Task 1 Notebook File - 20MIP10033 - Chandan Thota

In [1]:
```
# Importing required libraries
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
from statsmodels.tsa.seasonal import seasonal_decompose
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
import shap
from sklearn.preprocessing import StandardScaler
import xgboost as xgb
import lightgbm as lgb
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from tensorflow.keras.callbacks import ModelCheckpoint
from sklearn.metrics import mean_squared_error
```

In [2]:
```
# Loading the dataset
train = pd.read_csv("orgData/train.csv")
```

In [3]:
```
# Checking the size of the dataset
train.shape
```

Out[3]:
```
(101490, 8)
```

In [4]:
```
# Checking the data types
train.dtypes
```

Out[4]:
```
ID              object
date            object
Item Id         object
Item Name       object
ad_spend       float64
anarix_id       object
units          float64
unit_price     float64
dtype: object
```

In [5]:
```
# Coverting the datatype of "date" column to datatime
train['date'] = pd.to_datetime(train['date'])
train.set_index('date', inplace=True)
print(train.dtypes)
```

```
ID              object
Item Id         object
Item Name       object
ad_spend       float64
anarix_id       object
units          float64
unit_price     float64
dtype: object
```

In [6]:
```
# Checking the data
train.head()
```

Out[6]:

date	ID	Item Id	Item Name	ad_spend	anarix_id	units	unit_p
2022-04-12	2022-04-12_B09KDTS4DC	B09KDTS4DC	NapQueen Elizabeth 8" Gel Memory Foam Mattress...	NaN	NAPQUEEN	0.0	
2022-04-12	2022-04-12_B09MR2MLZH	B09MR2MLZH	NapQueen 12 Inch Bamboo Charcoal Queen Size Me...	NaN	NAPQUEEN	0.0	
2022-04-12	2022-04-12_B09KSYL73R	B09KSYL73R	NapQueen Elsa 8" Innerspring Mattress, Twin XL	NaN	NAPQUEEN	0.0	
2022-04-12	2022-04-12_B09KT5HMNY	B09KT5HMNY	NapQueen Elsa 6" Innerspring Mattress, Twin	NaN	NAPQUEEN	0.0	
2022-04-12	2022-04-12_B09KTF8ZDQ	B09KTF8ZDQ	NapQueen Elsa 6" Innerspring Mattress, Twin XL	NaN	NAPQUEEN	0.0	

Data Preprocessing Stage 1

In [7]:
```
# Checking if there are any null values in the entire DataFrame
exists = train.isnull().values.any()
print(exists)
```

```
True
```

In [8]:
```
# Creating a function with calculates the null percentage of a column/feature
def null_percent(df):
    null_df = df.isnull().sum().reset_index()
    null_df.columns = ['Column', 'Null Count']
    null_df['Null Percentage'] = round((null_df['Null Count'] / len(train)) * 10

    return null_df
```

In [9]:
```
# Checking the count and percent of nulls present in features
nulls = null_percent(train)
nulls
```

Out[9]:

	Column	Null Count	Null Percentage
0	ID	0	0.000
1	Item Id	2	0.002
2	Item Name	1832	1.805
3	ad_spend	24187	23.832
4	anarix_id	0	0.000
5	units	17898	17.635
6	unit_price	0	0.000

In [10]:
```
# checking if nulls exist in both item id and name
count_both_null = train[(train['Item Id'].isnull()) & (train['Item Name'].isnull
count_both_null.head()
```

Out[10]:

	ID	Item Id	Item Name	ad_spend	anarix_id	units	unit_price
date							
2024-04-07	2024-04-07_nan	NaN	NaN	0.0	NAPQUEEN	NaN	0.0
2024-04-18	2024-04-18_nan	NaN	NaN	0.0	NAPQUEEN	NaN	0.0

In [11]:
```
# Removing the null rows from the dataset [based on above result]
train = train.dropna(subset=['Item Id', 'Item Name'], how='all')
train.shape
```

Out[11]: (101488, 7)

In [12]:
```
# Filling the null values of feature "Item Name" using forward fill
# Save the original indices
train['Original Index'] = train.index

# Sort by 'Item Id'
train_sorted = train.sort_values(by='Item Id')

# Forward fill 'Item Name'
train_sorted['Item Name'] = train_sorted['Item Name'].ffill()

# Restore the original order using the saved index
train = train_sorted.sort_values(by='Original Index').drop(columns='Original Ind
```

In [13]:
```
# Checking the count and percent of nulls present in features
nulls = null_percent(train)
nulls
```

Out[13]:

	Column	Null Count	Null Percentage
0	ID	0	0.000
1	Item Id	0	0.000
2	Item Name	3	0.003
3	ad_spend	24187	23.832
4	anarix_id	0	0.000
5	units	17896	17.634
6	unit_price	0	0.000

In [14]:
```
# Checking why are the nulls still present in Item Name
nulls = train[(train['Item Name'].isnull())]
nulls.head()
```

Out[14]:

	ID	Item Id	Item Name	ad_spend	anarix_id	units	unit_price
date							
2023-09-25	2023-09-25_ASIN_BLANK	ASIN_BLANK	NaN	0.0	NAPQUEEN	NaN	0.0
2023-10-10	2023-10-10_ASIN_BLANK	ASIN_BLANK	NaN	0.0	NAPQUEEN	NaN	0.0
2023-11-02	2023-11-02_ASIN_BLANK	ASIN_BLANK	NaN	0.0	NAPQUEEN	NaN	0.0

In [15]:
```
# Checking the count of ASIN_Blank [based on above result]
count_asin_blank = (train['Item Id'].str.contains('ASIN_BLANK')).sum()
print(count_asin_blank)
```

```
3
```

In [16]:
```
# Dropping this rows since they contain mostly null values [based on above resul
train = train[~(train['Item Id'].str.contains('ASIN_BLANK'))]
print(train.shape)
```

```
(101485, 7)
```

In [17]:
```
# Checking the count and percent of nulls present in features
nulls = null_percent(train)
nulls
```

Out[17]:

	Column	Null Count	Null Percentage
0	ID	0	0.000
1	Item Id	0	0.000
2	Item Name	0	0.000
3	ad_spend	24187	23.833
4	anarix_id	0	0.000
5	units	17893	17.631
6	unit_price	0	0.000

In [18]:
```
# Imputing missing values for 'ad_spend' using forward and backward fill
train['ad_spend'] = train['ad_spend'].ffill().bfill()
```

In [19]:
```
# Checking the count and percent of nulls present in features
nulls = null_percent(train)
nulls
```

Out[19]:

	Column	Null Count	Null Percentage
0	ID	0	0.000
1	Item Id	0	0.000
2	Item Name	0	0.000
3	ad_spend	0	0.000
4	anarix_id	0	0.000
5	units	17893	17.631
6	unit_price	0	0.000

