In [193…
```
# DSC630
# Week 10
# Term Project
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# 08/10/24
```

Milestone 5 - Term Project

In [194…
```
# Import packages
import warnings

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.metrics.pairwise import cosine_similarity
from statsmodels.tsa.holtwinters import ExponentialSmoothing
```

In [195…
```
# Import data
data = pd.read_csv("jewelry - Copy.csv")
```

In [196…
```
# Dataframe check
type(data)
```

Out[196]:
```
pandas.core.frame.DataFrame
```

In [197…
```
# Dataframe shape
print(f'Data dimensions: {data.shape}')
```

```
Data dimensions: (95911, 13)
```

In [198…
```
# Preview first row of dataset
data.head(1).stack()
```

Out[198]:
```
0  order_datetime    2018-12-01 11:40:29 UTC
   order_id              1924719191579951782
   product_id            1842195256808833386
   qty                                     1
   category_id         1806829201890738432.0
   category_alias            jewelry.earring
   brand_id                              0.0
   price                              561.51
   user_id             1515915625207851264.0
   main_color                            red
   main_metal                           gold
   main_gem                          diamond
dtype: object
```

I noticed some rows had empty values in the 'user_id' and 'price' columns because the values were shifted two spaces to the left. I observed this issue while inspecting the data in Excel, so it's best to correct it now.

In [199…
```
# New dataframe that contains the rows that contain
# NaN values in the 'user_id' column
empty_users = data[data["user_id"].isnull()]
```

In [200…
```
# Count of rows that contain NA values in the 'user_id' column
len(empty_users)
```

Out[200]:
```
5352
```

In [201…
```
# 'Moves' the misplaced data to the correct columns
for idx, row in empty_users.iterrows():
    # Sets price value equal to category_alias value
    row["price"] = row["category_alias"]
    row["category_alias"] = np.nan  # Sets category_alias value to NaN

    row["user_id"] = row["brand_id"]  # Sets user_id value equal to brand_id value
    row["brand_id"] = np.nan  # Sets brand_id value to NaN

    data.loc[idx] = row  # Updates the original dataset with these changes
```

In [202…
```
# Count of rows that contain NaN values in the 'user_id' column
# after making the above changes
data['user_id'].isnull().sum()
```

Out[202]:
```
0
```

I will replace empty values in the 'product_gender' column with 'u', which represents unisex. To fill in this column, I can use the 'category_alias' column as a reference. For instance, every record with 'jewelry.necklace' has 'f' in the 'product_gender' column. However, since there can be male or unisex necklaces, I have decided to use 'u' for the null values.

Null values in the 'main_gem' column will be filled with 'unknown-gem'. There is already a value 'unknown-color' in the 'main_color' column, so this approach maintains consistency with the existing dataset.

Null values in the 'brand_id' column will be replaced with -1 to indicate that the product does not have a brand.

These are the null values that will be addressed. The remaining null values will be dropped from the dataset altogether.

In [203…
```
# Fill in NaN values in the data
data['product_gender'].fillna('u', inplace = True)
data['main_gem'].fillna('unknown-gem', inplace = True)
data['brand_id'].fillna(-1, inplace = True)
```

In [204…
```
# Create new dataframe using copy() and dropna() functions
dropped_na_data = data.copy().dropna()
```

In [205…
```
# Filling in some of the NaN values has helped keep a large amount of records
print(f'Original record count: {len(data)}')
print(f'New record count:      {len(dropped_na_data)}')
print(f'Records lost:          {len(data) - len(dropped_na_data)}')
```

```
Original record count: 95911
New record count:      78391
Records lost:          17520
```

Next, I'll update the column data types as needed.

