Measures of Central Tendency & Dispersion Measures of Central Tendency [Mean, Median, Mode], and Location [Quartile, Decile, Percentile]. Which Measure is the Best one in which situation? Measures of Dispersion [Range, Variance, Standard Deviation, Coefficient of Variation]. Descriptive statistics summarize and organize characteristics of a dataset. Measures of Central Tendency: Mean, Median, and Mode help identify the 'center' of the data.

Mean: The arithmetic average, useful when there are no extreme outliers.

• Mode: The most frequently occurring value, useful for categorical data.

Measures of Location: Quartiles, Deciles, and Percentiles help understand the spread of data.

Median: The middle value, preferred when data has outliers as it is resistant to extreme values.

Quartiles: Q1 (25%), Q2 (Median - 50%), Q3 (75%).

• Deciles: Divide data into ten equal parts. Percentiles: Show the relative standing of a value in the dataset.

Loading the required Libraries and Data

import pandas as pd

import numpy as np

import seaborn as sns import matplotlib.pyplot as plt from scipy import stats import statsmodels.api as sm

Load the dataset df = pd.read_csv("Amazon Sale Report.csv") # Display basic info display(df.head()) display(df.info())

df = pd.read_csv("Amazon Sale Report.csv")

5731545

1 9198151-

2 0687676-

7273146

1101146

1

171-

404-

403-

407-

9615377-

1069790-

5 rows × 24 columns

0 index

21 B2B

memory usage: 10.0+ MB

In []: # Example: Analyzing a numeric column

if len(numeric_columns) > 0:

2 Date

1 Order ID

7240320

8133951

04-

30-

22

30-

22

30-

<class 'pandas.core.frame.DataFrame'> RangeIndex: 54651 entries, 0 to 54650 Data columns (total 24 columns):

Shipped

Cancelled

Shipped

Column Non-Null Count Dtype

3 Status 54651 non-null object 4 Fulfilment 54650 non-null object 5 Sales Channel 54650 non-null object

ship-service-level 54650 non-null object

 6
 ship-service-level
 54650 non-null object

 7
 Style
 54650 non-null object

 8
 SKU
 54650 non-null object

 9
 Category
 54650 non-null object

 10
 Size
 54650 non-null object

 11
 ASIN
 54650 non-null object

 12
 Courier Status
 51638 non-null object

 13
 Qty
 54650 non-null float64

 14
 currency
 51334 non-null object

 15
 Amount
 51334 non-null object

 16
 ship-city
 54637 non-null object

 17
 ship-state
 54637 non-null float64

 18
 ship-postal-code
 54637 non-null float64

18 ship-postal-code 54637 non-null float64 19 ship-country 54637 non-null object 20 promotion-ids 34126 non-null object

22 fulfilled-by 17028 non-null object 23 Unnamed: 22 5600 non-null object

dtypes: float64(3), int64(1), object(20)

Measures of Central Tendency mean = df[sample_column].mean() median = df[sample_column].median() mode = df[sample_column].mode()[0]

Quartiles, Deciles, Percentiles q1 = df[sample_column].quantile(0.25) $q3 = df[sample_column].quantile(0.75)$

print(f"Deciles: {deciles.values}")

Percentiles (10% & 90%): [1719.9 15479.1]

Quartiles, Deciles, Percentiles q1 = df["Amount"].quantile(0.25) q3 = df["Amount"].quantile(0.75)

print(f"Deciles: {deciles.values}")

print(f"Q1: {q1}, Q3: {q3}")

Percentiles (10% & 90%): [360. 1033.]

In []: # Select only the 'Qty' and 'Amount' columns qty_amount_df = df[['Qty', 'Amount']]

qty_amount_df.describe().round().T

1.0

Create a sample dataset with an outlier

count mean

Mean: 140.25, Median: 19.0

coef_var = std_dev / mean

In []: # Compute Skewness and Kurtosis

Qty 54650.0

Q1: 435.0, Q3: 782.0

Measures of Central Tendency mean = df["Amount"].mean() median = df["Amount"].median() mode = df["Amount"].mode()[0]

print(f"Q1: {q1}, Q3: {q3}")

Mean: 8599.5, Median: 8599.5, Mode: 0

Q1: 4299.75, Q3: 12899.25

Sales index Order ID Date Status Fulfilment service-

Channel

level

<ipython-input-1-673e5e9f11c6>:10: DtypeWarning: Columns (21,23) have mixed types. Specify dtype option on import or set low_memory=False. Style