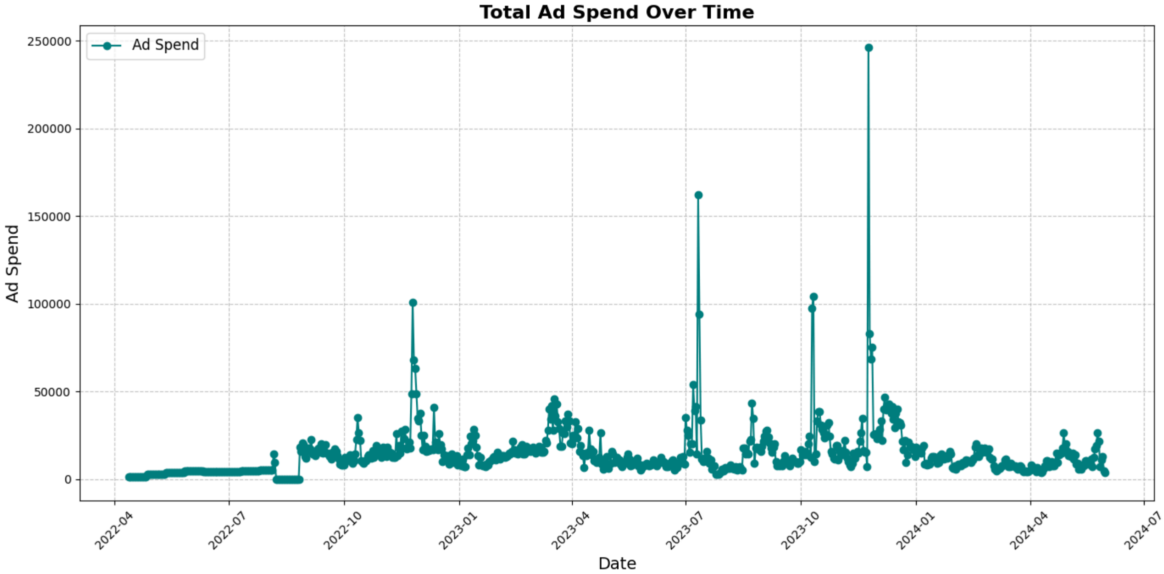
In [20]:
```
### Splitting the datasets [Known and Unknown] [based on nulls present in the co
known_df = train[train['units'].notnull()]
unknown_df = train[train['units'].isnull()]
print(known_df.shape)
print(unknown_df.shape)
```

```
(83592, 7)
(17893, 7)
```

EDA

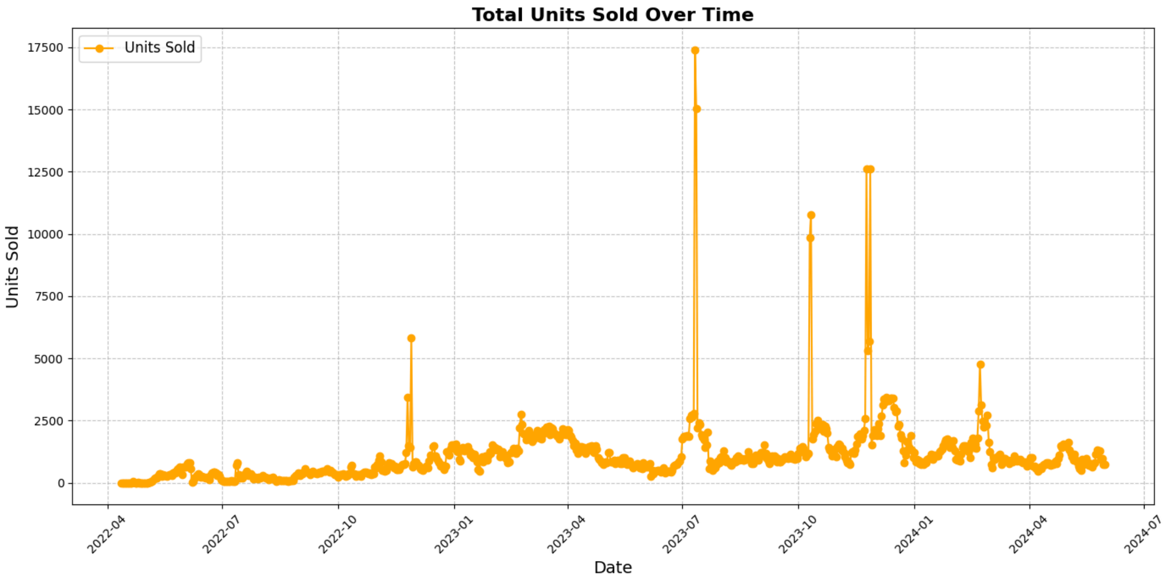
In [21]:
```
# Graph 1: - Plotting total and spend over time
plt.figure(figsize=(14, 7))
plt.plot(known_df.groupby('date')['ad_spend'].sum(), color='teal', linestyle='-'
plt.title('Total Ad Spend Over Time', fontsize=16, fontweight='bold')
plt.xlabel('Date', fontsize=14)
plt.ylabel('Ad Spend', fontsize=14)
plt.legend(loc='upper left', fontsize=12)
plt.grid(True, linestyle='--', alpha=0.7)
plt.xticks(rotation=45)
```

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



In [22]:

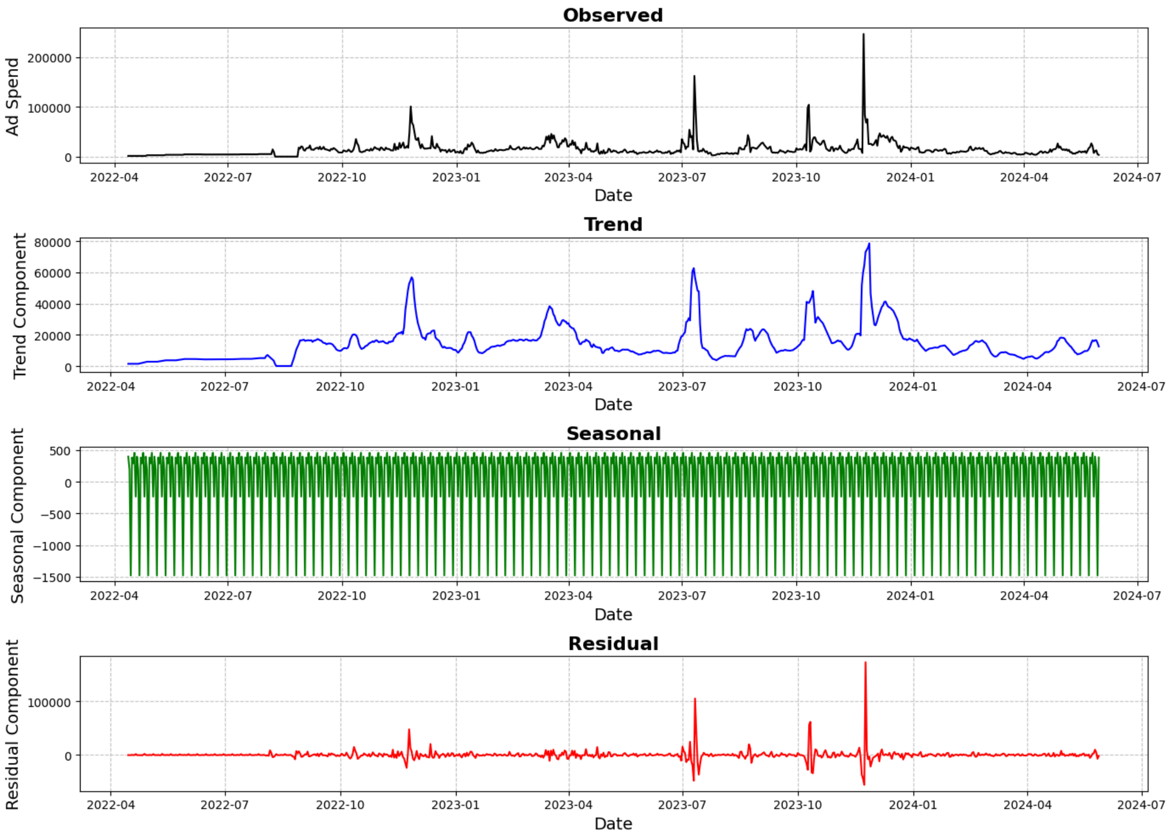
```
# Graph 2: - Plot total units sold over time
plt.figure(figsize=(14, 7))
plt.plot(known_df.groupby('date')['units'].sum(), color='orange', linestyle='-',
plt.title('Total Units Sold Over Time', fontsize=16, fontweight='bold')
plt.xlabel('Date', fontsize=14)
plt.ylabel('Units Sold', fontsize=14)
plt.legend(loc='upper left', fontsize=12)
plt.grid(True, linestyle='--', alpha=0.7)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [23]:

