Exploratory Data Analysis of Zara Sales

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Introduction

Zara, a global fashion brand, maintains a vast catalog of clothing products across different seasons, sections, materials and countries of origin.

Our Dataset contains over 20,000 product entries, each representing unique combination of attributes - such as product position, promotional status, season, material and more - alongside their respective sales volumes.

The goal of this analysis is to uncover insights about Zara's sales trends and prepare the data for predictive modeling to forecast future sales performance.

Data Loading

```
import pandas as pd
# Data Loading
import os

# It is important to set the correct delimiter and encoding while reading the file.
# In case of error during reading, double-check these parameters as they are common pitfalls.

file_path = '/kaggle/input/zara-sales-for-eda/Zara_sales_EDA.csv'
try:
    df = pd.read_csv(file_path, delimiter=';', encoding='utf-8')
    print('Data loaded successfully with shape:', df.shape)
except Exception as e:
    print('An error occurred while reading the CSV file:', e)

# Display the first few rows of the dataframe
df.head()
```

```
Data loaded successfully with shape: (20252, 17)
```

	Product ID	Product Position	Promotion	Product Category	Seasonal	Sales Volume	brand	url	name	description	pr
0	185102	Aisle	Yes	clothing	Yes	1243	Zara	https://www.zara.com/us/en/basic-puffer-jacket...	BASIC PUFFER JACKET	Puffer jacket made of tear-resistant ripstop f...	78
1	188771	Aisle	Yes	clothing	No	1429	Zara	https://www.zara.com/us/en/tuxedo-jacket-p0889...	TUXEDO JACKET	Straight fit blazer. Pointed lapel collar and ...	14
2	180176	End-cap	Yes	clothing	Yes	1168	Zara	https://www.zara.com/us/en/slim-fit-suit-jacke...	SLIM FIT SUIT JACKET	Slim fit jacket. Notched lapel collar. Long sl...	71
3	112917	Aisle	Yes	clothing	No	1348	Zara	https://www.zara.com/us/en/stretch-suit-jacket	STRETCH SUIT	Slim fit jacket made of viscose	30

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
df.shape
```

```
(20252, 17)
```

```
df.columns
```

```
Index(['Product ID', 'Product Position', 'Promotion', 'Product Category',
       'Seasonal', 'Sales Volume', 'brand', 'url', 'name', 'description',
       'price', 'currency', 'terms', 'section', 'season', 'material',
```

```
       'origin'],
      dtype='object')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20252 entries, 0 to 20251
Data columns (total 17 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Product ID        20252 non-null  int64  
 1   Product Position  20252 non-null  object 
 2   Promotion         20252 non-null  object 
 3   Product Category  20252 non-null  object 
 4   Seasonal          20252 non-null  object 
 5   Sales Volume      20252 non-null  int64  
 6   brand             20252 non-null  object 
 7   url               20252 non-null  object 
 8   name              20251 non-null  object 
 9   description       20250 non-null  object 
 10  price             20252 non-null  float64
 11  currency          20252 non-null  object 
 12  terms             20252 non-null  object 
 13  section           20252 non-null  object 
 14  season            20252 non-null  object 
 15  material          20252 non-null  object 
 16  origin            20252 non-null  object 
dtypes: float64(1), int64(2), object(14)
memory usage: 2.6+ MB
```

```
df.describe()
```

	Product ID	Sales Volume	price
count	20252.000000	20252.000000	20252.000000
mean	208931.432303	1097.400454	41.949061
std	8961.076507	298.234609	23.380960
min	110075.000000	518.000000	12.000000
25%	204442.750000	849.000000	23.950000
50%	209505.500000	990.000000	35.950000
75%	214568.250000	1364.250000	53.950000
max	219631.000000	1940.000000	134.990000

```
#Missing Values Check
df.isnull().sum()
```

```
Product ID          0
Product Position    0
Promotion           0
Product Category    0
Seasonal            0
Sales Volume        0
brand               0
url                 0
name                1
description         2
price               0
currency            0
terms               0
section             0
season              0
material            0
origin              0
dtype: int64
```

From the Missing Value Check we can See there is 1 missing value in name and 2 missing values in description. we will drop this 3 values from dataset

```
df = df.dropna()
```

```
#Again check for missing values
df.isnull().sum()
```

```
Product ID          0
Product Position    0
Promotion           0
Product Category    0
```

```
Seasonal            0
Sales Volume        0
brand               0
url                 0
name                0
description         0
price               0
currency            0
terms               0
section             0
season              0
material            0
origin              0
dtype: int64
```

