# Exploratory Data Analysis (EDA) with Pandas in E-commerce

The purpose of this project is to explore and analyze an e-commerce dataset using the Pandas framework to derive insights into customer behavior, product trends, and sales performance.

# **Goals of the Project:**

- Explore the e-commerce dataset using Pandas.
- Perform feature engineering to derive useful insights.
- Visualize data distributions and trends with various plot types.
- Summarize key findings that can aid in business decision-makin

#### **Materials and Methods**

The data for this project is from a simulated e-commerce platform, containing information about orders, products, customer regions, and shipping details. This dataset includes sales data, product categories, order dates, profit margins, and more. The analysis aims to understand sales performance, customer behavior, product trends, and shipping delays.

#### **General Part**

- Libraries Import: Pandas, NumPy, Seaborn, Matplotlib
- **Dataset Exploration**: Initial exploration of the dataset, checking for missing values, duplicates, and generating summary statistics.
- **Feature Engineering**: Transformation of date columns and creation of new features like shipping delay and profit margin.
- **Visualization in Pandas**: Distribution analysis, relationships between variables, and time-based trends.

## **Project Outcome & Insights**

The project performs **Exploratory Data Analysis (EDA)** on an **e-commerce dataset** to gain meaningful insights into **sales performance**, **customer behavior**, **and shipping efficiency**. Below are the key outcomes:

#### 1. Sales Performance

- **Customer Segment Wise Top Sales**: The project groups sales based on different customer segments to identify the most profitable segments.
- Time Series Analysis: It shows sales trends over time, helping businesses identify seasonal fluctuations and peak sales periods.
- **Top Performing Categories**: Identifies the product categories with the highest sales and revenue.

#### 2. Customer Behavior Analysis

- **Returning Customers**: The analysis helps in understanding customer retention by identifying customers who have made multiple purchases.
- **Top 10 High-Spending Customers**: Helps businesses recognize their most valuable customers and plan targeted marketing strategies.

#### 3. Shipping Performance

- Shipping Delay Categorization: The shipping\_category feature segments shipments into Same Day, Fast, Moderate, and Delayed, allowing better logistics management.
- **Profitability by Shipping Type**: Analyzes which shipping methods are most profitable and efficient.

#### 4. Profitability & Business Growth

- **Profit Margin Analysis**: Helps understand **profitability per order** and identify areas for improving profit margins.
- **Year-over-Year Sales Growth**: Tracks annual sales growth percentages, enabling better financial planning.

## Feature Engineering:

Created new columns such as:

- actual\_shipping\_delay (Days between order date and ship date).
- profit\_margin (Profit per order / Sales per order).
- order\_year, order\_month, order\_weekday (Extracted from order\_date).
- returning\_customer (Boolean flag indicating repeated customers).
- **shipping\_category** (Binned shipping delays into categories: Same Day, Fast, Moderate, Delayed).

### Key Questions and Insights to be Addressed:

What is the total sales by region?

```
sales_by_region =
df.groupby('customer_region')['sales_per_order'].sum().sort_v
alues(ascending=False)
print(sales_by_region)

Answer: customer_region

West    2.207444e+06

East    1.970007e+06

Central    1.621669e+06

South    1.076112e+06
```

Which product categories have the highest sales?

• What is the relationship between sales and profit margins?

```
correlation
=df[['sales_per_order','profit_per_order']].corr()
print(correlation)
```

#### Answer:

Correlation between sales and profit:

sales\_per\_order profit\_per\_order

sales\_per\_order 1.000000 0.130008

profit\_per\_order 0.130008 1.000000

• How does the sales trend change over time?

```
monthly_sales=df.groupby(['order_year','order_month'])['sales
_per_order'].sum()
print(monthly_sales)
```

#### Answer:

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order\_year order\_month sales\_per\_order

0	2021	2021-01	278026.849371
1	2021	2021-02	359211.126956
2	2021	2021-03	428262.210236
3	2021	2021-04	370351.629310
4	2021	2021-05	365224.566823
5	2021	2021-06	402157.323752

2021 2021-07 350417.948708

```
7
     2021
            2021-08 295852.041774
8
     2021
            2021-09 257718.098723
9
     2021
            2021-10 109834.018045
10
      2021
            2021-11 39807.478701
11
      2021
            2021-12 24551.260457
12
      2022
             2022-01 427267.288370
13
      2022
            2022-02 425011.068305
      2022
             2022-03 409340.048349
14
      2022
            2022-04 388161.257242
15
      2022
             2022-05 414351.287871
16
17
      2022
             2022-06 381887.037021
      2022
             2022-07 372165.315867
18
      2022
             2022-08 310705.086154
19
      2022
             2022-09 276254.015330
20
21
      2022
            2022-10 115058.862121
22
      2022
             2022-11
                      58542.990361
23
      2022
             2022-12
                      15073.950001
```

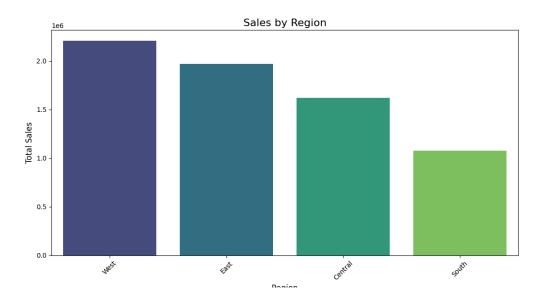
• What is the average shipping delay, and how does it vary by shipping type?

```
avg_shipping_delay =
df.groupby('shipping_type')['actual_shipping_d
elay'].mean()
print(avg_shipping_delay)
```

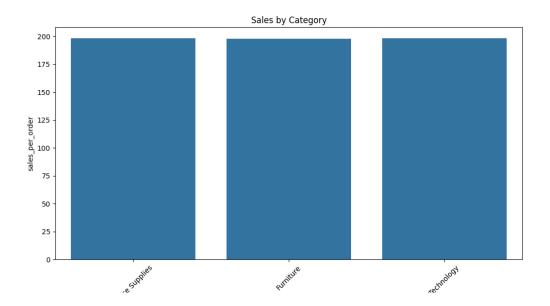
## Visualization:

Several charts created to present inside including:

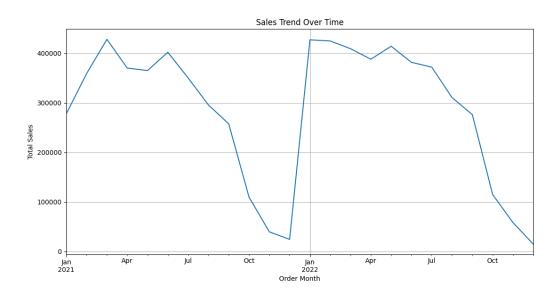
• Sales by region (Bar chart)



• Sales by category (Bar chart)



• Sales trends over time (Line chart)



Boxplot showing sales distribution across customer segments

