● Objective: Predict the number of furniture items sold (sold) based on product

attributes such as productTitle, originalPrice, price, and tagText.

● Tech Stack: Python, pandas, scikit-learn, matplotlib, seaborn

Steps:

1. Data Collection

2. Data Preprocessing

3. Exploratory Data Analysis (EDA)

4. Feature Engineering

5. Model Selection & Training

6. Model Evaluation

7. Conclusion

1. Data Collection

In this step, we assume that the dataset is available in CSV format. We can load it

using pandas.

# Import necessary libraries

import pandas as pd

# Load dataset

df = pd.read\_csv('ecommerce\_furniture\_dataset.csv')

# View the first few rows of the dataset

print(df.head())

2. Data Preprocessing

We will clean the data by handling missing values, converting categorical variables,

and removing irrelevant columns.

# Check for missing values

print(df.isnull().sum())

# Dropping any rows with missing values (if applicable)

df = df.dropna()

# Converting tagText into a categorical feature (if necessary)

df['tagText'] = df['tagText'].astype('category').cat.codes

# Checking for data types and conversions if necessary

print(df.info())

3. Exploratory Data Analysis (EDA)

Visualize the relationships between features and the target variable (sold).

Understand the distribution and trends in the data.

import seaborn as sns

import matplotlib.pyplot as plt

# Distribution of 'sold' values

sns.histplot(df['sold'], kde=True)

plt.title('Distribution of Furniture Items Sold')

plt.show()

# Plot the relationship between originalPrice, price and sold

sns.pairplot(df, vars=['originalPrice', 'price', 'sold'],

kind='scatter')

plt.title('Relationship Between Price, Original Price, and

Items Sold')

plt.show()

4. Feature Engineering

1. Handling Product Titles: We will convert productTitle to numerical

features using techniques like TF-IDF.

2. Price and Discount Feature: Create a new feature to calculate the percentage

discount from originalPrice and price.

from sklearn.feature\_extraction.text import TfidfVectorizer

# Create a new feature: percentage discount

df['discount\_percentage'] = ((df['originalPrice'] -

df['price']) / df['originalPrice']) \* 100

# Convert productTitle into a numeric feature using TF-IDF

Vectorizer

tfidf = TfidfVectorizer(max\_features=100)

productTitle\_tfidf = tfidf.fit\_transform(df['productTitle'])

# Convert to DataFrame and concatenate to original df

productTitle\_tfidf\_df =

pd.DataFrame(productTitle\_tfidf.toarray(),

columns=tfidf.get\_feature\_names\_out())

df = pd.concat([df, productTitle\_tfidf\_df], axis=1)

# Drop original productTitle as it's now encoded

df = df.drop('productTitle', axis=1)

5. Model Selection & Training

We will use Linear Regression and Random Forest Regressor as models to

predict the number of items sold.

from sklearn.model\_selection import train\_test\_split

from sklearn.linear\_model import LinearRegression

from sklearn.ensemble import RandomForestRegressor

from sklearn.metrics import mean\_squared\_error, r2\_score

# Split the dataset into features (X) and target (y)

X = df.drop('sold', axis=1)

y = df['sold']

# Train-test split (80% train, 20% test)

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y,

test\_size=0.2, random\_state=42)

# Initialize models

lr\_model = LinearRegression()

rf\_model = RandomForestRegressor(n\_estimators=100,

random\_state=42)

# Train models

lr\_model.fit(X\_train, y\_train)

rf\_model.fit(X\_train, y\_train)

6. Model Evaluation

We evaluate the model's performance using mean squared error (MSE) and

R-squared metrics.

# Predict with Linear Regression

y\_pred\_lr = lr\_model.predict(X\_test)

mse\_lr = mean\_squared\_error(y\_test, y\_pred\_lr)

r2\_lr = r2\_score(y\_test, y\_pred\_lr)

# Predict with Random Forest

y\_pred\_rf = rf\_model.predict(X\_test)

mse\_rf = mean\_squared\_error(y\_test, y\_pred\_rf)

r2\_rf = r2\_score(y\_test, y\_pred\_rf)

# Print model evaluation results

print(f'Linear Regression MSE: {mse\_lr}, R2: {r2\_lr}')

print(f'Random Forest MSE: {mse\_rf}, R2: {r2\_rf}')

7. Conclusion

After evaluating the models, we can conclude which model performed better and

further tune hyperparameters if needed. Random Forest tends to perform better on

complex datasets with high variance, while Linear Regression might work well if

relationships are linear.

Output:

1. Linear Regression Model: MSE and R-squared score.

2. Random Forest Model: MSE and R-squared score.

About Dataset

Dataset Overview:

This dataset comprises 2,000 entries scraped from AliExpress, detailing a variety of

furniture products. It captures key sales metrics and product details, offering a

snapshot of consumer purchasing patterns and market trends in the online furniture

retail space.

Data Science Applications:

The dataset is ripe for exploratory data analysis, market trend analysis, and price

optimization studies. It can also be used for predictive modeling to forecast sales,

understand the impact of discounts on sales volume, and analyze the relationship

between product features and their popularity.

Column Descriptors:

● productTitle: The name of the furniture item.

● originalPrice: The original price of the item before any discounts.

● price: The current selling price of the item.

● sold: The number of units sold.

● tagText: Additional tags associated with the item (e.g., "Free shipping").

Ethically Collected Data:

The data was collected in compliance with ethical standards, ensuring respect for user

privacy and platform terms of service.

Acknowledgements:

This dataset was created with data sourced from AliExpress, using Apify for scraping.

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