```
#Unique categories in Some important columns
for col in ["Product Category","brand","currency","section","season","material","origin"]:
    if col in df.columns:
        print(f"\nColumns:{col}")
        print("Unique Values: ",df[col].nunique())
        print(df[col].value_counts().head())
```

```
Columns:Product Category
Unique Values:  1
Product Category
clothing    20250
Name: count, dtype: int64

Columns:brand
Unique Values:  1
brand
Zara    20250
Name: count, dtype: int64

Columns:currency
Unique Values:  1
currency
USD    20250
Name: count, dtype: int64

Columns:section
Unique Values:  2
section
WOMAN    13253
MAN       6997
Name: count, dtype: int64

Columns:season
Unique Values:  4
season
Autumn    7664
Winter    5144
Spring    4536
Summer    2906
Name: count, dtype: int64

Columns:material
Unique Values:  11
material
Cotton        3850
Wool          3805
Wool Blend    3373
Polyester     2774
Linen         2573
Name: count, dtype: int64

Columns:origin
Unique Values:  12
origin
China         4026
Bangladesh    3617
Turkey        2475
India         2033
Morocco       1653
Name: count, dtype: int64
```

Exploratory Data Analysis (EDA)

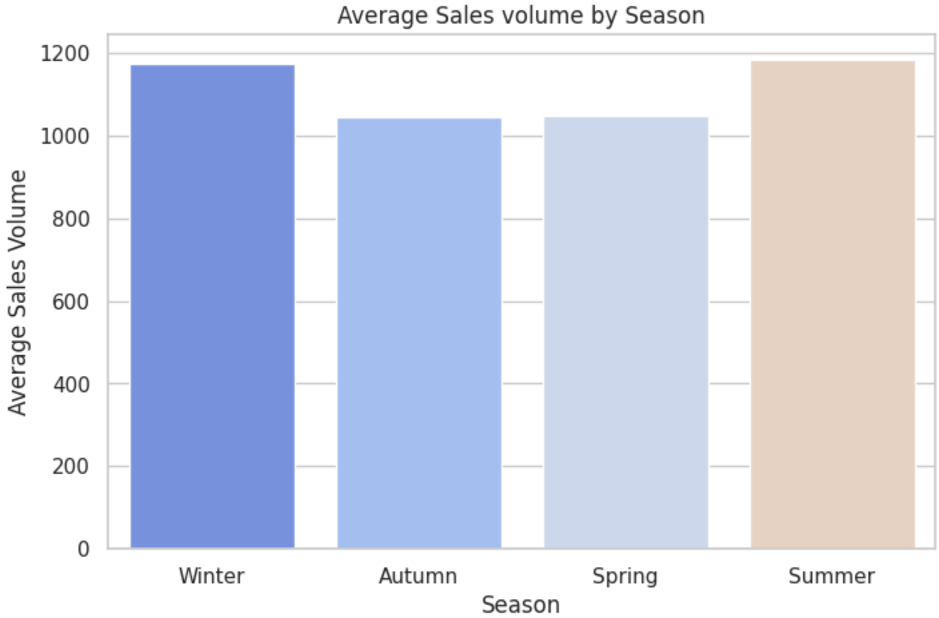
```
#Convert numeric columns
df["Sales Volume"] = pd.to_numeric(df["Sales Volume"],errors="coerce")
df["price"] = pd.to_numeric(df["price"],errors="coerce")
```

```
#Drop NaN rows for numeric analysis
df = df.dropna(subset=["Sales Volume","price"])
```