```
# Graph 3: - Plotting the observed, trend, seasonal and residual of column "ad_s
result = seasonal_decompose(known_df['ad_spend'].resample('D').sum(), model='add
plt.figure(figsize=(14, 10))

# Plotting observed
plt.subplot(4, 1, 1)
plt.plot(result.observed, color='black')
plt.title('Observed', fontsize=16, fontweight='bold')
plt.xlabel('Date', fontsize=14)
```

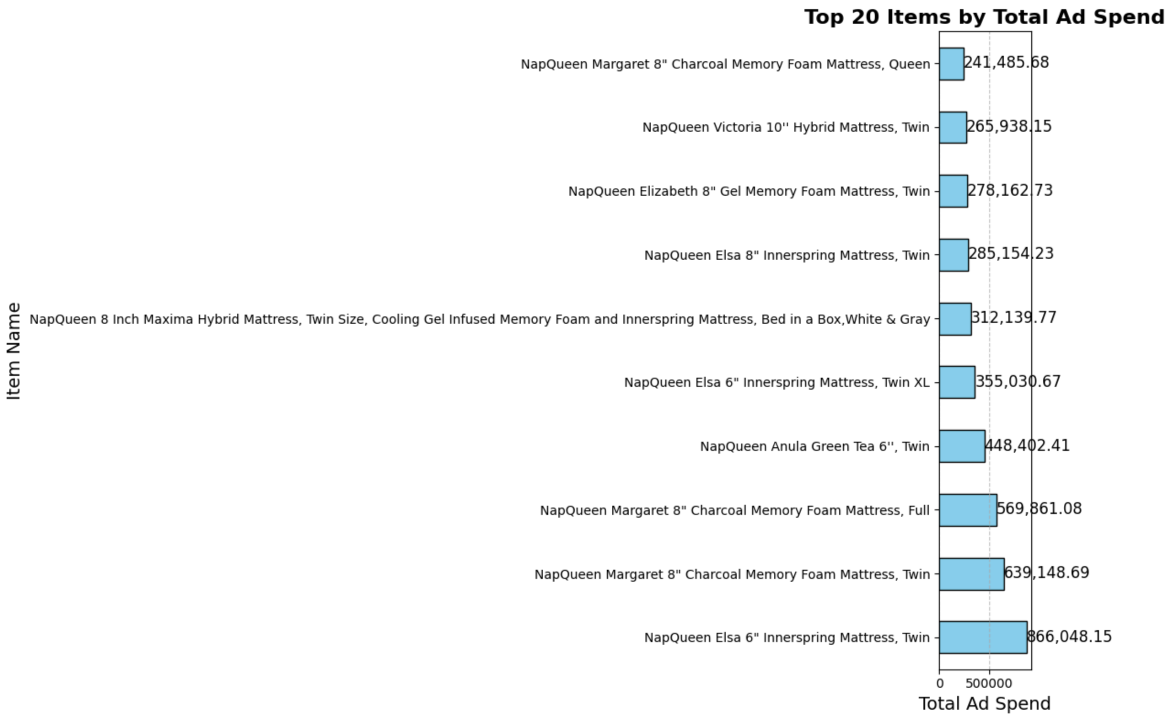
```python
plt.ylabel('Ad Spend', fontsize=14)
plt.grid(True, linestyle='--', alpha=0.7)

# Plotting trend
plt.subplot(4, 1, 2)
plt.plot(result.trend, color='blue')
plt.title('Trend', fontsize=16, fontweight='bold')
plt.xlabel('Date', fontsize=14)
plt.ylabel('Trend Component', fontsize=14)
plt.grid(True, linestyle='--', alpha=0.7)

# Plotting seasonal
plt.subplot(4, 1, 3)
plt.plot(result.seasonal, color='green')
plt.title('Seasonal', fontsize=16, fontweight='bold')
plt.xlabel('Date', fontsize=14)
plt.ylabel('Seasonal Component', fontsize=14)
plt.grid(True, linestyle='--', alpha=0.7)

# Plotting residual
plt.subplot(4, 1, 4)
plt.plot(result.resid, color='red')
plt.title('Residual', fontsize=16, fontweight='bold')
plt.xlabel('Date', fontsize=14)
plt.ylabel('Residual Component', fontsize=14)
plt.grid(True, linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



In [24]:

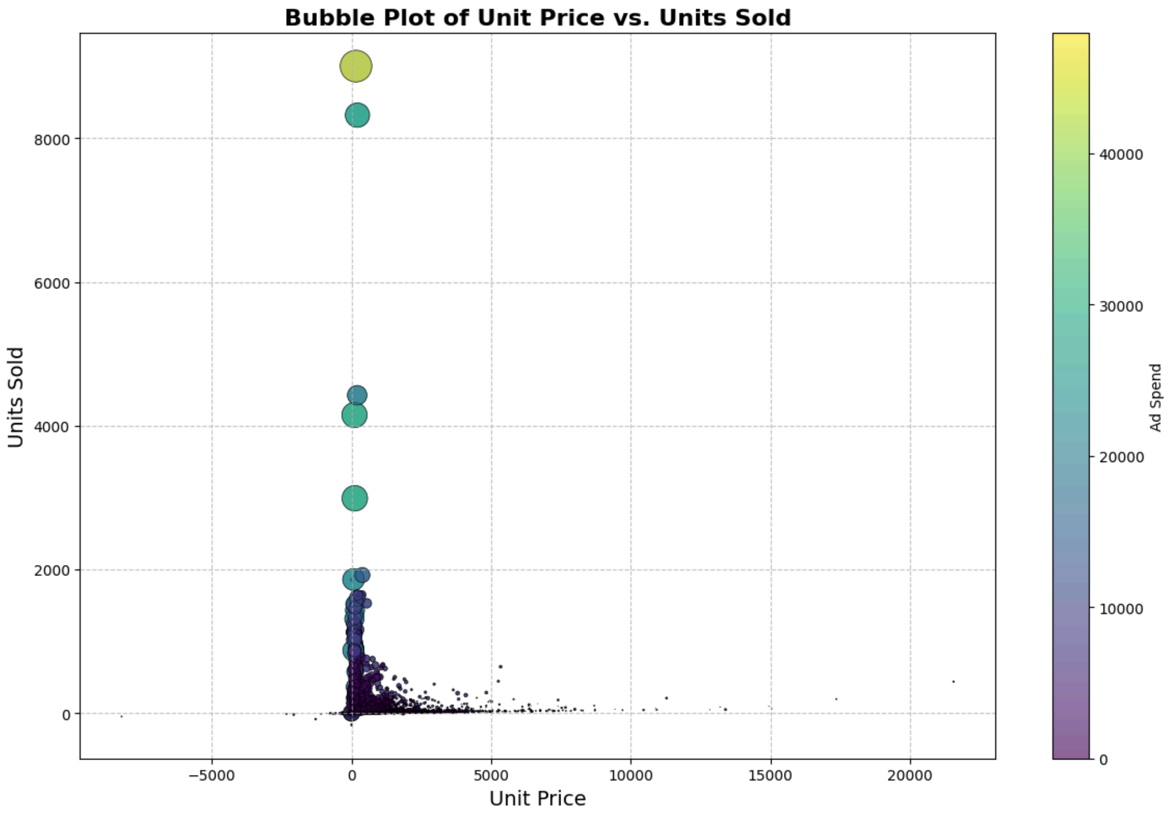
```python
# Graph 4: - top 10 items by total :ad_spend"
item_counts = known_df['Item Name'].value_counts()
top_items = known_df.groupby('Item Name')['ad_spend'].sum().nlargest(10)
plt.figure(figsize=(12, 8))
top_items.plot(kind='barh', color='skyblue', edgecolor='black')
```

```
plt.title('Top 20 Items by Total Ad Spend', fontsize=16, fontweight='bold')
plt.xlabel('Total Ad Spend', fontsize=14)
plt.ylabel('Item Name', fontsize=14)
for index, value in enumerate(top_items):
    plt.text(value, index, f'{value:,.2f}', va='center', fontsize=12, color='bla
plt.grid(axis='x', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



In [25]:

```
# Graph 5: - bubble plot of unit price vs units sold
plt.figure(figsize=(12, 8))
plt.scatter(
    known_df['unit_price'],
    known_df['units'],
    s=known_df['ad_spend'] / 100,
    c='teal',
    alpha=0.6,
    edgecolor='k',
    linewidth=0.5
)
plt.title('Bubble Plot of Unit Price vs. Units Sold', fontsize=16, fontweight='b
plt.xlabel('Unit Price', fontsize=14)
plt.ylabel('Units Sold', fontsize=14)
sc = plt.scatter(
    known_df['unit_price'],
    known_df['units'],
    s=known_df['ad_spend'] / 100,
    c=known_df['ad_spend'],
    cmap='viridis',
    alpha=0.6,
    edgecolor='k',
    linewidth=0.5
)
plt.colorbar(sc, label='Ad Spend')
plt.grid(True, linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



Feature Engineering

In [26]:
```
# Checking the correlation of numerical features
print(known_df[['ad_spend', 'units', 'unit_price']].corr())
```

```
             ad_spend     units  unit_price
ad_spend     1.000000  0.693707    0.026250
units        0.693707  1.000000    0.088579
unit_price   0.026250  0.088579    1.000000
```

In [27]:
```
# copying the dataset to remove unwanted errors
known_df = known_df.copy()
```

In [28]:
```
# Extract meaningful features from 'date' column
known_df.loc[:, 'year'] = known_df.index.year
known_df.loc[:, 'month'] = known_df.index.month
known_df.loc[:, 'day'] = known_df.index.day
known_df.loc[:, 'day_of_week'] = known_df.index.day_name()
known_df.loc[:, 'is_weekend'] = known_df.index.dayofweek >= 5
known_df.loc[:, 'quarter'] = known_df.index.quarter
```

In [29]:
```
# Checking the dataset
known_df.head()
```

Out[29]:

	ID	Item Id	Item Name	ad_spend	anarix_id	units	unit_pr
date							
2022-04-12	2022-04-12_B09MR5Q6HJ	B09MR5Q6HJ	NapQueen Margaret 10" Charcoal Memory Foam Mat...	83.21	NAPQUEEN	0.0	
2022-04-12	2022-04-12_B09KTF8ZDQ	B09KTF8ZDQ	NapQueen Elsa 6" Innerspring Mattress, Twin XL	83.21	NAPQUEEN	0.0	
2022-04-12	2022-04-12_B09MR4B13C	B09MR4B13C	NapQueen Margaret 8" Charcoal Memory Foam Matt...	83.21	NAPQUEEN	0.0	
2022-04-12	2022-04-12_B09MR5WS3Y	B09MR5WS3Y	NapQueen Margaret 8" Charcoal Memory Foam Matt...	83.21	NAPQUEEN	0.0	
2022-04-12	2022-04-12_B09KT5HMNY	B09KT5HMNY	NapQueen Elsa 6" Innerspring Mattress, Twin	83.21	NAPQUEEN	0.0	

In [30]:

```
# Splitting the known_df into 2 datasets with ratio (8:2)
X = known_df.drop(columns=['ID', 'units', 'Item Id', 'anarix_id'])
y = known_df["units"]

label_encoder = LabelEncoder()
X['Item Name'] = label_encoder.fit_transform(X['Item Name'])
X['day_of_week'] = label_encoder.fit_transform(X['day_of_week'])
X['is_weekend'] = label_encoder.fit_transform(X['is_weekend'])

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
```

In [31]:

```
# Loading and training the model Random Forest (ensemble) (Regressor)
model = RandomForestRegressor(
    n_estimators=100,
    criterion='squared_error',
    max_depth=10,
    min_samples_split=5,
```

```
    min_samples_leaf=4,
    max_features='sqrt',
    bootstrap=True,
    oob_score=True,
    n_jobs=-1,
    random_state=42,
    verbose=2,
    warm_start=False
)

model.fit(X_train, y_train)
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 8 concurrent workers.
building tree 1 of 100building tree 2 of 100
building tree 3 of 100

building tree 4 of 100
building tree 5 of 100
building tree 6 of 100
building tree 7 of 100
building tree 8 of 100
building tree 9 of 100
building tree 10 of 100
building tree 11 of 100
building tree 12 of 100
building tree 13 of 100
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building tree 32 of 100
building tree 33 of 100
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building tree 36 of 100
building tree 37 of 100
building tree 38 of 100
building tree 39 of 100
building tree 40 of 100
[Parallel(n_jobs=-1)]: Done  25 tasks      | elapsed:    0.4s
```

```
building tree 41 of 100
building tree 42 of 100
building tree 43 of 100
building tree 44 of 100
building tree 45 of 100
building tree 46 of 100
building tree 47 of 100
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building tree 97 of 100
building tree 98 of 100
building tree 99 of 100
building tree 100 of 100
```

```
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:    2.0s finished
```

