Aim: Introduction to Data science and Data preparation using Pandas steps.

Theory:

For machine learning algorithms to perform effectively, it is essential to preprocess raw data and convert it into a clean, usable dataset. This often involves encoding categorical data into numerical representations since most algorithms require numeric input. One common approach is to transform categorical labels into column vectors with binary values, a process known as one-hot encoding. This ensures that the categorical data is represented in a way that the algorithm can interpret without assigning implicit ordinal relationships between categories.

Another critical preprocessing step is handling missing values, which are often represented as NaNs (Not a Number). Missing values can arise from various issues, such as incomplete data collection, sensor malfunctions, or user input errors. These missing entries can lead to errors or biases in the training process if not addressed properly.

Problem Statement

The given dataset provides comprehensive details about retail product sales, focusing on the relationship between product attributes, outlet characteristics, and sales performance. This analysis aims to address the following key objectives:

- **Product Performance**: Identifying products or product types that drive the highest sales and those underperforming.
- **Outlet Insights**: Understanding the impact of outlet size, location, and type on overall sales performance.
- **Pricing Analysis**: Investigating how pricing strategies, such as maximum retail price (MRP), influence customer purchasing behavior.
- **Possible sales Prediction**: Developing models to predict item-level sales and provide actionable insights for inventory and pricing strategies.

By preprocessing the dataset and applying statistical analysis, the goal is to extract meaningful patterns that can guide data-driven decisions in retail operations.

Dataset Overview

The dataset comprises **12 columns**, each detailing specific aspects of retail products, their pricing, visibility, and sales performance across outlets. Below is a breakdown of the dataset's columns and their relevance:

1. **Item_Identifier**: A unique code for each product, essential for distinguishing between items in the inventory.

2. **Item_Weight**: Represents the weight of each product, which may impact logistics and consumer preference.
3. **Item_Fat_Content**: Categorizes items as Low Fat or Regular Fat, reflecting their nutritional value and target audience.
4. **Item_Visibility**: A measure of the shelf visibility of an item, influencing its likelihood of being purchased.
5. **Item_Type**: Broad categories like Dairy, Beverages, or Snacks, helping analyze trends across product types.
6. **Item_MRP**: The maximum retail price, a key factor in determining product affordability and customer demand.
7. **Outlet_Identifier**: A unique code assigned to each retail outlet, linking products to specific store locations.
8. **Outlet_Establishment_Year**: Indicates the year the outlet began operations, useful for analyzing store maturity's effect on sales.
9. **Outlet_Size**: Categorizes stores as Small, Medium, or Large, impacting foot traffic and product demand.
10. **Outlet_Location_Type**: Describes whether the store is Urban, Suburban, or in a Tier 3 area, capturing demographic influences.
11. **Outlet_Type**: Differentiates between store types, such as Grocery Stores or Supermarkets, reflecting varying business models.
12. **Item_Outlet_Sales**: The target variable, representing the total sales of a product at a specific outlet.

Workflow: Combining NumPy and Pandas

The typical data preparation workflow involves using NumPy for low-level numerical operations and array manipulations and Pandas for higher-level data manipulation and analysis tasks. For instance, you might use NumPy to handle missing values at a lower level, and then switch to Pandas to leverage its powerful tools for cleaning, transforming, and exploring tabular data.

OUTPUT :

1. **Load data in pandas**

Loading data into Pandas is a crucial initial step in the data analysis process. The pandas library provides functions like read_csv(), read_excel(), or read_sql() to read data from different file formats or databases into a Pandas DataFrame. Once loaded, a DataFrame provides a structured and flexible representation of the data, making it easy to perform various operations.

```
[2]  import pandas as pd
     df = pd.read_csv("/content/market_data.csv")
```

2. **Description of the dataset.**

Understanding the structure and characteristics of the dataset is important for effective analysis. The info(), describe(), and head() methods in Pandas provide information about the data types, summary statistics, and a preview of the dataset, respectively.