```
#Visualization Setup
sns.set(style="whitegrid", palette = "coolwarm")
```

```
#Sales Volume By Season
plt.figure(figsize=(8,5))
sns.barplot(x="season",y="Sales Volume",data=df,ci=None, errorbar=None)
plt.title("Average Sales volume by Season")
plt.ylabel("Average Sales Volume")
plt.xlabel("Season")
plt.show()
```

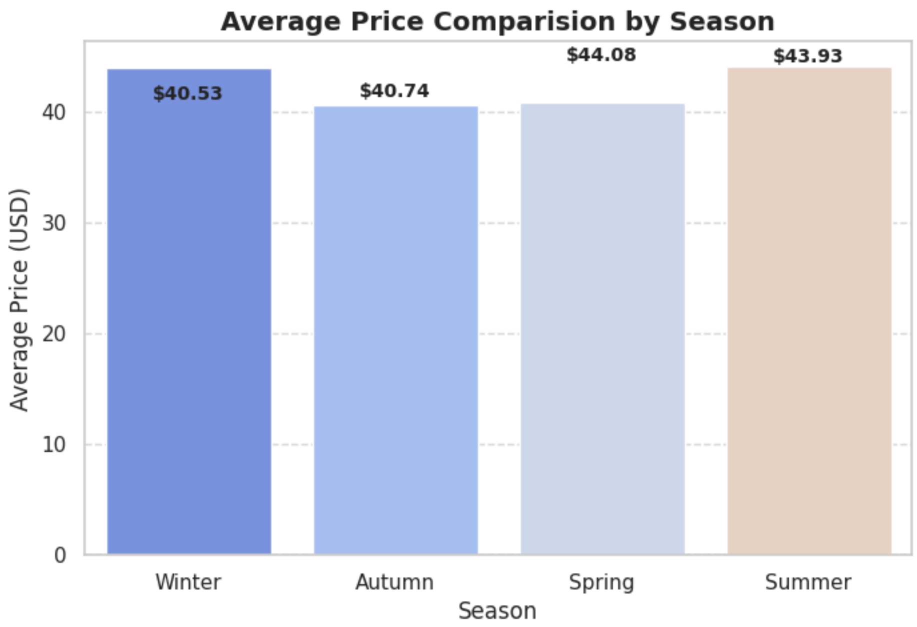
```
/tmp/ipykernel_49/1602612726.py:3: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(x="season",y="Sales Volume",data=df,ci=None, errorbar=None)
```



The Sales data reveals clear seasonal trends in Zara's performance throughout the year. Among all four seasons, winter and Summer stand out as the strongest sales periods, both surpassing 1150 units in average sales volume. This pattern suggests that Zara experience high customer demand during Extreme-weather seasons - Possibly driven bt new collections (e.g. coats, jackets, and sweaters in winters, or light dresses and vacation wear in summer).

In contrast, Autumn and Spring show slightly lower sales, averaging around 1040 - 1060 units. These moderate figures might correspond to transitional shopping periods, when customers are less inclined to make large waredrobe update.

```
#Price By Season co,5mperision Graph
plt.figure(figsize=(8,5))
sns.barplot(x="season",y="price",data=df, errorbar=None)

#Add details
plt.title("Average Price Comparision by Season", fontsize = 14, fontweight="bold")
plt.xlabel("Season", fontsize=12)
plt.ylabel("Average Price (USD)",fontsize=12)
plt.grid(axis="y", linestyle="--",alpha=0.7)

#Show Values on bars
for i, val in enumerate(df.groupby("season")["price"].mean().round(2)):
    plt.text(i,val+0.5,f"${val}",ha="center",fontsize=10,fontweight="bold")