Out[31]:

```
RandomForestRegressor

RandomForestRegressor(max_depth=10, max_features='sqrt', min_samples_le
af=4,
                      min_samples_split=5, n_jobs=-1, oob_score=True,
                      random_state=42, verbose=2)
```

In [32]:

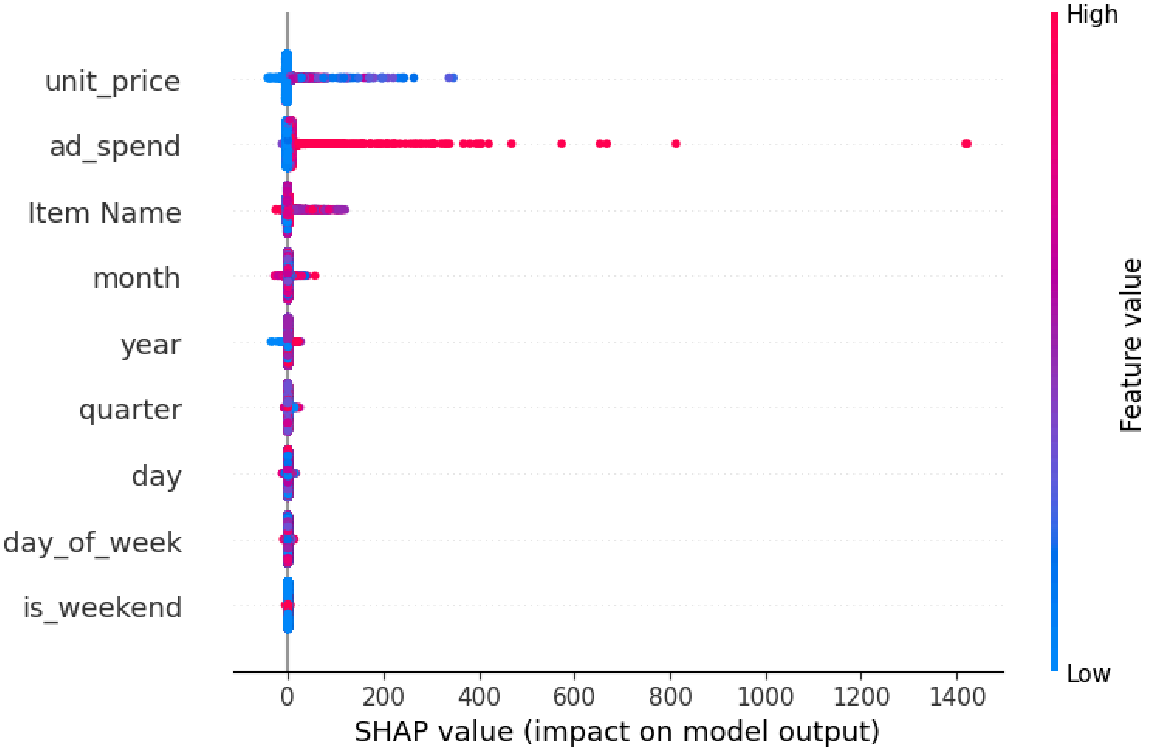
```python
# Creating a SHAP explainer using the trained random forest model
explainer = shap.TreeExplainer(model, X_train)

# Computing the SHAP values on the validation data
shap_values = explainer(X_test, check_additivity=False)
```

```
100%|===================| 16710/16719 [03:22<00:00]
```

In [33]:

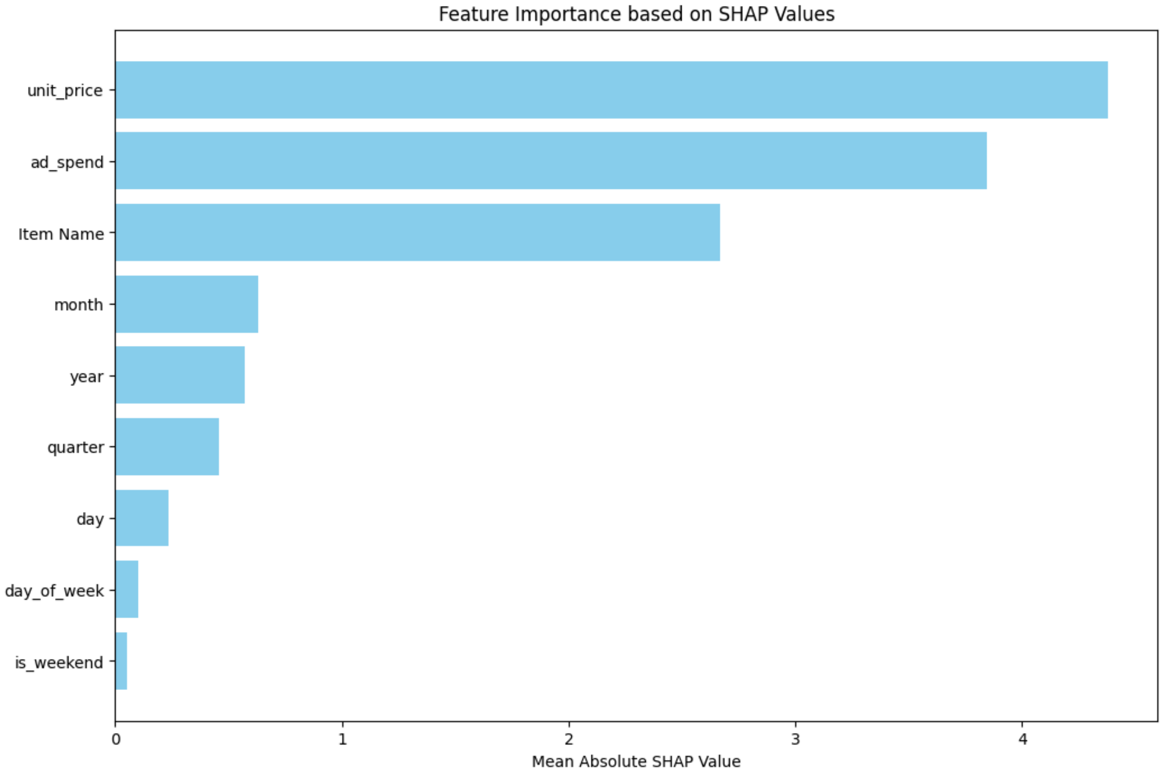
```python
# Graph 6: - Visualizing the calculated SHAP values
shap.summary_plot(shap_values, X_test, plot_type='dot')
```



In [34]:

```python
# Graph 7: - Feature importance based on SHAP values
shap_importance = pd.DataFrame({
    'feature': X_test.columns,
    'importance': np.abs(shap_values.values).mean(axis=0)
}).sort_values(by='importance', ascending=False)

# Plot the feature importances
plt.figure(figsize=(12, 8))
plt.barh(shap_importance['feature'], shap_importance['importance'], color='skybl
plt.xlabel('Mean Absolute SHAP Value')
plt.title('Feature Importance based on SHAP Values')
plt.gca().invert_yaxis()
plt.show()
```