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Year	Outlet_Size	Outlet_Location_Type	Outlet_Type	Item_Out
0	FDA15	9.300	Low Fat	0.016047	Dairy	249.8092	OUT049	1999	Medium	Tier 1	Supermarket Type1	
1	DRC01	5.920	Regular	0.019278	Soft Drinks	48.2692	OUT018	2009	Medium	Tier 3	Supermarket Type2	
2	FDN15	17.500	Low Fat	0.016760	Meat	141.6180	OUT049	1999	Medium	Tier 1	Supermarket Type1	
3	FDX07	19.200	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	1998	NaN	Tier 3	Grocery Store	
4	NCD19	8.930	Low Fat	0.000000	Household	53.8614	OUT013	1987	High	Tier 3	Supermarket Type1	

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8523 entries, 0 to 8522
Data columns (total 12 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Item_Identifier            8523 non-null   object
 1   Item_Weight                7060 non-null   float64
 2   Item_Fat_Content           8523 non-null   object
 3   Item_Visibility            8523 non-null   float64
 4   Item_Type                  8523 non-null   object
 5   Item_MRP                   8523 non-null   float64
 6   Outlet_Identifier          8523 non-null   object
 7   Outlet_Establishment_Year  8523 non-null   int64
 8   Outlet_Size                6113 non-null   object
 9   Outlet_Location_Type       8523 non-null   object
 10  Outlet_Type                8523 non-null   object
 11  Item_Outlet_Sales          8523 non-null   float64
dtypes: float64(4), int64(1), object(7)
memory usage: 799.2+ KB
```

3. **Drop columns that aren't useful**

Not all columns in a dataset are relevant for analysis or modeling. You can use the drop() method to eliminate columns that are not useful.

```
cols = ['Outlet_Establishment_Year']
df = df.drop(cols, axis=1)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8523 entries, 0 to 8522
Data columns (total 11 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Item_Identifier      8523 non-null   object
 1   Item_Weight          7060 non-null   float64
 2   Item_Fat_Content     8523 non-null   object
 3   Item_Visibility      8523 non-null   float64
 4   Item_Type            8523 non-null   object
 5   Item_MRP             8523 non-null   float64
 6   Outlet_Identifier    8523 non-null   object
 7   Outlet_Size          6113 non-null   object
 8   Outlet_Location_Type 8523 non-null   object
 9   Outlet_Type          8523 non-null   object
 10  Item_Outlet_Sales    8523 non-null   float64
dtypes: float64(4), object(7)
memory usage: 732.6+ KB
```

4. **Drop rows with maximum missing values**

Handling missing data is crucial. You can identify and drop rows with a significant number of missing values using the dropna() method.

```
[ ] df.size
```

```
102276
```

```
[ ] df = df.dropna()
```

```
df.size
```

```
73356
```

5. **Take care of missing data**

For columns with missing values, you can choose to fill them with a specific value or use methods like mean, median, or interpolation to impute missing values.

```
[3] df['Item_Weight'] = df['Item_Weight'].fillna(df['Item_Weight'].mean())
    df
```

	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Year	Outlet_Size	Outlet_Location_Type	Outlet_Type	Item_Outlet_Sales
0	FDA15	9.300	Low Fat	0.016047	Dairy	249.8092	OUT049	1999	Medium	Tier 1	Supermarket Type1	3735.1380
1	DRC01	5.920	Regular	0.019278	Soft Drinks	48.2692	OUT018	2009	Medium	Tier 3	Supermarket Type2	443.4228
2	FDN15	17.500	Low Fat	0.016760	Meat	141.6180	OUT049	1999	Medium	Tier 1	Supermarket Type1	2097.2700
3	FDX07	19.200	Regular	0.000000	Fruits and Vegetables	182.0950	OUT010	1998	NaN	Tier 3	Grocery Store	732.3800
4	NCD19	8.930	Low Fat	0.000000	Household	53.8614	OUT013	1987	High	Tier 3	Supermarket Type1	994.7052

6. **Create dummy variables**

For categorical variables, creating dummy variables is essential for including them in machine learning models.

```
dummy_data = {
    "Item_Identifier": "FDX01",
    "Item_Weight": 12.5,
    "Item_Fat_Content": "Low Fat",
    "Item_Visibility": 0.05,
    "Item_Type": "Snack Foods",
    "Item_MRP": 250.75,
    "Outlet_Identifier": "OUT013",
    "Outlet_Size": "Medium",
    "Outlet_Location_Type": "Tier 1",
    "Outlet_Type": "Supermarket Type1",
    "Item_Outlet_Sales": 3400.25
}
new_row = pd.DataFrame([dummy_data])
result = pd.concat([df, new_row], ignore_index=True)
```