plt.show()
```



We analyzed Zara's seasonal sales data, focusing on:

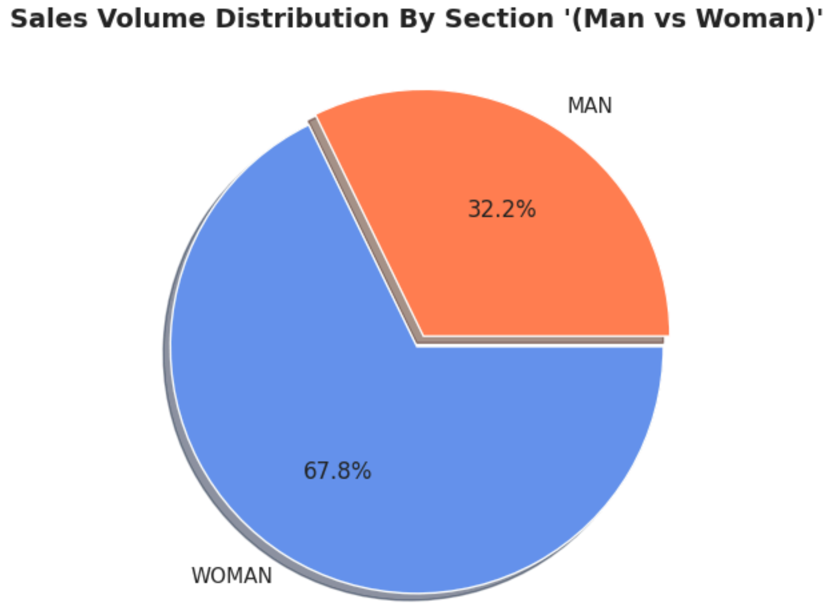
- Average Sales Volume (Units Sold)
- Average Price per Item (USD)

across Winter, Spring, Summer and Autumn

Zara's Seasonal data tell a Clear Story of strategic balance -

"Sell more in Winter, earn more in spring."

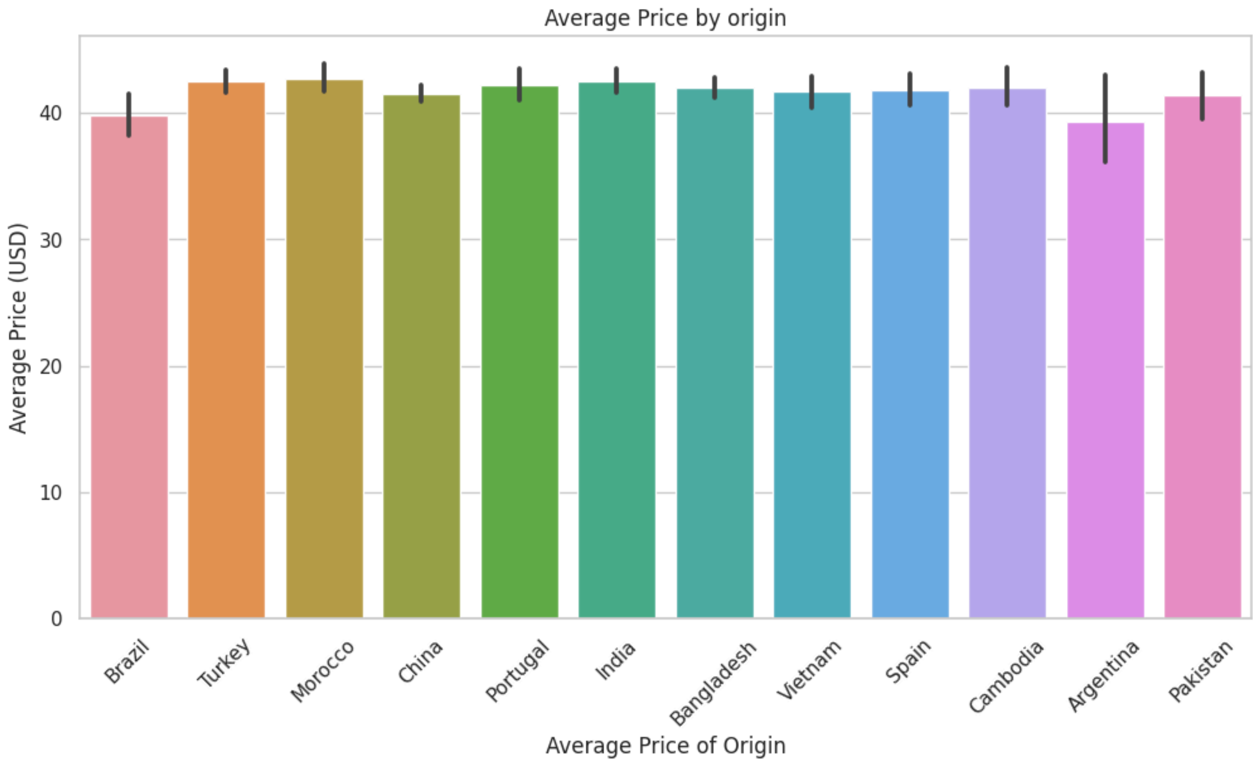
```
#Sales Volume by Section (Man vs Women)
#Group by Section and Sum up total sales volume
section_sales = df.groupby('section')['Sales Volume'].sum()

#Pie Chart Ploting
plt.figure(figsize=(6,6))
plt.pie(
    section_sales,
    labels=section_sales.index,
    autopct='%1.1f%%',
    colors = ["#ff7f50","#6495ed"],
    explode = (0.05, 0),
    shadow = True
)