Data Preprocessing Stage 2

In [35]:
```
# Copying the dataset to remove unwanted errors
unknown_df = unknown_df.copy()
```

In [36]:
```
# Extract features from 'date' column
unknown_df.loc[:, 'year'] = unknown_df.index.year
unknown_df.loc[:, 'month'] = unknown_df.index.month
unknown_df.loc[:, 'day'] = unknown_df.index.day
unknown_df.loc[:, 'day_of_week'] = unknown_df.index.day_name()
unknown_df.loc[:, 'is_weekend'] = unknown_df.index.dayofweek >= 5
unknown_df.loc[:, 'quarter'] = unknown_df.index.quarter
```

In [37]:
```
# Checking the dataset
unknown_df.head()
```

Out[37]:

date	ID	Item Id	Item Name	ad_spend	anarix_id	units	unit_pric
2022-08-06	2022-08-06_B09KDPXYG3	B09KDPXYG3	NapQueen Elizabeth 12" Gel Memory Foam Mattres...	83.21	NAPQUEEN	NaN	0.
2022-08-06	2022-08-06_B09X1H629F	B09X1H629F	NapQueen Elizabeth 14" Gel Memory Foam Mattres...	16.73	NAPQUEEN	NaN	0.
2022-08-06	2022-08-06_B0B69C4GST	B0B69C4GST	NapQueen Victoria 12'' Hybrid Mattress, King	0.00	NAPQUEEN	NaN	0.
2022-08-06	2022-08-06_B0B69SF1BT	B0B69SF1BT	NapQueen Victoria 12'' Hybrid Mattress, Twin	5.98	NAPQUEEN	NaN	0.
2022-08-06	2022-08-06_B09MR36MLJ	B09MR36MLJ	NapQueen Margaret 10" Charcoal Memory Foam Mat...	23.87	NAPQUEEN	NaN	0.

In [38]:
```
# processing the unknown_df for filling the nulls values in column "units"
test_data_nulls = unknown_df.drop(columns=['ID', 'units', 'Item Id', 'anarix_id'

test_data_nulls['Item Name'] = label_encoder.fit_transform(test_data_nulls['Item
test_data_nulls['day_of_week'] = label_encoder.fit_transform(test_data_nulls['da
test_data_nulls['is_weekend'] = label_encoder.fit_transform(test_data_nulls['is_
```

In [39]:
```
# Predicting the null values in unknown_df
predicted_units = model.predict(test_data_nulls)
```

```
[Parallel(n_jobs=8)]: Using backend ThreadingBackend with 8 concurrent workers.
[Parallel(n_jobs=8)]: Done  25 tasks      | elapsed:    0.0s
[Parallel(n_jobs=8)]: Done 100 out of 100 | elapsed:    0.0s finished
```

In [40]:
```
# Checking the length of the predicted nulls
assert len(predicted_units) == len(unknown_df)

# Creating a Series for easy updating
predicted_units_series = pd.Series(predicted_units, index=unknown_df.index)
```

```
# Updating the training dataset
train.loc[train['units'].isnull(), 'units'] = predicted_units_series
```

In [41]:
```
# Checking the count and percent of nulls present in features
nulls = null_percent(train)
nulls
```

Out[41]:

	Column	Null Count	Null Percentage
0	ID	0	0.0
1	Item Id	0	0.0
2	Item Name	0	0.0
3	ad_spend	0	0.0
4	anarix_id	0	0.0
5	units	0	0.0
6	unit_price	0	0.0

In [42]:
```
# Checking the dataset
train.head()
```

Out[42]:

date	ID	Item Id	Item Name	ad_spend	anarix_id	units	unit_pr
2022-04-12	2022-04-12_B09MR5Q6HJ	B09MR5Q6HJ	NapQueen Margaret 10" Charcoal Memory Foam Mat...	83.21	NAPQUEEN	0.0	
2022-04-12	2022-04-12_B09KTF8ZDQ	B09KTF8ZDQ	NapQueen Elsa 6" Innerspring Mattress, Twin XL	83.21	NAPQUEEN	0.0	
2022-04-12	2022-04-12_B09MR4B13C	B09MR4B13C	NapQueen Margaret 8" Charcoal Memory Foam Matt...	83.21	NAPQUEEN	0.0	
2022-04-12	2022-04-12_B09MR5WS3Y	B09MR5WS3Y	NapQueen Margaret 8" Charcoal Memory Foam Matt...	83.21	NAPQUEEN	0.0	
2022-04-12	2022-04-12_B09KT5HMNY	B09KT5HMNY	NapQueen Elsa 6" Innerspring Mattress, Twin	83.21	NAPQUEEN	0.0	

In [43]:
```
# Loading the test data
test = pd.read_csv("orgData/test.csv")
```

In [44]:
```
# Coverting the datatype of "date" column to datatime
test['date'] = pd.to_datetime(test['date'])
test.set_index('date', inplace=True)
print(test.dtypes)
```

```
ID             object
Item Id        object
Item Name      object
ad_spend      float64
anarix_id      object
unit_price    float64
dtype: object
```

In [45]:
```
# Checking the dataset
```

```
test.head()
```

Out[45]:

	ID	Item Id	Item Name	ad_spend	anarix_id	unit_price
date						
2024-07-01	2024-07-01_B09KDR64LT	B09KDR64LT	NapQueen Elizabeth 10" Gel Memory Foam Mattres...	NaN	NAPQUEEN	0.0
2024-07-01	2024-07-01_B09KDTS4DC	B09KDTS4DC	NapQueen Elizabeth 8" Gel Memory Foam Mattress...	NaN	NAPQUEEN	0.0
2024-07-01	2024-07-01_B09KDTHJ6V	B09KDTHJ6V	NapQueen Elizabeth 12" Gel Memory Foam Mattres...	NaN	NAPQUEEN	0.0
2024-07-01	2024-07-01_B09KDQ2BWY	B09KDQ2BWY	NapQueen Elizabeth 12" Gel Memory Foam Mattres...	NaN	NAPQUEEN	0.0
2024-07-01	2024-07-01_B09KDYY3SB	B09KDYY3SB	NapQueen Elizabeth 10" Gel Memory Foam Mattres...	101.72	NAPQUEEN	1094.5

In [46]:

```
# Extract features from the "date" column [Both the train and test datasets]
train.loc[:, 'year'] = train.index.year
train.loc[:, 'month'] = train.index.month
train.loc[:, 'day'] = train.index.day
train.loc[:, 'day_of_week'] = train.index.day_name()
train.loc[:, 'is_weekend'] = train.index.dayofweek >= 5
train.loc[:, 'quarter'] = train.index.quarter

test.loc[:, 'year'] = test.index.year
test.loc[:, 'month'] = test.index.month
test.loc[:, 'day'] = test.index.day
test.loc[:, 'day_of_week'] = test.index.day_name()
test.loc[:, 'is_weekend'] = test.index.dayofweek >= 5
test.loc[:, 'quarter'] = test.index.quarter
```

