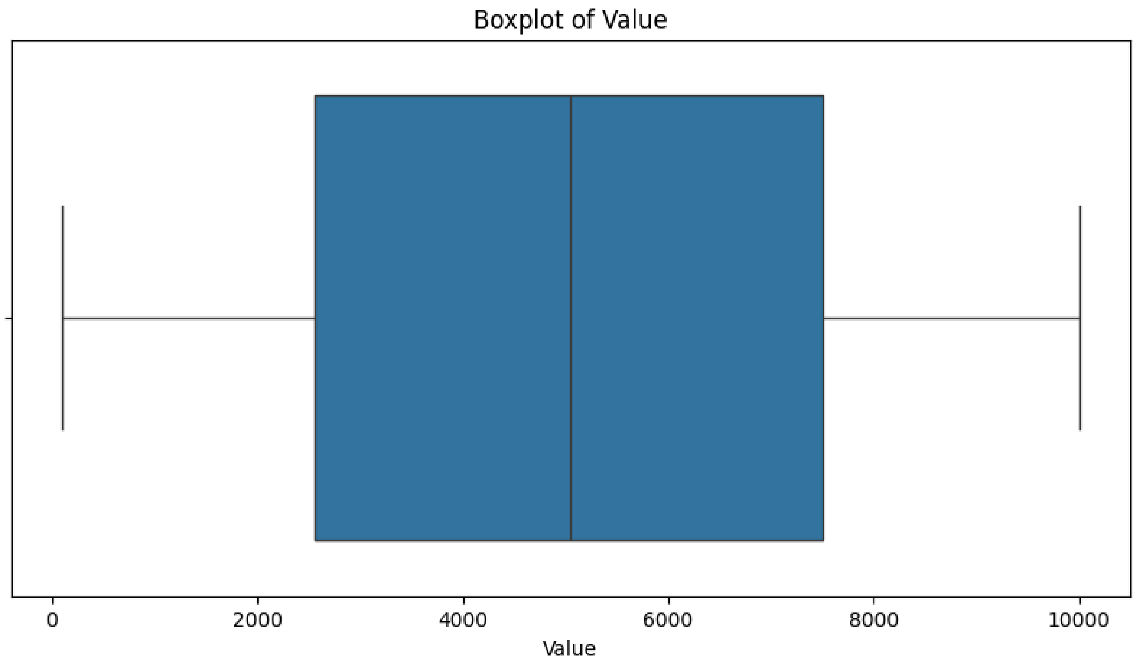
The box plot provides a summary of the distribution of the Quantity variable, highlighting key descriptive statistics such as the median, quartiles, and spread of the data. Here's a breakdown:

- **Median (50th Percentile)**:
  - The line inside the box represents the median value, which is around 5,000 units.
  - This indicates that half of the transactions involve quantities less than or equal to 5,000, and half involve more.
- **Interquartile Range (IQR)**:
  - The box itself represents the interquartile range (IQR), which covers the middle 50% of the data.
  - The lower boundary of the box is around 2,500 units (25th percentile), and the upper boundary is around 7,500 units (75th percentile).
  - This means that 50% of the transactions involve quantities between 2,500 and 7,500 units.
- **Whiskers**:
  - The whiskers extend from the box and represent the range of the data (excluding any outliers, if there were any).
  - The left (lower) whisker starts at 0 units, indicating that the smallest transaction involves no items.
  - The right (upper) whisker extends to 10,000 units, indicating that the largest transaction involves 10,000 items.
  - There are no apparent outliers in the data, as there are no points beyond the whiskers.
- **Symmetry**:

  - The box plot looks fairly symmetrical, suggesting that the quantity data is evenly distributed around the median.
  - The whiskers are approximately the same length, further supporting the idea that the data is spread relatively equally on both sides of the median.
- **General Insights**:
  - **Spread of Data**: The data shows a wide range of transaction quantities, from 0 to 10,000 units, with the middle 50% of transactions involving quantities between 2,500 and 7,500 units.
  - **No Outliers**: The absence of outliers suggests that there are no extreme values in the dataset that are significantly different from the rest of the data.

This box plot shows that the quantity of items involved in transactions is fairly evenly spread, with a typical transaction involving about 5,000 units, and no extreme values skewing the data.

```
# Value
plt.figure(figsize=(10,5))
sns.boxplot(x=dataset['Value'])
plt.xlabel('Value')
plt.title('Boxplot of Value')
plt.show()
```



Interpretation of the Box Plot for Value

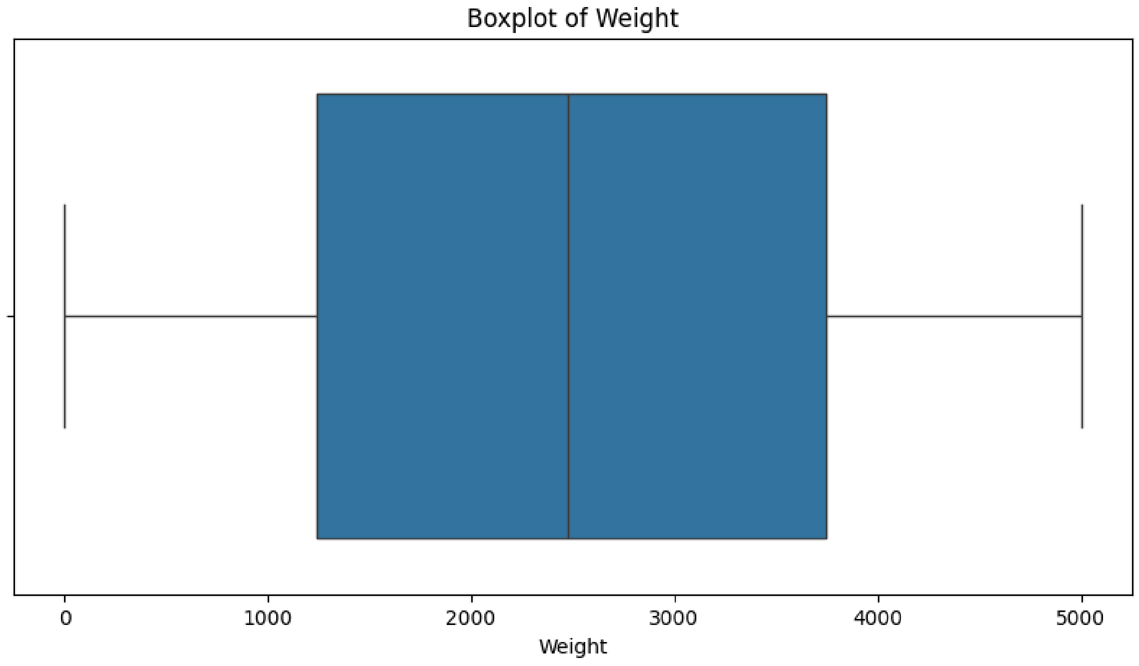
The box plot provides a summary of the Value variable (in USD) and highlights key descriptive statistics such as the median, quartiles, and the spread of the data.