plt.title("Sales Volume Distribution By Section '(Man vs Woman)'", fontsize=14, fontweight="bold")
plt.show()
```



The Pie Chart illustrates the Sales volume distribution between men's and women's sections. A clear trend emerges - the women's section dominates sales, accounting for 67.8% of total sales, while the men's section contributes 32.2%.

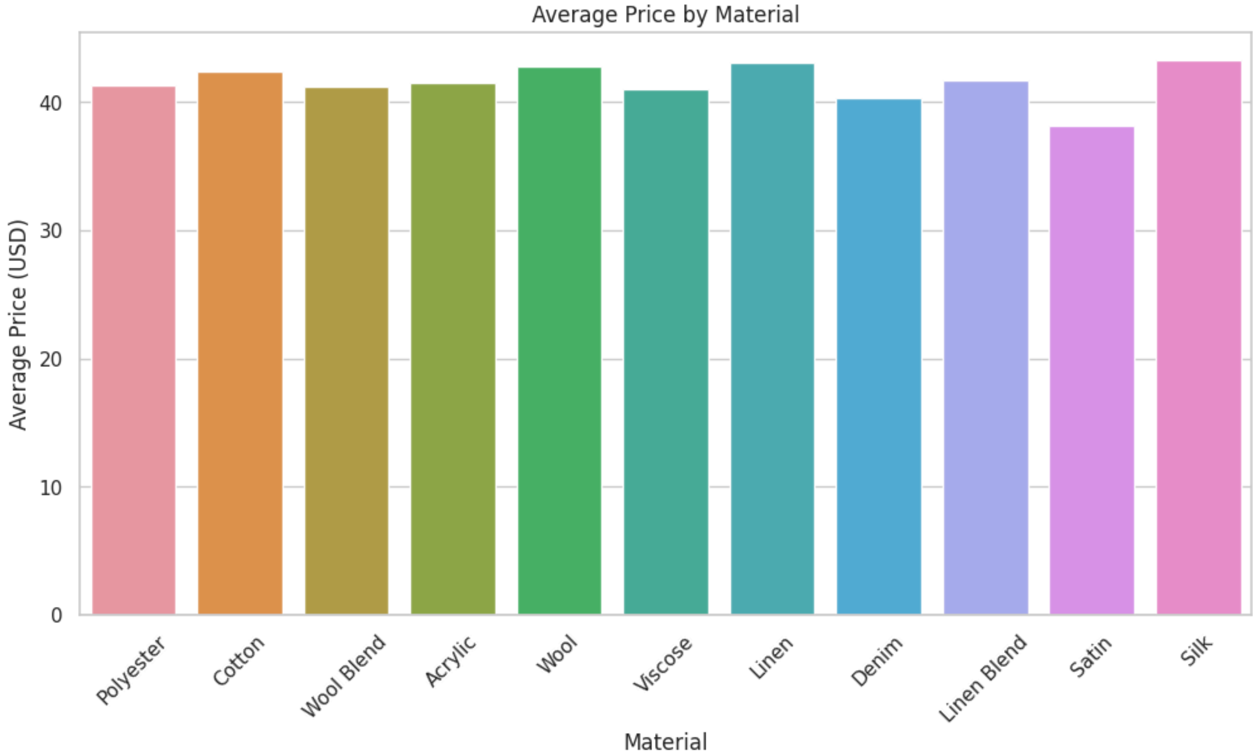
This indicates that female customers are either purchasing more items, or the women's product line has a wider veriety and stronger demand. It may also reflect marketing strategies that better resonate with women or a larger prooduct protfolio tailored for them.

```
#Price By Origin
plt.figure(figsize=(12,6))
sns.barplot(x="origin", y="price", data=df)
plt.title("Average Price by origin")
plt.ylabel("Average Price (USD)")
plt.xlabel("Average Price of Origin")
plt.xticks(rotation=45)
plt.show()
```



The Analysis reveals a globally consistent pricing landscape, with Turkey and Morocco leading as premium origins and Brazil and Argentina offering competitive price advantages. This balance suggests a well-structured pricing approach that aligns with both quality and affordability-a strong foundation for strategic market positioning.

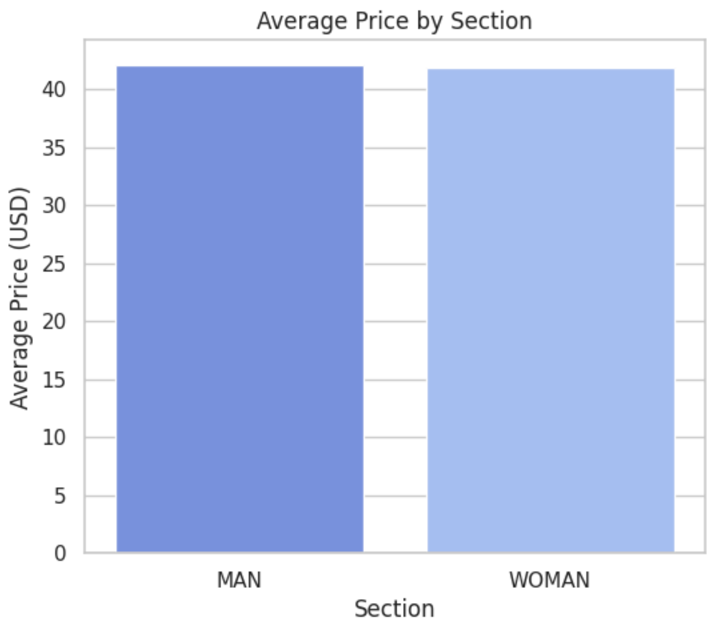
```
#Price by Meterials
plt.figure(figsize=(12,6))
sns.barplot(x="material",y="price", data=df,errorbar=None)
plt.title("Average Price by Material")
plt.ylabel("Average Price (USD)")
plt.xlabel("Material")
plt.xticks(rotation=45)
plt.show()
```



The bar chart shows the average product price (USD) based on material type. It highlights how different fabrics influence product pricing, reflecting variations in quality, production cost and market demand.

The pricing trend reveals that luxurious materials like silk, linen and wool dominate the higher end of the market, while blended fibres maintain balanced accessible pricing. This balance between quality and affordability indicates a diverse product strategy that caters to both premium and budget-conscious customers.