```
result.tail()
```

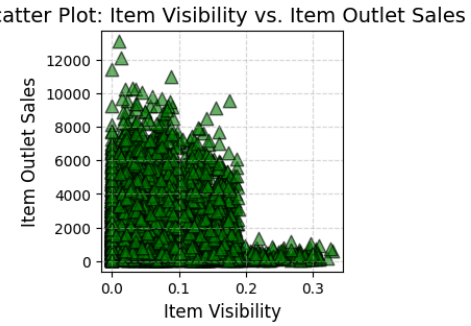
	Item_Identifier	Item_Weight	Item_Fat_Content	Item_Visibility	Item_Type	Item_MRP	Outlet_Identifier	Outlet_Establishment_Year	Outlet_Size	Outlet_Location_Type	Outlet_Type
6109	FDF22	6.865	Low Fat	0.056783	Snack Foods	214.5218	OUT013	1987.0	High	Tier 3	Supermarket Type1
6110	NCJ29	10.600	Low Fat	0.035186	Health and Hygiene	85.1224	OUT035	2004.0	Small	Tier 2	Supermarket Type1
6111	FDN46	7.210	Regular	0.145221	Snack Foods	103.1332	OUT018	2009.0	Medium	Tier 3	Supermarket Type2
6112	DRG01	14.800	Low Fat	0.044878	Soft Drinks	75.4670	OUT046	1997.0	Small	Tier 1	Supermarket Type1
6113	FDX01	12.500	Low Fat	0.050000	Snack Foods	250.7500	OUT013	NaN	Medium	Tier 1	Supermarket Type1

7. **Find out outliers (manually)**:
Outliers can be detected visually or using statistical methods. Visual inspection through box plots or scatter plots is a common approach.

```
import matplotlib.pyplot as plt

x = df['Item_Visibility']
y = df['Item_Outlet_Sales']

plt.figure(figsize=(3, 3))
plt.scatter(x, y, c="green", s=80, alpha=0.6, edgecolor="black", marker="^")
plt.title("Scatter Plot: Item Visibility vs. Item Outlet Sales", fontsize=14)
plt.xlabel("Item Visibility", fontsize=12)
plt.ylabel("Item Outlet Sales", fontsize=12)
plt.grid(True, linestyle="--", alpha=0.5)
plt.show()
```




```
[ ] import numpy as np
    print(np.where(df['Item_Weight'] > 10))
```

```
(array([   2,    4,    5, ..., 6108, 6110, 6112], dtype=int64),)
```

8. **Standardization of columns**
In statistics and machine learning, data **standardization** is a **process of converting data to z-score values based on the mean and standard deviation of the data**.
The resulting standardized value shows the number of standard deviations the raw value is away from the mean. Basically, each value of a given feature of a dataset will be converted to a representative number of standard deviations that it's away from the mean of the feature

9. **Normalization of columns**

In statistics and machine learning, **the min-max normalization of data** is a **process of converting the original range of data to the range between 0 and 1**.The resulting normalized values represent the original data on a 0-1 scale. This will allow us to compare multiple features together and get more relevant information since now all the data will be on the same scale.

```python
from sklearn.preprocessing import StandardScaler, MinMaxScaler
import pandas as pd


numerical_columns = ['Item_Weight', 'Item_Visibility', 'Item_MRP', 'Item_Outlet_Sales']

# Initialize scalers
standard_scaler = StandardScaler()
minmax_scaler = MinMaxScaler()

# Standardization of the data
standardized_data = standard_scaler.fit_transform(df[numerical_columns])
df_standardized = pd.DataFrame(standardized_data, columns=numerical_columns)

# Normalization of the data
normalized_data = minmax_scaler.fit_transform(df[numerical_columns])
df_normalized = pd.DataFrame(normalized_data, columns=numerical_columns)


print("Standardized Data:")
print(df_standardized.head())

print("\nNormalized Data:")
print(df_normalized.head())
```

```
Standardized Data:
   Item_Weight  Item_Visibility  Item_MRP  Item_Outlet_Sales
0    -0.881033        -0.967450  1.744524           0.811077
1    -1.710793        -0.902945 -1.494387          -1.079139
2     1.131996        -0.953220  0.005804          -0.129443
3    -0.971864        -1.287832 -1.404516          -0.762573
4    -0.612220        -1.287832 -1.444060          -1.014143

Normalized Data:
   Item_Weight  Item_Visibility  Item_MRP  Item_Outlet_Sales
0     0.282525         0.048866  0.927507           0.283550
1     0.081274         0.058705  0.072068           0.031370
2     0.770765         0.051037  0.468288           0.158072
3     0.260494         0.000000  0.095805           0.073604
4     0.347723         0.000000  0.085361           0.040041
```

Conclusion: In conclusion, the series of experiments performed on data preparation using NumPy and Pandas, along with various data preprocessing techniques, is essential for ensuring the data is in a suitable and meaningful form for analysis or machine learning applications.Here we used the retail sales data to understand the max profit of each product.