- **Median (50th Percentile)**:

    - The line inside the box represents the median value, which is around 5,000 USD.
    - This indicates that half of the transactions have values less than or equal to 5,000 USD, and half are more than this amount.
- **Interquartile Range (IQR)**:
    - The box itself represents the interquartile range (IQR), which covers the middle 50% of the data.
    - The lower boundary of the box (25th percentile) is around 2,500 USD, and the upper boundary (75th percentile) is around 7,500 USD.
    - This means that 50% of the transactions have values between 2,500 and 7,500 USD.
- **Whiskers**:
    - The whiskers extend from the box and represent the range of the data, excluding any outliers.
    - The left (lower) whisker starts near 0 USD, indicating that some transactions have very low values.
    - The right (upper) whisker extends to 10,000 USD, meaning the highest transaction values are around this amount.
    - Like the box plot for quantity, there are no visible outliers beyond the whiskers.
- **Symmetry**:
    - The box plot looks fairly symmetrical, with both whiskers and the box itself being evenly distributed around the median.
    - This symmetry suggests that the value data is uniformly distributed, with no strong skew to one side or the other.
- **General Insights**:
    - **Spread of Data**: The values of the transactions vary from close to 0 USD to 10,000 USD, with the middle 50% of transactions having values between 2,500 and 7,500 USD.
    - **No Outliers**: There are no extreme outliers in the dataset, as no points fall beyond the whiskers.
    - **Uniform Distribution**: The symmetry of the box plot suggests that transaction values are fairly evenly distributed, with no significant skewness.

This box plot shows that the Value of transactions is well-distributed, with most transactions falling between 2,500 and 7,500 USD, and no extreme values in the dataset.

```python
# Weight
plt.figure(figsize=(10,5))
sns.boxplot(x=dataset['Weight'])
plt.xlabel('Weight')
plt.title('Boxplot of Weight')
plt.show()
```



Interpretation of the Box Plot for Weight

The box plot summarizes the distribution of the Weight variable (likely in kg), showcasing key descriptive statistics like the median, quartiles, and the overall range.

- **Median (50th Percentile)**:
  - The line inside the box represents the median weight, which is around 2,500 kg.
  - This indicates that half of the transactions have weights less than or equal to 2,500 kg, and the other half have weights above this amount.
- **Interquartile Range (IQR)**:
  - The box itself represents the interquartile range (IQR), which covers the middle 50% of the data.
  - The lower boundary of the box (25th percentile) is around 1,250 kg, and the upper boundary (75th percentile) is around 3,750 kg.
  - This means that 50% of the transactions have weights between 1,250 and 3,750 kg.
- **Whiskers**:
  - The whiskers extend from the box and represent the range of the data, excluding any outliers.
  - The left (lower) whisker starts close to 0 kg, indicating that some shipments have very low weights.
  - The right (upper) whisker extends to 5,000 kg, meaning the heaviest transactions involve shipments of 5,000 kg.
  - There are no visible outliers beyond the whiskers.
- **Symmetry**:
  - The box plot appears symmetrical, with the whiskers and the box evenly distributed around the median. This suggests a balanced spread of weights around the median value.

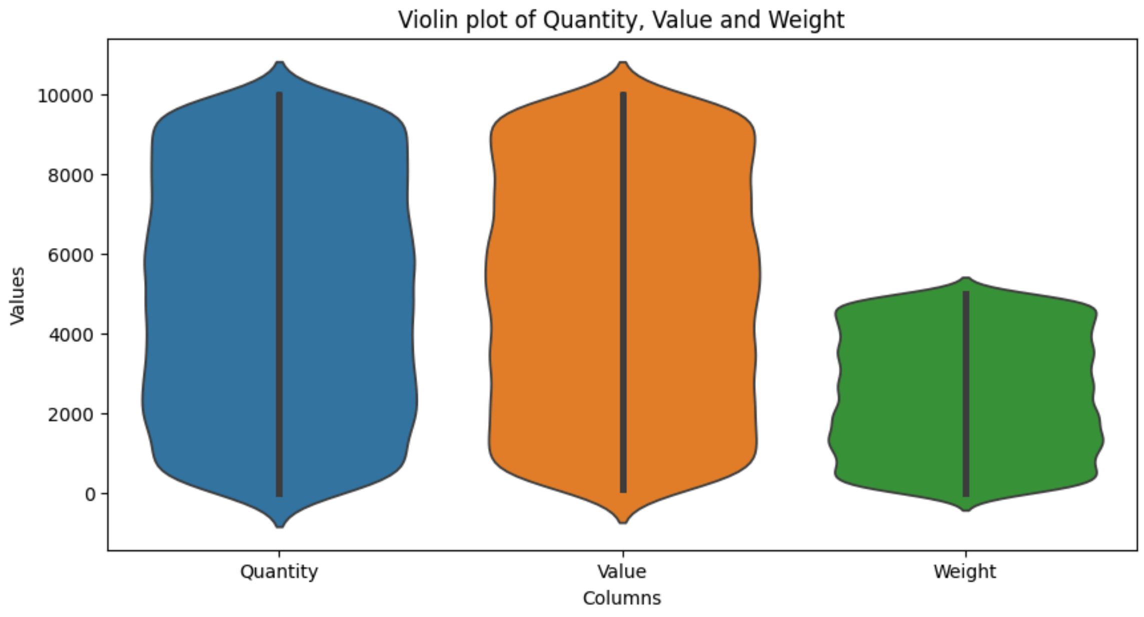
- **General Insights**:
  - **Spread of Data**: The weights of the shipments range from close to 0 kg to 5,000 kg, with the middle 50% of transactions having weights between 1,250 and 3,750 kg.
  - **No Outliers**: There are no extreme outliers in the data, as no points are plotted outside the whiskers.
  - **Uniform Distribution**: The symmetry in the box plot suggests that the distribution of weights is fairly even, with no significant skew.