In [206…

```python
# View column data types
dropped_na_data.dtypes
```

Out[206]:

```
order_datetime     object
order_id            int64
product_id          int64
qty                 int64
category_id       float64
category_alias     object
brand_id          float64
price              object
user_id           float64
product_gender     object
main_color         object
main_metal         object
main_gem           object
dtype: object
```

In [207…

```python
# Use this to convert 'order_datetime' to datetime format
dropped_na_data['order_datetime'] = pd.to_datetime(dropped_na_data['order_datetime'])

# Set as index and drop original 'order_datetime' column
dropped_na_data.set_index('order_datetime', inplace = True)
```

In [208…

```python
# Convert columns to appropriate data types
dropped_na_data["category_id"] = dropped_na_data["category_id"].astype('Int64')
dropped_na_data["category_alias"] = dropped_na_data["category_alias"].astype(str)
dropped_na_data["brand_id"] = dropped_na_data["brand_id"].astype(int)
dropped_na_data["price"] = dropped_na_data["price"].astype(float)
dropped_na_data["user_id"] = dropped_na_data["user_id"].astype('Int64')
dropped_na_data["product_gender"] = dropped_na_data["product_gender"].astype(str)
dropped_na_data["main_color"] = dropped_na_data["main_color"].astype(str)
dropped_na_data["main_metal"] = dropped_na_data["main_metal"].astype(str)
dropped_na_data["main_gem"] = dropped_na_data["main_gem"].astype(str)
```

In [209…

```python
# Ensure the changes were made correctly
dropped_na_data.dtypes
```

Out[209]:

```
order_id            int64
product_id          int64
qty                 int64
category_id         Int64
category_alias     object
brand_id            int32
price             float64
user_id             Int64
product_gender     object
main_color         object
main_metal         object
main_gem           object
dtype: object
```

In [210…
```
# Preview first row of data after updating column data types
dropped_na_data.head(1).stack()
```

Out[210]:
```
order_datetime
2018-12-01 11:40:29+00:00  order_id          1924719191579951782
                           product_id        1842195256808833386
                           qty                                 1
                           category_id       1806829201890738432
                           category_alias        jewelry.earring
                           brand_id                            0
                           price                          561.51
                           user_id           1515915625207851264
                           product_gender                      u
                           main_color                        red
                           main_metal                       gold
                           main_gem                      diamond
dtype: object
```

Product Recommender System - Content-Based Filtering

In [211…
```
# Create a copy of the dataset and name it something different
rec_sys = dropped_na_data.copy()
```

In [212…
```
# Drop duplicates based on product_id
features = rec_sys[['product_id', 'category_alias', 'product_gender',
                    'main_color', 'main_metal']].drop_duplicates()
```

In [213…
```
# One-hot encode the categorical features
encoded = pd.get_dummies(features, columns = ['category_alias', 'product_gender',
                                              'main_color', 'main_metal'])
```

In [214…
```
# Create item-feature matrix with product_id as index
item_feature_matrix = encoded.set_index('product_id')
```

In [215…
```
# Compute cosine similarity between items
item_similarity = cosine_similarity(item_feature_matrix)
item_similarity_df = pd.DataFrame(item_similarity,
                                  index = item_feature_matrix.index,
                                  columns = item_feature_matrix.index)
```

In [216…
```
# Function that returns 10 recommended items from the store.
# These items have not been purchased by the user.
def recommend_items(user_id, df, item_similarity_df, top_n = 10):
    # Get items purchased by the user
    user_purchases = df[df['user_id'] == user_id]['product_id']

    # Calculate scores for items not purchased by the user
    scores = pd.Series(0, index = item_similarity_df.columns)

    for item in user_purchases:
        if item in item_similarity_df.index:
            similar_items = item_similarity_df[item]
            scores += similar_items
```

```python
    # Remove items already purchased by the user
    scores = scores.drop(user_purchases, errors = 'ignore')

    # Return top N recommended items
    return scores.sort_values(ascending = False).head(top_n)
```

In [217…

```python
# User with the most purchases will be used
chosen_user = rec_sys['user_id'].mode().iloc[0]
recommendations = recommend_items(chosen_user, rec_sys, item_similarity_df)
```