```
#Price by Section
plt.figure(figsize=(6, 5))
sns.barplot(x="section", y="price", data=df, errorbar=None)
plt.title("Average Price by Section")
plt.ylabel("Average Price (USD)")
plt.xlabel("Section")
plt.show()
```



The bar chart presents the average price of products categorized by gender section (Man vs Woman). Interestingly, the average prices are nearly identical, with men's products having a slightly higher average price (around $42.2USD) compared to women's products (approximately$41.8 USD).

Features Engineering

```
#Convert numeric Columns
df["Sales Volume"] = pd.to_numeric(df["Sales Volume"], errors="coerce")
df["Price"] = pd.to_numeric(df["price"], errors="coerce")
```

```
#Drop missing values for main numeric columns
df = df.dropna(subset=["Sales Volume","price"])
```

```
#List of Irrelevent Columns
cols_to_drop = [
    "Product ID",
    "Product Position",
    "Promotion",
    "Product Category",
    "brand",
    "url",
    "name",
    "description",
    "currency",
    "terms"
]
```

```
#Drop the Columns Safely (ignore if missing)
df = df.drop(columns=[c for c in cols_to_drop if c in df.columns], errors="ignore")
```

```
#Display remaining Columns
print("Remaining Columns after cleanup")
print(df.columns.tolist())
```

```
Remaining Columns after cleanup
['Seasonal', 'Sales Volume', 'price', 'section', 'season', 'material', 'origin', 'Price']
```

```
#Quick Preview
print("\nSample Data:")
print(df.head())
```

```
Sample Data:
  Seasonal  Sales Volume  price section  season   material   origin  Price
0      Yes          1243  78.99     MAN  Winter  Polyester   Brazil  78.99
1       No          1429  14.99     MAN  Autumn     Cotton   Turkey  14.99
2      Yes          1168  71.95   WOMAN  Autumn  Polyester  Morocco  71.95
```

```
3      No         1348  30.99     MAN  Spring   Polyester    China  30.99
4     Yes         1602  22.99   WOMAN  Winter  Wool Blend    China  22.99
```

Encoding Categorial Data

```
#Check current columns
print("Columns before encoding:\n",df.columns.tolist())
```

```
Columns before encoding:
 ['Seasonal', 'Sales Volume', 'price', 'section', 'season', 'material', 'origin', 'Price']
The history saving thread hit an unexpected error (OperationalError('attempt to write a readonly database')).History will nc
```

```
#Identify Categorial columns automatically (Object type)
categorial_cols = df.select_dtypes(include=["object"]).columns.tolist()
print("\nCateforical Columns to encode:\n",categorial_cols)
```

```

Cateforical Columns to encode:
 ['Seasonal', 'section', 'season', 'material', 'origin']
```

```
#One-hot encode categorical columns
df_encoded = pd.get_dummies(df, columns=categorial_cols, drop_first = True)

print("\nColumnsa after encoding:\n",df_encoded.columns.tolist())
print("\nEncoded data sample")
print(df_encoded.head())
```

```

Columnsa after encoding:
 ['Sales Volume', 'price', 'Price', 'Seasonal_Yes', 'section_WOMAN', 'season_Spring', 'season_Summer', 'season_Winter', 'mat