This box plot suggests that the weight of shipments is well distributed, with typical transactions falling between 1,250 kg and 3,750 kg, and no extreme values in the dataset.

5.5 Violin Plots

The violin plots of the numerical columns are plotted to visualize the distribution of the data and compare the spread of the data between different categories.

```python
# plot the violin plot of the numerical columns in the dataset i.e. 'Quantity',
'Value' and 'Weight' columns
# show all three in one plot
plt.figure(figsize=(10,5))
sns.violinplot(data=dataset[['Quantity','Value','Weight']], inner="points")
plt.xlabel('Columns')
plt.ylabel('Values')
plt.title('Violin plot of Quantity, Value and Weight')
plt.show()
```



Interpretation of the Violin Plot for Quantity, Value, and Weight

The violin plot combines features of a box plot with a density plot, providing insights into the distribution of the data while also showing the probability density at different values. Here's an interpretation of each variable:

1. **Quantity**

- The violin plot for Quantity shows a fairly uniform distribution with slight bulges at the upper and lower portions, indicating a slight concentration of transactions around those values.
- The width of the violin shows how frequent each value range is. Since the plot has almost the same width throughout, it suggests that the quantity data is fairly evenly distributed, meaning that all quantity ranges occur with similar frequency.
- The central vertical line represents the interquartile range (IQR) and the median. The median appears around 5,000, confirming the uniform spread observed in previous plots.

2. **Value**

- The violin plot for Value (in USD) is very similar to that of Quantity, indicating a nearly uniform distribution of transaction values across the range.
- The slight bulges at both the top and bottom indicate that transactions around 1,000 and 9,000 USD are slightly more common than values in the middle.
- The central line suggests that the median value is also around 5,000 USD, with the interquartile range spread similarly to the Quantity plot.

3. **Weight**

- The violin plot for Weight (in kg) has a different shape compared to Quantity and Value. It has a slight hourglass shape, indicating that most shipments cluster around the middle values (between 1,000 and 4,000 kg).
- The plot is narrower at the extremes (close to 0 and 5,000 kg), suggesting that there are fewer very small or very large shipments.
- The central line shows that the median weight is around 2,500 kg, consistent with the previous plots, and most of the data is centered around the middle, with fewer extremes.

General Insights: - **Quantity and Value**: Both show almost uniform distributions, with slight concentration at the lower and upper ends. This suggests that all quantity and value ranges are relatively equally represented in the dataset. - **Weight**: The weight distribution is slightly more concentrated in the middle, indicating that most shipments are around average weights, with fewer very light or very heavy shipments. - **No Skew**: None of the distributions show significant skewness, which means that the data is **well-balanced** across different ranges for all three variables.

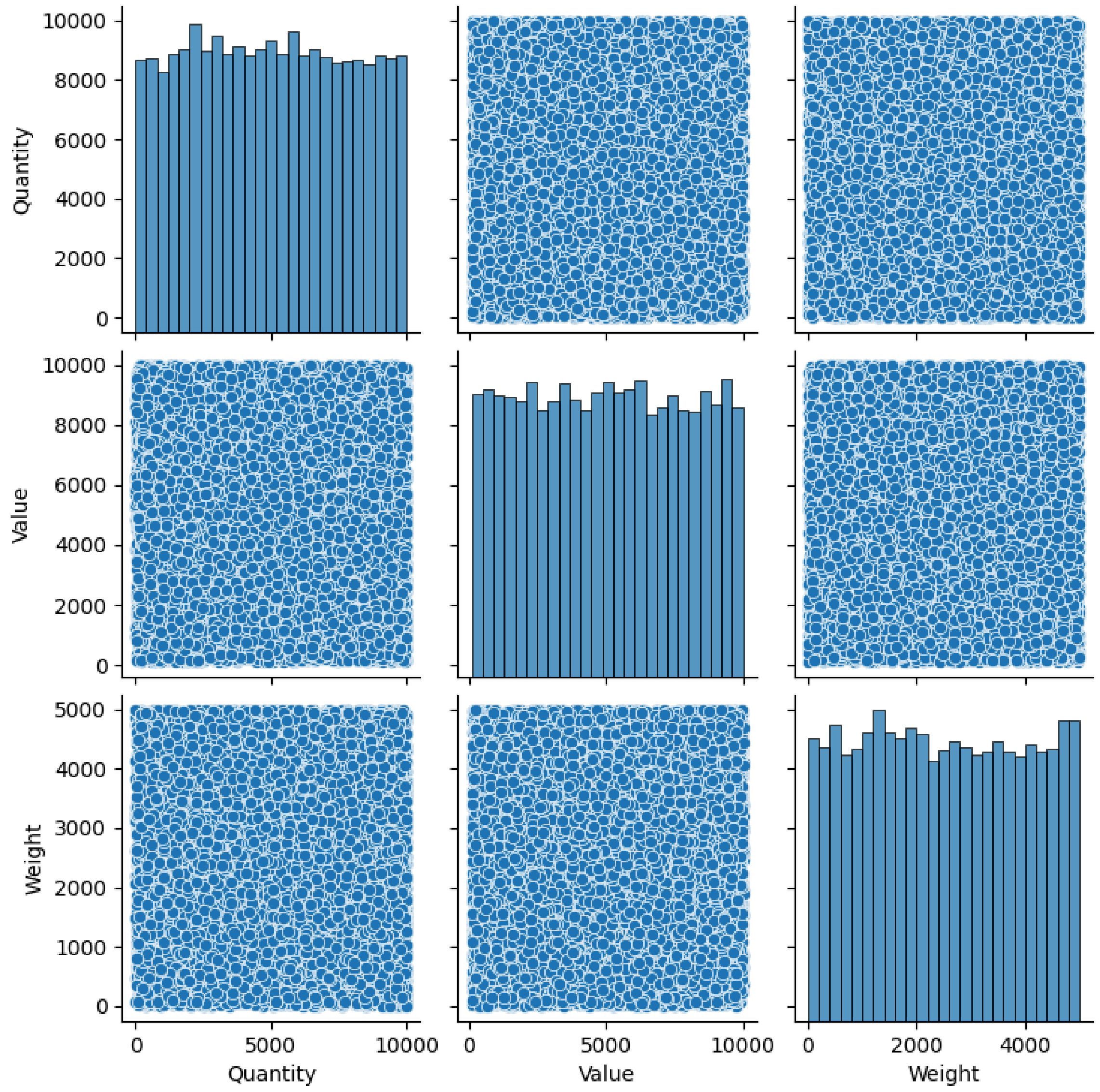
The violin plot provides a clear visualization of how Quantity, Value, and Weight are distributed, with Quantity and Value being fairly uniform, and Weight having a more typical bell-shaped distribution centered around the median.