In [218…

```python
# Display output and loop through returned series
print(f"The following store items are recommended for user {chosen_user}.")
print()
string1 = "product_id: category_alias - product_gender - "
string2 = "main_color - main_metal - main_gem - price"
print(string1 + string2)
for product_id in recommendations.index:
    category = rec_sys[rec_sys['product_id'] == product_id]['category_alias'].iloc[0]
    gender = rec_sys[rec_sys['product_id'] == product_id]['product_gender'].iloc[0]
    color = rec_sys[rec_sys['product_id'] == product_id]['main_color'].iloc[0]
    metal = rec_sys[rec_sys['product_id'] == product_id]['main_metal'].iloc[0]
    gem = rec_sys[rec_sys['product_id'] == product_id]['main_gem'].iloc[0]
    price = rec_sys[rec_sys['product_id'] == product_id]['price'].iloc[0]
    string3 = f"{product_id}: {category} - {gender} - "
    string4 = f"{color} - {metal} - {gem} - ${price}"
    print(string3 + string4)
```

```
The following store items are recommended for user 1515915625245643008.

product_id: category_alias - product_gender - main_color - main_metal - main_gem - pr
ice
1515966222980043408: jewelry.ring - f - red - gold - diamond - $335.48
1515966223158066417: jewelry.ring - f - red - gold - diamond - $280.68
1855231075249291734: jewelry.ring - f - red - gold - diamond - $123.15
1515966223275024801: jewelry.ring - f - red - gold - fianit - $123.15
1515966223478625523: jewelry.ring - f - red - gold - diamond - $343.15
1515966223183803116: jewelry.ring - f - red - gold - unknown-gem - $168.36
1956663848211579723: jewelry.ring - f - red - gold - emerald - $280.68
1852230387330188242: jewelry.ring - f - red - gold - unknown-gem - $308.08
1839998982592397760: jewelry.ring - f - red - gold - diamond - $177.95
1956663847666319768: jewelry.ring - f - red - gold - topaz - $102.6
```

The recommender will be extremely useful as it suggests items that are very similar. I excluded the 'main_gem' column during the development phase to ensure some variability in the recommendations.

Inventory Management - Exponential Smoothing

I encountered some issues with my dataset while trying to create an ARIMA model for inventory management. As a result, I decided to use an Exponential Smoothing model instead. For the model analysis, I selected the product with the most occurrences in the dataset. I have also included a preview of the variables that describe the item I will be using.

In [219…

```
# A preview of the variables that describe the product we are going to use
# for analysis
q = 'product_id == 1956663840242401751'
dropped_na_data.query(q)[['category_alias', 'brand_id', 'price',
                          'product_gender', 'main_color', 'main_metal',
                          'main_gem']].iloc[0]
```

Out[219]:

```
category_alias    jewelry.ring
brand_id                     0
price                   259.97
product_gender               f
main_color                 red
main_metal                gold
main_gem           unknown-gem
Name: 2019-01-20 17:03:41+00:00, dtype: object
```

In [220…

```
# Aggregate sales data by month
monthly_sales = dropped_na_data.groupby([pd.Grouper(freq = 'M'),
                                         'product_id'])['qty'].sum().reset_index()

# Select a specific product_id for analysis
product_id = 1956663840242401751
product_sales = monthly_sales[monthly_sales['product_id'] == product_id]

# Set 'order_datetime' as index
product_sales.set_index('order_datetime', inplace = True)
```

In [221…

```
with warnings.catch_warnings():
    warnings.simplefilter('ignore')

    # Apply Exponential Smoothing (Holt-Winters' multiplicative seasonal method)
    model = ExponentialSmoothing(product_sales['qty'], trend = 'add',
                                 seasonal = 'mul', seasonal_periods = 12)
    fit = model.fit()

    # Forecasting
    forecast_periods = 12
    forecast = fit.forecast(steps = forecast_periods)

    # Generate future dates for plotting
    variable = pd.DateOffset(months = 1)
    future_dates = pd.date_range(start = product_sales.index[-1] + variable,
                                 periods = forecast_periods,
                                freq = 'M')
```