In [47]:

```
# Checking the datasets
train.head()
```

Out[47]:

date	ID	Item Id	Item Name	ad_spend	anarix_id	units	unit_pr
2022-04-12	2022-04-12_B09MR5Q6HJ	B09MR5Q6HJ	NapQueen Margaret 10" Charcoal Memory Foam Mat...	83.21	NAPQUEEN	0.0	
2022-04-12	2022-04-12_B09KTF8ZDQ	B09KTF8ZDQ	NapQueen Elsa 6" Innerspring Mattress, Twin XL	83.21	NAPQUEEN	0.0	
2022-04-12	2022-04-12_B09MR4B13C	B09MR4B13C	NapQueen Margaret 8" Charcoal Memory Foam Matt...	83.21	NAPQUEEN	0.0	
2022-04-12	2022-04-12_B09MR5WS3Y	B09MR5WS3Y	NapQueen Margaret 8" Charcoal Memory Foam Matt...	83.21	NAPQUEEN	0.0	
2022-04-12	2022-04-12_B09KT5HMNY	B09KT5HMNY	NapQueen Elsa 6" Innerspring Mattress, Twin	83.21	NAPQUEEN	0.0	

In [48]:

```
# Checking the datasets
test.head()
```

Out[48]:

	ID	Item Id	Item Name	ad_spend	anarix_id	unit_price	ye
date							
2024-07-01	2024-07-01_B09KDR64LT	B09KDR64LT	NapQueen Elizabeth 10" Gel Memory Foam Mattres...	NaN	NAPQUEEN	0.0	20
2024-07-01	2024-07-01_B09KDTS4DC	B09KDTS4DC	NapQueen Elizabeth 8" Gel Memory Foam Mattress...	NaN	NAPQUEEN	0.0	20
2024-07-01	2024-07-01_B09KDTHJ6V	B09KDTHJ6V	NapQueen Elizabeth 12" Gel Memory Foam Mattres...	NaN	NAPQUEEN	0.0	20
2024-07-01	2024-07-01_B09KDQ2BWY	B09KDQ2BWY	NapQueen Elizabeth 12" Gel Memory Foam Mattres...	NaN	NAPQUEEN	0.0	20
2024-07-01	2024-07-01_B09KDYY3SB	B09KDYY3SB	NapQueen Elizabeth 10" Gel Memory Foam Mattres...	101.72	NAPQUEEN	1094.5	20

In [49]:
```
# Drop the unnecessary columns for the datasets
train_data = train.drop(columns=['ID', 'Item Id', 'anarix_id', 'units'], axis=1)
test_data = test.drop(columns=['ID', 'Item Id', 'anarix_id'], axis=1)
```

In [50]:
```
# Identify categorical and numerical features from the datasets
categorical_features = ['Item Name', 'day_of_week', 'day', 'is_weekend']
numerical_features = ['ad_spend', 'unit_price']
```

In [51]:
```
# Initializing the scaler for scaling the numeric features
scaler = StandardScaler()
```

In [52]:
```
# Fit and transform on train dataset
train_data[numerical_features] = scaler.fit_transform(train_data[numerical_featu

# Transform test dataset
test_data[numerical_features] = scaler.transform(test_data[numerical_features])
```

In [53]:
```python
# Applying the one hot encoding to the train and test datasets
for column in categorical_features:
    train_data[column] = label_encoder.fit_transform(train_data[column])
    test_data[column] = label_encoder.fit_transform(test_data[column])
```

In [54]:
```python
# Checking the dataset
train_data.head()
```

Out[54]:

	Item Name	ad_spend	unit_price	year	month	day	day_of_week	is_weekend	quar
date									
2022-04-12	162	-0.055726	-0.250771	2022	4	11	5	0	
2022-04-12	154	-0.055726	-0.250771	2022	4	11	5	0	
2022-04-12	180	-0.055726	-0.250771	2022	4	11	5	0	
2022-04-12	178	-0.055726	-0.250771	2022	4	11	5	0	
2022-04-12	153	-0.055726	-0.250771	2022	4	11	5	0	

In [55]:
```python
# Checking the dataset
test_data.head()
```

Out[55]:

	Item Name	ad_spend	unit_price	year	month	day	day_of_week	is_weekend	quar
date									
2024-07-01	79	NaN	-0.250771	2024	7	0	1	0	
2024-07-01	92	NaN	-0.250771	2024	7	0	1	0	
2024-07-01	83	NaN	-0.250771	2024	7	0	1	0	
2024-07-01	81	NaN	-0.250771	2024	7	0	1	0	
2024-07-01	78	-0.018401	2.320214	2024	7	0	1	0	

In [56]:
```python
# Saving the preprocessed datasets to variables for further processing
train = pd.concat([train_data, train['units']], axis=1)
test = pd.concat([test_data], axis=1)
```

In [57]:
```python
# Checking the dataset
```

```
train.head()
```

Out[57]:

date	Item Name	ad_spend	unit_price	year	month	day	day_of_week	is_weekend	quar
2022-04-12	162	-0.055726	-0.250771	2022	4	11	5	0	
2022-04-12	154	-0.055726	-0.250771	2022	4	11	5	0	
2022-04-12	180	-0.055726	-0.250771	2022	4	11	5	0	
2022-04-12	178	-0.055726	-0.250771	2022	4	11	5	0	
2022-04-12	153	-0.055726	-0.250771	2022	4	11	5	0	

In [58]:

```
# Checking the dataset
test.head()
```

Out[58]:

date	Item Name	ad_spend	unit_price	year	month	day	day_of_week	is_weekend	quar
2024-07-01	79	NaN	-0.250771	2024	7	0	1	0	
2024-07-01	92	NaN	-0.250771	2024	7	0	1	0	
2024-07-01	83	NaN	-0.250771	2024	7	0	1	0	
2024-07-01	81	NaN	-0.250771	2024	7	0	1	0	
2024-07-01	78	-0.018401	2.320214	2024	7	0	1	0	

In [59]:

```
# Creating a directory to save the processed train and test dataset
output_dir = 'proData'
if not os.path.exists(output_dir):
    os.makedirs(output_dir)
```

In [60]:

```
# Saving the processed datasets to the system
train.to_csv(os.path.join(output_dir, 'train_processed.csv'), index=True)
test.to_csv(os.path.join(output_dir, 'test_processed.csv'), index=True)
```