5.6 Pair Plots

The pair plots of the numerical columns are plotted to visualize the relationships between the variables and identify any patterns or correlations.

```
# plot the pairplot of the numerical columns in the dataset i.e. 'Quantity',
'Value' and 'Weight' columns
plt.figure(figsize=(10,5))
sns.pairplot(dataset[['Quantity','Value','Weight']])
plt.show()
```

```
<Figure size 1000x500 with 0 Axes>
```



Interpretation of the Pair Plot

A pair plot (or scatter plot matrix) visualizes the pairwise relationships between multiple variables, along with the distribution of each individual variable. In this case, the pair plot shows the relationships between Quantity, Value, and Weight. Here's the detailed interpretation:

1. **Diagonal Elements (Histograms)**:

- The **diagonal** elements show the histograms for each variable (Quantity, Value, Weight), giving an insight into their individual distributions.
- **Quantity**: The histogram shows a relatively uniform distribution, with some small fluctuations, indicating that quantities of items in transactions are spread fairly evenly across the range of 0 to 10,000 units.
- **Value**: The value histogram also shows a uniform distribution, similar to Quantity, with values spread evenly from 0 to 10,000 USD.
- **Weight**: The distribution for Weight (in kg) shows a slightly different pattern, with some minor peaks and valleys, but overall the distribution is still relatively even, with a slightly more pronounced concentration of transactions around 1,000 to 4,000 kg.

2. **Scatter Plots (Off-diagonal elements)**: The scatter plots between pairs of variables are displayed in the off-diagonal elements of the matrix. These help identify potential relationships between variables.

- **Quantity vs Value**:
  - The scatter plot for Quantity and Value shows a random pattern with no clear trend. The points are spread evenly across the entire range.
  - This suggests no strong linear relationship between the quantity of items in a transaction and the transaction's value. In other words, higher quantities do not necessarily correspond to higher values, and vice versa.
- **Quantity vs Weight**:
  - The scatter plot between Quantity and Weight also shows a random distribution of points with no visible pattern or trend.
  - This suggests that there is no significant relationship between the number of items and the weight of the shipment. Large or small quantities of items do not appear to correlate directly with the weight.
- **Value vs Weight**:
  - The scatter plot for Value and Weight shows a similar random spread as the other pairs, indicating that the monetary value of transactions does not strongly correlate with the weight of the shipment.
  - Transactions with higher values do not necessarily involve heavier shipments, and vice versa.

3. **General Insights**:

- **No Strong Relationships**: The scatter plots between Quantity, Value, and Weight show no clear patterns or trends, indicating that these variables are largely independent of one another.

There is no significant linear relationship between the quantity of items, their value, and their weight.
- **Uniform Distributions**: Both the Quantity and Value histograms show a nearly uniform distribution, meaning the transactions are evenly distributed across different ranges. Weight shows a more varied distribution, but it's still fairly balanced.

In summary, the pair plot highlights that Quantity, Value, and Weight do not have strong pairwise relationships and are relatively independent of one another in this dataset. The uniformity in the distributions suggests that the dataset is diverse, covering a wide range of transaction types.

5.3. Normality Tests

The normality tests are performed on the numerical columns to check if the data follows a normal distribution.

5.3.1. Shapiro-Wilk Test

The Shapiro-Wilk test is used to check the normality of the data. The null hypothesis is that the data is normally distributed.

```
# perform the shapiro-wilk test to check the normality of the numerical columns
in the dataset i.e. 'Quantity', 'Value' and 'Weight' columns
from scipy.stats import shapiro

# Quantity
stat, p = shapiro(dataset['Quantity'])
print('Quantity:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Sample looks Gaussian (fail to reject H0)')
else:
    print('Sample does not look Gaussian (reject H0)')
print('-------------------------------------')

# Value
stat, p = shapiro(dataset['Value'])
print('Value:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Sample looks Gaussian (fail to reject H0)')
else:
    print('Sample does not look Gaussian (reject H0)')
print('-------------------------------------')

# Weight
stat, p = shapiro(dataset['Weight'])
print('Weight:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Sample looks Gaussian (fail to reject H0)')
else:
    print('Sample does not look Gaussian (reject H0)')
print('------------------------------------')
```

```
Quantity:
Statistics=0.957, p=0.000
Sample does not look Gaussian (reject H0)
------------------------------------
Value:
Statistics=0.955, p=0.000
Sample does not look Gaussian (reject H0)
------------------------------------
Weight:
Statistics=0.954, p=0.000
Sample does not look Gaussian (reject H0)
------------------------------------
```

```
c:\Users\Asad          Raza          Virk\miniconda3\envs\python_eda\Lib\site-
packages\scipy\stats\_axis_nan_policy.py:573: UserWarning: scipy.stats.shapiro:
For N > 5000, computed p-value may not be accurate. Current N is 15000.
  res = hypotest_fun_out(*samples, **kwds)
```

1. **Understanding the Shapiro-Wilk Test**:
   - The Shapiro-Wilk test is used to assess whether a given dataset follows a normal distribution.
   - The null hypothesis (H0) for this test is that the data is normally distributed.
   - If the p-value is greater than 0.05, you fail to reject H0, meaning the data may be normal.
   - If the p-value is less than 0.05, you reject H0, meaning the data does not appear to be normally distributed.
2. **Test Results Interpretation**: For each column, the test provided the following results:

- **Quantity**:
  - Statistics=0.957, p=0.000.
  - **Interpretation**: The p-value is extremely small (0.000), which means we reject the null hypothesis (H0).
  - **Conclusion**: The Quantity data does not follow a normal (Gaussian) distribution.
- **Value**:
  - Statistics=0.955, p=0.000.
  - **Interpretation**: Similarly, the p-value is 0.000, so we reject H0.
  - **Conclusion**: The Value data does not follow a normal (Gaussian) distribution.
- **Weight**:
  - Statistics=0.954, p=0.000.