In [222…

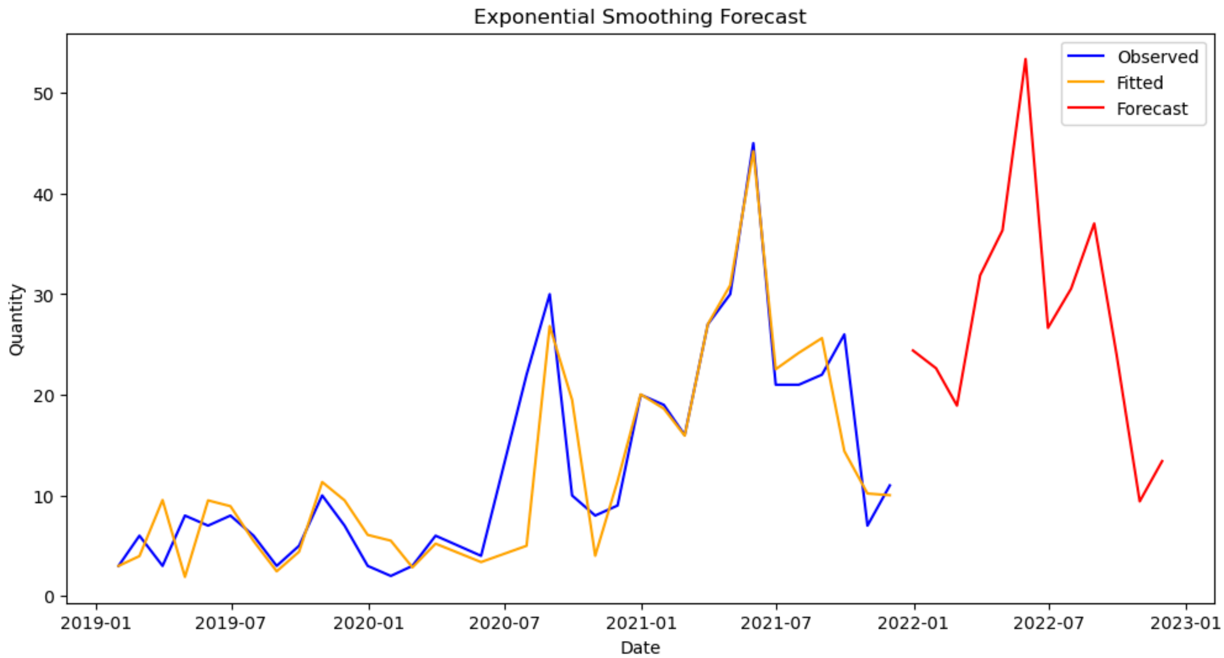
```
# Plotting
plt.figure(figsize = (12, 6))

plt.plot(product_sales.index, product_sales['qty'], label='Observed', color='blue')
plt.plot(product_sales.index, fit.fittedvalues, label='Fitted', color='orange')
plt.plot(future_dates, forecast, label='Forecast', color='red')

# Title and axis labes
plt.title('Exponential Smoothing Forecast')
plt.xlabel('Date')
plt.ylabel('Quantity')

# Add legend and show plot
```

```
plt.legend()
plt.show()
```



In [223…

```
# Use the fitted model to make in-sample predictions
in_sample_predictions = fit.fittedvalues

# Calculate MAE and MSE
mae = mean_absolute_error(product_sales['qty'], in_sample_predictions)
mse = mean_squared_error(product_sales['qty'], in_sample_predictions)

print(f"Mean Absolute Error: {mae:.2f}")
print(f"Mean Squared Error: {mse:.2f}")
```

```
Mean Absolute Error: 2.85
Mean Squared Error: 21.43
```

On average, each forecast deviates by 2.85 units. Given the size of the dataset (78,391 records), this level of error is very reasonable. This an improvement from the previous value of 5.13.

Resources

Kechinov, M. (2021, December 1). ECommerce purchase history from Jewelry Store. Kaggle. https://www.kaggle.com/datasets/mkechinov/ecommerce-purchase-history-from-jewelry-store

Drive more revenue with niche-specific personalization engine. REES46. (n.d.). https://rees46.com/

GeeksforGeeks. (2024b, May 23). Movie Recommender based on plot summary using TF-IDF vectorization and cosine similarity. https://www.geeksforgeeks.org/movie-recommender-based-on-plot-summary-using-tf-idf-vectorization-and-cosine-similarity/