405-04-8078784-

Cancelled Merchant Amazon.in Standard

30-22 Shipped -

30-Delivered to Buyer

Merchant Amazon.in Standard JNE3781

Merchant Amazon.in

Amazon Amazon.in

54651 non-null int64 54651 non-null object 54651 non-null object

54650 non-null object

numeric_columns = df.select_dtypes(include=[np.number]).columns

print(f"Mean: {mean}, Median: {median}, Mode: {mode}")

percentiles = df[sample_column].quantile([0.10, 0.90])

print(f"Percentiles (10% & 90%): {percentiles.values}")

Deciles: [360. 399. 459. 517. 579. 654. 744. 807. 1033.]

1.0

data = [10, 12, 15, 18, 20, 22, 25, 1000] # 1000 is an outlier

50%

1.0

75%

1.0

Standard Deviation: The square root of variance, shows how much values deviate from the mean.

• Coefficient of Variation: Ratio of standard deviation to mean, useful for comparing variability across datasets.

Skewness: Measures symmetry. Positive skew means a long right tail, negative skew means a long left tail.

• Kurtosis: Measures how heavy or light-tailed the distribution is compared to a normal distribution.

max

15.0

prompt: Give me case with this data where Median is a better measure than mean due to the presence of outliers

In this case, the outlier (1000) significantly influences the mean, pulling it much higher than the typical values in the dataset.

print(f"Range: {range_val}, Variance: {variance}, Standard Deviation: {std_dev}, Coefficient of Variation: {coef_var}")

Range: 5495.0, Variance: 73946.67972762829, Standard Deviation: 271.93138790442765, Coefficient of Variation: 0.03162176730093932

• Positive Skew (Skewness > 0): A positive skew indicates that the tail on the right side of the distribution is longer or fatter than the left side. This means there are more extreme

The median, on the other hand, is not affected by the outlier and represents the central value more accurately, making it a better measure of cent

sample_column = numeric_columns[0] # Choose first numeric column

deciles = df[sample_column].quantile([i/10 for i in range(1, 10)])

Deciles: [1719.9 3439.8 5159.7 6879.6 8599.5 10319.4 12039.3 13759.2 15479.1]

Amazon Amazon.in Expedited JNE3371

Standard

Expedited

JNE3671

SET389-

KR-NP-S

JNE3781-

JNE3371kurta ... J0341-DR-L JNE3671-TU-XXXL

Western Top

SKU Category ... currency Amount

Set ...

kurta ...

INR

753.33 PUDUCHERRY 574.00

647.62

406.00

329.00

INR

INR

INR

CHENNAI

ship-city

BENGALURU

PUDUCHERRY 605008.0 TAMIL NADU 600073.0

NAVI MUMBAI MAHARASHTRA 410210.0

ship.

code

postal-

ship-state

KARNATAKA 560085.0

MUMBAI MAHARASHTRA 400081.0

ship-

country

promotion-

ids

NaN

Amazon **PLCC**

Financing

Universal Merchant

> IN Core Free

Shipping

23-48-5-108

NaN

2015/04/08

Free-

IN

NaN

print(f"Mean: {mean}, Median: {median}, Mode: {mode}") deciles = df["Amount"].quantile([.10, .20, .30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90]) percentiles = df["Amount"].quantile([0.10, 0.90]) print(f"Percentiles (10% & 90%): {percentiles.values}") Mean: 631.4720477656134, Median: 579.0, Mode: 399.0

Calculate the mean mean_data = np.mean(data) # Calculate the median median_data = np.median(data) print(f"Mean: {mean_data}, Median: {median_data}") # Explanation:

Measures of Dispersion/Spread

Generate descriptive statistics for these columns

0.0 0.0

Amount 51334.0 631.0 274.0 0.0 435.0 579.0 782.0 5584.0

std min 25%

Compute Measures of Dispersion range_val = df["Amount"].max() - df["Amount"].min() variance = df["Amount"].var() std_dev = df["Amount"].std()

Shape Characteristics

Measures of Shape describe the distribution of data.

Measures of Dispersion describe the spread of data.

Range: The difference between max and min values.

• **Variance:** The average squared deviation from the mean.