  - **Interpretation**: The p-value is 0.000 again, so we reject H0.
  - **Conclusion**: The Weight data does not follow a normal (Gaussian) distribution.

3. **Implications of Non-Gaussian Distributions**:
   - **Non-normality**: Since the data for Quantity, Value, and Weight does not follow a normal distribution, some statistical techniques (e.g., parametric tests like t-tests or ANOVA) that assume normality might not be appropriate for this data.
   - **Alternative Approaches**: You may need to use non-parametric tests (such as the Mann-Whitney U test, Kruskal-Wallis test) or consider data transformations (like log or square root transformations) to normalize the data if needed for specific analyses.
4. **Understanding the Warning**:
   - **Warning**: scipy.stats.shapiro: For N > 5000, computed p-value may not be accurate. Current N is 15000.
   - This warning is issued because the Shapiro-Wilk test is not designed for very large datasets. It works best for small to medium-sized datasets. When you have more than 5,000 samples, the test might still give a p-value, but its accuracy diminishes.
   - In your case, you have 15,000 data points, which exceeds the recommended limit for the Shapiro-Wilk test.
5. **How to Address the Warning**:
   - **Alternative Tests**: Since the dataset is large, consider using other normality tests that handle large datasets better, such as:
     - Kolmogorov-Smirnov (K-S) Test
     - Anderson-Darling Test
     - Lilliefors Test
6. **Conclusion**:
   - The Quantity, Value, and Weight columns do not follow a normal distribution according to the Shapiro-Wilk test ($p < 0.05$).
   - Due to the large sample size, the warning suggests that the p-value may not be perfectly accurate, so it is recommended to use alternative tests such as the K-S test for datasets with over 5,000 entries.
   - Depending on your analysis, you might need to use non-parametric statistical methods or apply data transformations to address the non-normality.

5.3.2 Mann-Whitney U Test (Wilcoxon Rank-Sum Test)

The Mann-Whitney U test (also known as the Wilcoxon rank-sum test) is used to compare two independent samples to assess if they come from the same distribution.

```python
# perform Mann-Whitney U test to check the difference in the distribution of the
numerical columns in the dataset i.e. 'Quantity', 'Value' and 'Weight' columns
from scipy.stats import mannwhitneyu

# Quantity vs Value
stat, p = mannwhitneyu(dataset['Quantity'], dataset['Value'])
print('Quantity vs Value:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Same distribution (fail to reject H0)')
else:
    print('Different distribution (reject H0)')
print('------------------------------------')

# Quantity vs Weight
stat, p = mannwhitneyu(dataset['Quantity'], dataset['Weight'])
print('Quantity vs Weight:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Same distribution (fail to reject H0)')
else:
    print('Different distribution (reject H0)')
print('------------------------------------')

# Value vs Weight
stat, p = mannwhitneyu(dataset['Value'], dataset['Weight'])
print('Value vs Weight:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Same distribution (fail to reject H0)')
else:
    print('Different distribution (reject H0)')
print('------------------------------------')
```

```
Quantity vs Value:
Statistics=111318135.000, p=0.115
Same distribution (fail to reject H0)
------------------------------------
Quantity vs Weight:
Statistics=169020986.000, p=0.000
Different distribution (reject H0)
------------------------------------
Value vs Weight:
Statistics=170346902.000, p=0.000
Different distribution (reject H0)
------------------------------------
```

Interpretation of Mann-Whitney U Test Results The Mann-Whitney U Test is a non-parametric test used to compare the distributions of two independent groups. It tests whether one group tends to have larger values than the other or if they are drawn from the same distribution. The null hypothesis (H0) is that the two samples come from the same distribution.

Let's break down each result:

- + **Quantity vs Value**:
  - Statistics = 111318135.000, p = 0.115
  - **Interpretation**:
    - The p-value is 0.115, which is greater than 0.05.
    - This means we fail to reject the null hypothesis (H0), implying that the Quantity and Value variables likely come from the same distribution.
  - **Conclusion**: There is no significant difference in the distributions of Quantity and Value. This suggests that the values for both variables are distributed similarly, even though they measure different things.
- 2. **Quantity vs Weight**:
  - Statistics = 169020986.000, p = 0.000
  - **Interpretation**:
    - The p-value is 0.000, which is less than 0.05.
    - This means we reject the null hypothesis (H0), implying that the Quantity and Weight variables come from different distributions.
  - **Conclusion**: There is a significant difference in the distributions of Quantity and Weight. This suggests that the values for these two variables differ in terms of their spread, range, or shape, meaning that the quantity of items and their weight do not follow similar patterns.
- 3. **Value vs Weight**:
  - Statistics = 170346902.000, p = 0.000
  - **Interpretation**:
    - The p-value is 0.000, which is less than 0.05.
    - This means we reject the null hypothesis (H0), implying that the Value and Weight variables come from different distributions.
  - **Conclusion**: There is a significant difference in the distributions of Value and Weight. The monetary value of transactions and their corresponding weights do not follow the same distribution pattern, indicating different underlying behaviors for these two variables.
- **Summary of Results**:
  - **Quantity vs Value**: The two variables have similar distributions, suggesting that the quantities and values of transactions follow similar patterns.
  - **Quantity vs Weight**: The two variables have different distributions, indicating that the number of items in a transaction and their total weight vary in a non-similar way.
  - **Value vs Weight**: The two variables have different distributions, suggesting that the monetary value of a transaction and the weight of items involved follow distinct patterns.
- **Implications**:

- The fact that Quantity and Value are distributed similarly might indicate that in this dataset, larger quantities tend to correlate with higher transaction values, although this is not a direct correlation but a distributional similarity.
- The differences in distribution between Quantity and Weight and between Value and Weight highlight that, despite potential correlations, the total number of items or the value does not consistently translate into weight in the same way. There might be other factors (like the type of product) affecting the weight differently from quantity and value.