Encoded data sample
   Sales Volume  price  Price  Seasonal_Yes  section_WOMAN  season_Spring  \
0          1243  78.99  78.99          True          False          False
1          1429  14.99  14.99         False          False          False
2          1168  71.95  71.95          True           True          False
3          1348  30.99  30.99         False          False           True
4          1602  22.99  22.99          True           True          False

   season_Summer  season_Winter  material_Cotton  material_Denim  ...  \
0          False           True            False           False  ...
1          False          False             True           False  ...
2          False          False            False           False  ...
3          False          False            False           False  ...
4          False           True            False           False  ...

   origin_Brazil  origin_Cambodia  origin_China  origin_India  origin_Morocco  \
0           True            False         False         False           False
1          False            False         False         False           False
2          False            False         False         False            True
3          False            False          True         False           False
4          False            False          True         False           False

   origin_Pakistan  origin_Portugal  origin_Spain  origin_Turkey  \
0            False            False         False          False
1            False            False         False           True
2            False            False         False          False
3            False            False         False          False
4            False            False         False          False

   origin_Vietnam
0           False
1           False
2           False
3           False
4           False

[5 rows x 29 columns]
```

```
df_encoded.head()
```

	Sales Volume	price	Price	Seasonal_Yes	section_WOMAN	season_Spring	season_Summer	season_Winter	material_Cotton	material_
0	1243	78.99	78.99	True	False	False	False	True	False	
1	1429	14.99	14.99	False	False	False	False	False	True	
2	1168	71.95	71.95	True	True	False	False	False	False	
3	1348	30.99	30.99	False	False	True	False	False	False	
4	1602	22.99	22.99	True	True	False	False	True	False	

5 rows × 29 columns

Split into Features (X) and Target (Y)

```
#Target Variable
y = df_encoded["Sales Volume"]

#Features (drop target)
X = df_encoded.drop("Sales Volume",axis=1)
```

```
print("Feature Shape: ",X.shape)
print("Target Shape: ",y.shape)
```

```
Feature Shape:  (20250, 28)
Target Shape:  (20250,)
```

Model Training

RandomForest Regressor

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
from sklearn.linear_model import LinearRegression
```

```
X_train, X_test, y_train, y_test = train_test_split(
    X,y,test_size=0.2, random_state=42
)
```

```
#Model Training
model = RandomForestRegressor(
    n_estimators = 200,
    random_state = 42,
    n_jobs=-1
)

model.fit(X_train, y_train)
```

```
RandomForestRegressor
RandomForestRegressor(n_estimators=200, n_jobs=-1, random_state=42)
```

```
#Evaluation
y_pred = model.predict(X_test)
```

```
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
```

```
print("\n=========================Model Performance================================")
print(f"R2 Score      :{r2:.4f}")
print(f"MAE           :{mae:.4f}")
print(f"MSE           :{mse:.4f}")
print(f"RMSE          :{rmse:.4f}")
```

```
========================Model Performance===============================
R2 Score      :0.5025
MAE           :143.4247
MSE           :42005.7537
RMSE          :204.9531
```

Linear Regression Model

```
#Train Linear Regression Model
lr_model = LinearRegression()
```

```
lr_model.fit(X_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
#Predict and Evaluate
y_pred = lr_model.predict(X_test)
```