Skewness: 1.0887312442703134, Kurtosis: 5.74381629988207 **Skewness:**

values on the higher end of the data.

skewness = stats.skew(df["Amount"].dropna()) kurtosis = stats.kurtosis(df["Amount"].dropna())

print(f"Skewness: {skewness}, Kurtosis: {kurtosis}")

• Negative Skew (Skewness < 0): A negative skew indicates that the tail on the left side of the distribution is longer or fatter than the right side. This means there are more extreme values on the lower end of the data. Zero Skew (Skewness ≈ 0): A skewness value close to zero suggests that the distribution is roughly symmetrical.

Kurtosis: • Definition: Kurtosis measures the heaviness of the tail of the distribution. It tells us how concentrated the data is around the mean and how spread out the tails are. • Leptokurtic (Kurtosis > 0): A positive kurtosis means the distribution has heavier tails and a sharper peak compared to a normal distribution. This indicates more extreme values and a more concentrated distribution around the mean.

• **Definition:** Skewness measures the asymmetry of the probability distribution of a real-valued random variable about its mean.

By examining the skewness and kurtosis, you gain valuable information about how your "Amount" data is distributed. This can help you understand if there are any unusual patterns or outliers and how they might affect your analysis or modeling efforts. **Important Notes:** Context Matters: The interpretation of skewness and kurtosis always depends on the specific context of your data.

The skewness and kurtosis values we are calculating for the "Amount" column in your Amazon dataset provide insights into the shape of its distribution:

• If Skewness is positive: The "Amount" values tend to have a longer tail on the higher end, implying that some orders/sales are significantly larger than the average.

• If Kurtosis is positive: This means the "Amount" distribution has heavier tails than a normal distribution, indicating more outlier values in the data, possibly very high or very low

• Platykurtic (Kurtosis < 0): A negative kurtosis means the distribution has lighter tails and a flatter peak compared to a normal distribution. This indicates fewer extreme values and a more spread-out distribution. • Mesokurtic (Kurtosis ≈ 0): A kurtosis value close to zero suggests that the distribution has similar tail behavior and peak shape to a normal distribution. In the context of Our Code:

sns.histplot(df['Amount'], kde=True, stat='density')

finite_data = df['Amount'][np.isfinite(df['Amount'])]

1000

2000

helpful when the skewness is unknown or when the data is highly skewed.

3000

Amount

Logarithmic Transformation: Taking the logarithm of the target variable can reduce right-skewness.

Reciprocal Transformation: Taking the reciprocal of the target variable can address left-skewness.

• Square Root Transformation: The square root transformation can also be used to reduce right-skewness.

4000

mu, std = stats.norm.fit(finite_data) # Fit to finite data only

plt.text(0.05, 0.95, f'Skewness: {skewness:.2f}', transform=plt.gca().transAxes, fontsize=10) plt.text(0.05, 0.90, f'Kurtosis: {kurtosis:.2f}', transform=plt.gca().transAxes, fontsize=10)

Filter out non-finite values before fitting

plt.title('Histogram of Amount')

x = np.linspace(xmin, xmax, 100)p = stats.norm.pdf(x, mu, std)plt.plot(x, p, 'r', linewidth=2)

Add skewness and kurtosis text

Add normal probability line

xmin, xmax = plt.xlim()

Box Plot

plt.subplot(1, 2, 2)

sale amounts.

In summary:

• Visualizations: It's always helpful to plot histograms or box plots of your data to gain a visual understanding of its distribution and confirm what the skewness and kurtosis values are telling you. In []: # Histogram with normal probability, skewness, and kurtosis plt.figure(figsize=(12, 6)) plt.subplot(1, 2, 1)

sns.boxplot(y=df['Amount']) plt.title('Box Plot of Amount') plt.tight_layout() plt.show() Histogram of Amount Box Plot of Amount Skewness: 1.17 0 Kurtosis: 7.44 5000 0.0025 4000 0.0020 3000 Amount 0.0015 2000 0.0010 1000 0.0005 0 0.0000

In the context of linear regression, the target variable might require transformation if it shows significant skewness or kurtosis. This can help improve the model's performance by addressing issues like non-normality of the target variable. **Transformation Methods** If transformation of the target variable is deemed necessary, several methods can be applied to address skewness or kurtosis. Some of these methods include:

6000

• Box-Cox Transformation: The Box-Cox transformation is a more general approach that can automatically find the optimal transformation based on the data. It can be especially

5000

Impact of Transformation Transforming the target variable can improve the performance of a linear regression model by:

 Addressing Non-Normality: It can help to normalize the distribution of the target variable, aligning it closer to a normal distribution. • Stabilizing Variance: Some transformations can help to stabilize the variance of the target variable, which can be crucial for achieving accurate model estimations.