5.3.3 Kolmogorov-Smirnov Test

The Kolmogorov-Smirnov test is used to compare the distributions of two samples and assess if they come from the same distribution.

```
# perform kolmogorov-smirnov test to check the difference in the distribution
of the numerical columns in the dataset i.e. 'Quantity', 'Value' and 'Weight'
columns
from scipy.stats import ks_2samp

# Quantity vs Value
stat, p = ks_2samp(dataset['Quantity'], dataset['Value'])
print('Quantity vs Value:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Same distribution (fail to reject H0)')
else:
    print('Different distribution (reject H0)')
print('-------------------------------------')

# Quantity vs Weight
stat, p = ks_2samp(dataset['Quantity'], dataset['Weight'])
print('Quantity vs Weight:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Same distribution (fail to reject H0)')
else:
    print('Different distribution (reject H0)')
print('-------------------------------------')

# Value vs Weight
stat, p = ks_2samp(dataset['Value'], dataset['Weight'])
print('Value vs Weight:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Same distribution (fail to reject H0)')
else:
    print('Different distribution (reject H0)')
print('------------------------------------')
```

```
Quantity vs Value:
Statistics=0.010, p=0.413
Same distribution (fail to reject H0)
------------------------------------
Quantity vs Weight:
Statistics=0.495, p=0.000
Different distribution (reject H0)
------------------------------------
Value vs Weight:
Statistics=0.505, p=0.000
Different distribution (reject H0)
------------------------------------
```

The results from the Kolmogorov-Smirnov (K-S) Test, which is a non-parametric test used to compare two distributions. The K-S test compares the cumulative distributions of two datasets and tests whether they come from the same distribution or not.

The null hypothesis (H0) in the K-S test is that the two samples being compared come from the same distribution.

Let's break down the results for each pair:

- + **Quantity vs Value**:
  - Statistics = 0.010, p = 0.413
  - **Interpretation**:
    - The p-value is 0.413, which is greater than 0.05. This means we fail to reject the null hypothesis (H0).
  - **Conclusion**: The test indicates that Quantity and Value likely come from the same distribution. In other words, there is no significant difference between how these two variables are distributed, even though they measure different things.
  - **Significance**: The K-S statistic is very small (0.010), reinforcing that the distributions of Quantity and Value are similar.
- 2. **Quantity vs Weight**:
  - Statistics = 0.495, p = 0.000
  - **Interpretation**:
    - The p-value is 0.000, which is less than 0.05. This means we reject the null hypothesis (H0).
  - **Conclusion**: The test indicates that Quantity and Weight come from different distributions. The distributions of these two variables are significantly different.
  - **Significance**: The K-S statistic is relatively large (0.495), indicating a strong difference between the distributions of Quantity and Weight.

- 3. **Value vs Weight**:
  - Statistics = 0.505, p = 0.000
  - **Interpretation**:
    - The p-value is 0.000, which is less than 0.05. This means we reject the null hypothesis (H0).
  - **Conclusion**: The test indicates that Value and Weight come from different distributions. There is a significant difference between how these two variables are distributed.
  - **Significance**: The K-S statistic is relatively large (0.505), indicating a strong difference between the distributions of Value and Weight.
- **Summary of Results**:
  - **Quantity vs Value**: The two variables share a similar distribution (fail to reject H0). This suggests that the number of items (Quantity) and the transaction values (Value) follow similar patterns or distributions.
  - **Quantity vs Weight**: The two variables come from different distributions (reject H0). This indicates that the Quantity of items in a transaction and their Weight are distributed differently, and they do not follow the same pattern.
  - **Value vs Weight**: The two variables come from different distributions (reject H0). The Value of a transaction and the Weight of the items are not distributed in a similar way, meaning there is no clear relationship in how they vary together.
- **Implications**:
  - The fact that Quantity and Value share a similar distribution might suggest a proportional relationship between these variables, where larger quantities tend to correlate with higher transaction values. However, it's important to note that this is a distributional comparison, not necessarily a direct linear correlation.
  - Quantity vs Weight and Value vs Weight being distributed differently suggests that there is no uniform relationship between the number of items, their value, and their total weight. This could imply that some items are very light but expensive, while others may be heavier but not necessarily more valuable.

---

6. Comparsion

6.1. Variance Comparison with Levene's Test

Levene's test is used to compare the variances of two or more groups to check if they are equal or not. The null hypothesis (H0) is that the variances are equal.

```python
# perform the levene test to check the homogeneity of variance of the numerical
columns in the dataset i.e. 'Quantity', 'Value' and 'Weight' columns
from scipy.stats import levene
```

```python
# Quantity vs Value
stat, p = levene(dataset['Quantity'], dataset['Value'])
print('Quantity vs Value:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Equal variance (fail to reject H0)')
else:
    print('Different variance (reject H0)')

print('------------------------------------')

# Quantity vs Weight
stat, p = levene(dataset['Quantity'], dataset['Weight'])
print('Quantity vs Weight:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Equal variance (fail to reject H0)')
else:
    print('Different variance (reject H0)')
print('------------------------------------')

# Value vs Weight
stat, p = levene(dataset['Value'], dataset['Weight'])
print('Value vs Weight:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Equal variance (fail to reject H0)')
else:
    print('Different variance (reject H0)')
print('------------------------------------')
```

```
Quantity vs Value:
Statistics=0.168, p=0.682
Equal variance (fail to reject H0)
------------------------------------
Quantity vs Weight:
Statistics=8545.130, p=0.000
Different variance (reject H0)
------------------------------------
Value vs Weight:
Statistics=8500.710, p=0.000
Different variance (reject H0)
------------------------------------
```

The Levene's Test is used to assess the equality of variances between two or more groups. The null hypothesis (H0) for Levene's test is that the variances are equal across the groups being tested. If the p-value is greater than 0.05, we fail to reject the null hypothesis, indicating equal variances. If the p-value is less than 0.05, we reject the null hypothesis, indicating unequal variances.