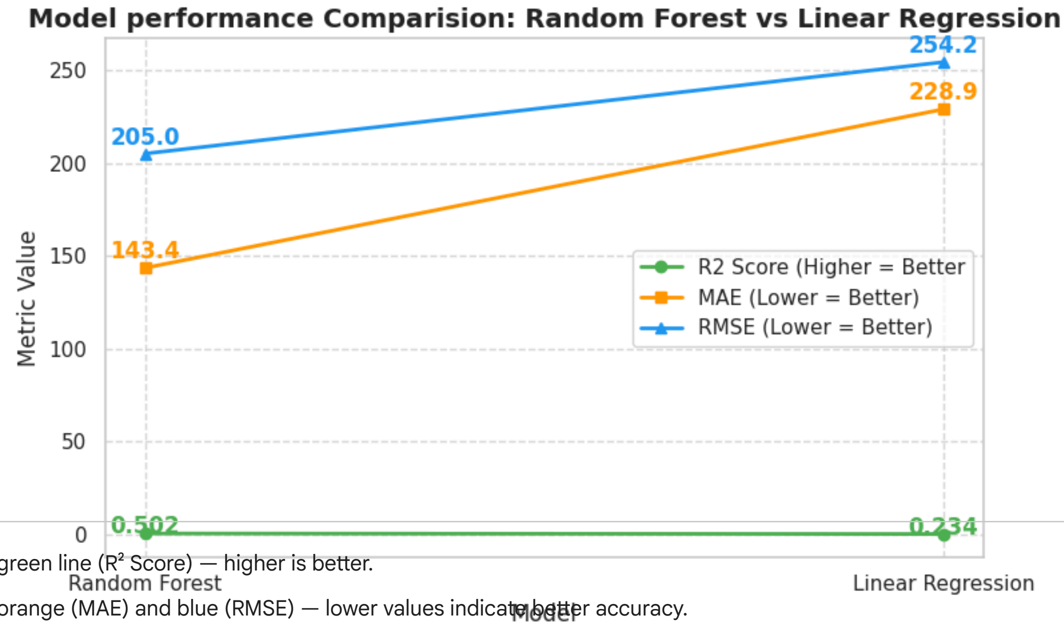
```
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
```

```
print("\n========================Model Performance===============================")
print(f"R2 Score      :{r2:.4f}")
print(f"MAE           :{mae:.4f}")
print(f"MSE           :{mse:.4f}")
print(f"RMSE          :{rmse:.4f}")
```

```
========================Model Performance===============================
R2 Score      :0.2344
MAE           :228.8881
MSE           :64642.2345
RMSE          :254.2484
```

```
#2 Model Comperision Graph
models = ["Random Forest", "Linear Regression"]

#metrics
r2_scores = [0.5025, 0.2344]
mae_scores = [143.4247, 228.8881]
rmse_scores = [204.9531, 254.2484]
```

```
#Create Figure
plt.figure(figsize=(8,5))

plt.plot(models, r2_scores, marker = "o", label="R2 Score (Higher = Better",color="#4CAF50", linewidth=2)
plt.plot(models, mae_scores, marker="s", label="MAE (Lower = Better)", color="#FF9800",linewidth=2)
plt.plot(models, rmse_scores, marker="^", label="RMSE (Lower = Better)",color="#2196F3", linewidth=2)

#Add labels and title
plt.title("Model performance Comparision: Random Forest vs Linear Regression", fontsize=14, fontweight="bold")
plt.xlabel("Model",fontsize=12)
plt.ylabel("Metric Value", fontsize=12)
plt.legend()
plt.grid(True, linestyle="--", alpha = 0.7)

#Add Value labels on each point
for i in range(len(models)):
    plt.text(models[i], r2_scores[i]+0.02, f"{r2_scores[i]:.3f}", color="#4CAF50", ha="center", fontweight="bold")
    plt.text(models[i], mae_scores[i]+5, f"{mae_scores[i]:.1f}", color="#FF9800", ha='center', fontweight="bold")
    plt.text(models[i], rmse_scores[i]+5, f"{rmse_scores[i]:.1f}", color="#2196F3", ha="center", fontweight="bold"


plt.tight_layout()
plt.show()
```



The green line (R^2 Score) — higher is better.

The orange (MAE) and blue (RMSE) — lower values indicate better accuracy.

You'll clearly see Random Forest above the Linear Regression for R^2, and below for MAE/RMSE → confirming it's the stronger model.

Predict Sales Volume for New Product

```
new_product = {
    "price":50,
    "section":"WOMAN",
    "season":"Winter",
    "material": "Cotton",
    "origin":"Bangladesh"
}
```

```
#Convert to Datafram
new_df = pd.DataFrame([new_product])
```

```
# Create a figure with two subplots
plt.figure(figsize=(12,5))

# --- Left: Random Forest ---
plt.subplot(1, 2, 1)
plt.scatter(y_test, y_pred, color="#4CAF50", alpha=0.6, label="Predicted")
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2)
plt.title("Random Forest: Actual vs Predicted Sales Volume", fontsize=12, fontweight='bold')
plt.xlabel("Actual Sales Volume")
plt.ylabel("Predicted Sales Volume")
plt.legend()

# --- Right: Linear Regression ---
# Re-run predictions for Linear Regression if not already done
y_pred_lr = lr_model.predict(X_test)

plt.subplot(1, 2, 2)
plt.scatter(y_test, y_pred_lr, color="#2196F3", alpha=0.6, label="Predicted")
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2)
plt.title("Linear Regression: Actual vs Predicted Sales Volume", fontsize=12, fontweight='bold')
plt.xlabel("Actual Sales Volume")
plt.ylabel("Predicted Sales Volume")
plt.legend()

plt.suptitle("Model Comparison: Random Forest vs Linear Regression", fontsize=14, fontweight='bold')
plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```

Model Comparison: Random Forest vs Linear Regression