Here's a breakdown of the results for each comparison:

- + **Quantity vs Value**
  - Statistics = 0.168, p = 0.682
  - **Interpretation**:
    - The p-value is 0.682, which is greater than 0.05.
    - This means we fail to reject the null hypothesis (H0), indicating that Quantity and Value have equal variances.
  - **Conclusion**: The variances of Quantity and Value are likely similar, which suggests that these two variables have a consistent spread or dispersion around their means. This similarity in variances may indicate that Quantity and Value are relatively comparable in terms of variability within the dataset.
- 2. **Quantity vs Weight**
  - Statistics = 8545.130, p = 0.000
  - **Interpretation**:
    - The p-value is 0.000, which is less than 0.05.
    - This means we reject the null hypothesis (H0), indicating that Quantity and Weight have different variances.
  - **Conclusion**: There is a significant difference in the variance of Quantity and Weight. This suggests that the Weight variable has a different level of spread compared to Quantity. One variable may have a much wider range or dispersion of values than the other, which could imply that Weight is less consistent or more varied compared to Quantity.
- 3. **Value vs Weight**
  - Statistics = 8500.710, p = 0.000
  - **Interpretation**:
    - The p-value is 0.000, which is less than 0.05.
    - This means we reject the null hypothesis (H0), indicating that Value and Weight have different variances.
  - **Conclusion**: There is a significant difference in the variance of Value and Weight. This suggests that these two variables do not share similar variability, and one of them has a much wider distribution or range than the other. This may imply that Weight is more variable or inconsistent compared to Value.
- **Summary of Results**:
  - **Quantity vs Value**: The variances are equal (fail to reject H0), meaning the spread or dispersion of Quantity and Value is similar.

- **Quantity vs Weight**: The variances are different (reject H0), indicating that Quantity and Weight have significantly different levels of spread.
- **Value vs Weight**: The variances are different (reject H0), indicating that Value and Weight also have significantly different levels of spread.

• **Implications**:
  - **Equal Variance (Quantity vs Value)**: Since Quantity and Value have similar variances, their spread around the mean is relatively consistent. This could support the findings from previous tests suggesting a distributional similarity between these two variables.
  - **Unequal Variance (Quantity vs Weight and Value vs Weight)**: The high variance differences between Quantity and Weight and between Value and Weight suggest that Weight is distributed differently, with potentially greater variability or a different scale of values. This reinforces previous findings that Weight may behave differently compared to Quantity and Value.

6.2. Categorical Comparisons

Categorical comparisons are performed to analyze the relationships between different categorical variables in the dataset.

6.2.1. Chi-Square Test of Independence

The Chi-Square Test of Independence is used to determine if there is a significant association between two categorical variables. The null hypothesis (H0) is that the two variables are independent.

```
# perform the chi-square test to check the independence of the categorical columns
in the dataset i.e. 'Country', 'Product' and 'Import_Export', 'Shipping_Method',
'Port' and 'Category' columns
from scipy.stats import chi2_contingency

# Country vs Product
contingency_table = pd.crosstab(dataset['Country'], dataset['Product'])
stat, p, dof, expected = chi2_contingency(contingency_table)
print('Country vs Product:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Independent (fail to reject H0)')
else:
    print('Dependent (reject H0)')
print('-------------------------------------')

# Country vs Import_Export
contingency_table = pd.crosstab(dataset['Country'], dataset['Import_Export'])
stat, p, dof, expected = chi2_contingency(contingency_table)
print('Country vs Import_Export:')
```

```python
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Independent (fail to reject H0)')
else:
    print('Dependent (reject H0)')
print('-------------------------------------')

# Country vs Shipping_Method
contingency_table = pd.crosstab(dataset['Country'], dataset['Shipping_Method'])
stat, p, dof, expected = chi2_contingency(contingency_table)
print('Country vs Shipping_Method:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Independent (fail to reject H0)')
else:
    print('Dependent (reject H0)')
print('-------------------------------------')

# Country vs Corrected_Port
contingency_table = pd.crosstab(dataset['Country'], dataset['Corrected_Port'])
stat, p, dof, expected = chi2_contingency(contingency_table)
print('Country vs Corrected_Port:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Independent (fail to reject H0)')
else:
    print('Dependent (reject H0)')
print('-------------------------------------')

# Country vs Category
contingency_table = pd.crosstab(dataset['Country'], dataset['Category'])
stat, p, dof, expected = chi2_contingency(contingency_table)
print('Country vs Category:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Independent (fail to reject H0)')
else:
    print('Dependent (reject H0)')
print('-------------------------------------')


# Product vs Import_Export
contingency_table = pd.crosstab(dataset['Product'], dataset['Import_Export'])
stat, p, dof, expected = chi2_contingency(contingency_table)
```

```python
print('Product vs Import_Export:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Independent (fail to reject H0)')
else:
    print('Dependent (reject H0)')
print('------------------------------------')

# Product vs Shipping_Method
contingency_table = pd.crosstab(dataset['Product'], dataset['Shipping_Method'])
stat, p, dof, expected = chi2_contingency(contingency_table)
print('Product vs Shipping_Method:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Independent (fail to reject H0)')
else:
    print('Dependent (reject H0)')
print('------------------------------------')

# Product vs Correct_Port
contingency_table = pd.crosstab(dataset['Product'], dataset['Corrected_Port'])
stat, p, dof, expected = chi2_contingency(contingency_table)
print('Product vs Corrected_Port:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Independent (fail to reject H0)')
else:
    print('Dependent (reject H0)')
print('------------------------------------')

# Product vs Category
contingency_table = pd.crosstab(dataset['Product'], dataset['Category'])
stat, p, dof, expected = chi2_contingency(contingency_table)
print('Product vs Category:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Independent (fail to reject H0)')
else:
    print('Dependent (reject H0)')
print('------------------------------------')


# Import_Export vs Shipping_Method
contingency_table           =           pd.crosstab(dataset['Import_Export'],
dataset['Shipping_Method'])
stat, p, dof, expected = chi2_contingency(contingency_table)
print('Import_Export vs Shipping_Method:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Independent (fail to reject H0)')
else:
    print('Dependent (reject H0)')
print('------------------------------------')

# Import_Export vs Corrected_Port
contingency_table           =           pd.crosstab(dataset['Import_Export'],
dataset['Corrected_Port'])
stat, p, dof, expected = chi2_contingency(contingency_table)
print('Import_Export vs Corrected_Port:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Independent (fail to reject H0)')
else:
    print('Dependent (reject H0)')
print('------------------------------------')

# Import_Export vs Category
contingency_table = pd.crosstab(dataset['Import_Export'], dataset['Category'])
stat, p, dof, expected = chi2_contingency(contingency_table)
print('Import_Export vs Category:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Independent (fail to reject H0)')
else:
    print('Dependent (reject H0)')
print('------------------------------------')


# Shipping_Method vs Corrected_Port
contingency_table          =          pd.crosstab(dataset['Shipping_Method'],
dataset['Corrected_Port'])
stat, p, dof, expected = chi2_contingency(contingency_table)
print('Shipping_Method vs Corrected_Port:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Independent (fail to reject H0)')
else:
    print('Dependent (reject H0)')
print('------------------------------------')

# Shipping_Method vs Category
contingency_table          =          pd.crosstab(dataset['Shipping_Method'],
dataset['Category'])
stat, p, dof, expected = chi2_contingency(contingency_table)
print('Shipping_Method vs Category:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Independent (fail to reject H0)')
else:
    print('Dependent (reject H0)')
print('------------------------------------')

# Corrected_Port vs Category
contingency_table = pd.crosstab(dataset['Corrected_Port'], dataset['Category'])
stat, p, dof, expected = chi2_contingency(contingency_table)
print('Corrected_Port vs Category:')
print('Statistics=%.3f, p=%.3f' % (stat, p))
alpha = 0.05
if p > alpha:
    print('Independent (fail to reject H0)')
else:
    print('Dependent (reject H0)')
print('------------------------------------')
```

```
Country vs Product:
Statistics=233796.691, p=0.916
Independent (fail to reject H0)
------------------------------------
Country vs Import_Export:
Statistics=238.355, p=0.554
Independent (fail to reject H0)
------------------------------------
Country vs Shipping_Method:
Statistics=459.272, p=0.784
Independent (fail to reject H0)
------------------------------------
Country vs Corrected_Port:
Statistics=1517141.480, p=0.861
Independent (fail to reject H0)
------------------------------------
Country vs Category:
Statistics=952.410, p=0.633
```

```
Independent (fail to reject H0)
-----------------------------------
Product vs Import_Export:
Statistics=961.762, p=0.568
Independent (fail to reject H0)
-----------------------------------
Product vs Shipping_Method:
Statistics=1835.276, p=0.956
Independent (fail to reject H0)
-----------------------------------
Product vs Corrected_Port:
Statistics=6080244.032, p=0.992
Independent (fail to reject H0)
-----------------------------------
Product vs Category:
Statistics=3817.000, p=0.762
Independent (fail to reject H0)
-----------------------------------
Import_Export vs Shipping_Method:
Statistics=14.813, p=0.001
Dependent (reject H0)
-----------------------------------
Import_Export vs Corrected_Port:
Statistics=6281.495, p=0.482
Independent (fail to reject H0)
-----------------------------------
Import_Export vs Category:
Statistics=4.764, p=0.312
Independent (fail to reject H0)
-----------------------------------
Shipping_Method vs Corrected_Port:
Statistics=12519.772, p=0.584
Independent (fail to reject H0)
-----------------------------------
Shipping_Method vs Category:
Statistics=8.334, p=0.402
Independent (fail to reject H0)
-----------------------------------
Corrected_Port vs Category:
Statistics=25036.786, p=0.624
Independent (fail to reject H0)
-----------------------------------
```

The Chi-Square test of independence assesses whether there is a significant association between two categorical variables. The null hypothesis (H0) states that the two variables are independent (no association), while the alternative hypothesis (H1) suggests dependence (an association exists).

Pairs Showing Independence (Fail to Reject H0) For the following pairs, the p-value is greater than 0.05, meaning we fail to reject the null hypothesis (H0). This indicates that the variables are likely independent:

- **Country vs Product**: Statistics=233796.691, p=0.916
  - Conclusion: Country and Product are independent, implying no significant association between them.
- **Country vs Import_Export**: Statistics=238.355, p=0.554
  - Conclusion: Country and Import/Export status are independent.
- **Country vs Shipping_Method**: Statistics=459.272, p=0.784
  - Conclusion: Country and Shipping Method are independent.
- **Country vs Corrected_Port**: Statistics=1517141.480, p=0.861
  - Conclusion: Country and Corrected Port are independent.
- **Country vs Category**: Statistics=952.410, p=0.633

Conclusion: Country and Category are independent. Product vs Import_Export: Statistics=961.762, p=0.568

Conclusion: Product and Import/Export status are independent. Product vs Shipping_Method: Statistics=1835.276, p=0.956

Conclusion: Product and Shipping Method are independent. Product vs Corrected_Port: Statistics=6080244.032, p=0.992

Conclusion: Product and Corrected Port are independent. Product vs Category: Statistics=3817.000, p=0.762

Conclusion: Product and Category are independent. Import_Export vs Corrected_Port: Statistics=6281.495, p=0.482

Conclusion: Import/Export status and Corrected Port are independent. Import_Export vs Category: Statistics=4.764, p=0.312

Conclusion: Import/Export status and Category are independent. Shipping_Method vs Corrected_Port: Statistics=12519.772, p=0.584

Conclusion: Shipping Method and Corrected Port are independent. Shipping_Method vs Category: Statistics=8.334, p=0.402

Conclusion: Shipping Method and Category are independent. Corrected_Port vs Category: Statistics=25036.786, p=0.624

Conclusion: Corrected Port and Category are independent. Overall Interpretation for Independent Pairs:

These results indicate that most of the categorical variables tested do not show significant associations with each other. For example, Country appears to be independent of Product, Shipping Method, and Category. Similarly, Product is not significantly associated with variables like Category or Corrected Port.

This independence suggests that the variables, in these cases, do not influence each other directly, and any differences in their distributions are likely due to chance.