Memory Optimization

In [61]:
```
# Checking the initial size of the datasets
print(train.info(memory_usage='deep'))
print(test.info(memory_usage='deep'))
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 101485 entries, 2022-04-12 to 2024-05-31
Data columns (total 10 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   Item Name    101485 non-null  int32
 1   ad_spend     101485 non-null  float64
 2   unit_price   101485 non-null  float64
 3   year         101485 non-null  int32
 4   month        101485 non-null  int32
 5   day          101485 non-null  int64
 6   day_of_week  101485 non-null  int32
 7   is_weekend   101485 non-null  int64
 8   quarter      101485 non-null  int32
 9   units        101485 non-null  float64
dtypes: float64(3), int32(5), int64(2)
memory usage: 6.6 MB
None
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2833 entries, 2024-07-01 to 2024-07-28
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Item Name    2833 non-null   int32
 1   ad_spend     1382 non-null   float64
 2   unit_price   2833 non-null   float64
 3   year         2833 non-null   int32
 4   month        2833 non-null   int32
 5   day          2833 non-null   int64
 6   day_of_week  2833 non-null   int32
 7   is_weekend   2833 non-null   int64
 8   quarter      2833 non-null   int32
dtypes: float64(2), int32(5), int64(2)
memory usage: 166.0 KB
None
```

In [62]:
```
# Creating a function which helps in downcasting the data for better memory opti
def optimize_memory(df):
    float_cols = df.select_dtypes(include=['float64']).columns
    for col in float_cols:
        df[col] = pd.to_numeric(df[col], downcast='float')

    int_cols = df.select_dtypes(include=['int64']).columns
    for col in int_cols:
        df[col] = pd.to_numeric(df[col], downcast='integer')

    return df
```

In [63]:
```
# Applying the created function
train = optimize_memory(train)
test = optimize_memory(test)
```

In [64]:
```
# Checking the results [based on above operations]
print(train.info(memory_usage='deep'))
print(test.info(memory_usage='deep'))
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 101485 entries, 2022-04-12 to 2024-05-31
Data columns (total 10 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   Item Name    101485 non-null  int32  
 1   ad_spend     101485 non-null  float32
 2   unit_price   101485 non-null  float32
 3   year         101485 non-null  int32  
 4   month        101485 non-null  int32  
 5   day          101485 non-null  int8   
 6   day_of_week  101485 non-null  int32  
 7   is_weekend   101485 non-null  int8   
 8   quarter      101485 non-null  int32  
 9   units        101485 non-null  float32
dtypes: float32(3), int32(5), int8(2)
memory usage: 4.1 MB
None
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2833 entries, 2024-07-01 to 2024-07-28
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Item Name    2833 non-null   int32  
 1   ad_spend     1382 non-null   float32
 2   unit_price   2833 non-null   float32
 3   year         2833 non-null   int32  
 4   month        2833 non-null   int32  
 5   day          2833 non-null   int8   
 6   day_of_week  2833 non-null   int32  
 7   is_weekend   2833 non-null   int8   
 8   quarter      2833 non-null   int32  
dtypes: float32(2), int32(5), int8(2)
memory usage: 105.1 KB
None
```

Model Training and Selection

In [65]:
```
# Creating a directory to save the trained models
output_dir = 'Models'
if not os.path.exists(output_dir):
    os.makedirs(output_dir)
```

In [66]:
```
# Selected Features [based on feature importance results from SHAP library]
Features = ['Item Name', 'ad_spend', 'unit_price', 'year', 'month']
```

In [67]:
```
test_data = test[Features]
```

In [68]:
```
# Splitting the train dataset into train and val datasets to verify which model
X_train, X_val, y_train, y_val = train_test_split(train[Features], train['units'
```

XGB Model

In [69]:
```
# Creating datasets that the XGB model supports for faster training
XGBtrain = xgb.DMatrix(X_train, label=y_train)
XGBval = xgb.DMatrix(X_val, label=y_val)
```

In [70]:
```
# Hyper parameters for the XGB model
params = {
    'objective': 'reg:squarederror',
    'eval_metric': 'rmse',
    'max_depth': 6,
    'learning_rate': 0.1,
    'n_estimators': 100,
    'booster': 'gbtree'
}
```

In [71]:
```
# Training the XGB model
model_xgb = xgb.train(params, XGBtrain, 100, [(XGBval, 'eval')], early_stopping_
```

```
[0]	eval-rmse:76.31437
[1]	eval-rmse:74.44389
[2]	eval-rmse:72.89602
[3]	eval-rmse:71.63792
[4]	eval-rmse:70.42870
[5]	eval-rmse:69.42615
[6]	eval-rmse:68.54495
[7]	eval-rmse:67.81645
[8]	eval-rmse:67.15848
[9]	eval-rmse:66.67339
[10]	eval-rmse:66.30491
[11]	eval-rmse:65.78539
[12]	eval-rmse:65.43641
[13]	eval-rmse:65.16329
[14]	eval-rmse:64.79755
[15]	eval-rmse:64.53260
```

```
C:\Users\chand\Py_Env\nap\lib\site-packages\xgboost\core.py:723: FutureWarning: P
ass `evals` as keyword args.
  warnings.warn(msg, FutureWarning)
C:\Users\chand\Py_Env\nap\lib\site-packages\xgboost\core.py:158: UserWarning: [2
0:24:21] WARNING: C:\buildkite-agent\builds\buildkite-windows-cpu-autoscaling-gro
up-i-0015a694724fa8361-1\xgboost\xgboost-ci-windows\src\learner.cc:740:
Parameters: { "n_estimators" } are not used.

  warnings.warn(smsg, UserWarning)
```

```
[16]	eval-rmse:63.89511
[17]	eval-rmse:63.62669
[18]	eval-rmse:63.44537
[19]	eval-rmse:63.19340
[20]	eval-rmse:63.02082
[21]	eval-rmse:62.84669
[22]	eval-rmse:62.22917
[23]	eval-rmse:62.08995
[24]	eval-rmse:61.90511
[25]	eval-rmse:61.83697
[26]	eval-rmse:61.76782
[27]	eval-rmse:61.62800
[28]	eval-rmse:61.07284
[29]	eval-rmse:60.86791
[30]	eval-rmse:60.49026
[31]	eval-rmse:60.02949
[32]	eval-rmse:59.83114
[33]	eval-rmse:59.81296
[34]	eval-rmse:59.80103
[35]	eval-rmse:59.67987
[36]	eval-rmse:59.30052
[37]	eval-rmse:59.14504
[38]	eval-rmse:59.12859
[39]	eval-rmse:59.14493
[40]	eval-rmse:58.99356
[41]	eval-rmse:58.78530
[42]	eval-rmse:58.82518
[43]	eval-rmse:58.57084
[44]	eval-rmse:58.53925
[45]	eval-rmse:58.52116
[46]	eval-rmse:58.52676
[47]	eval-rmse:58.24153
[48]	eval-rmse:58.20483
[49]	eval-rmse:57.92163
[50]	eval-rmse:57.86894
[51]	eval-rmse:57.83338
[52]	eval-rmse:57.79821
[53]	eval-rmse:57.79050
[54]	eval-rmse:57.77893
[55]	eval-rmse:57.75414
[56]	eval-rmse:57.73679
[57]	eval-rmse:57.70871
[58]	eval-rmse:57.70359
[59]	eval-rmse:57.69639
[60]	eval-rmse:57.68865
[61]	eval-rmse:57.68472
[62]	eval-rmse:57.65481
[63]	eval-rmse:57.63001
[64]	eval-rmse:57.62785
[65]	eval-rmse:57.60726
[66]	eval-rmse:57.57039
[67]	eval-rmse:57.55281
[68]	eval-rmse:57.55001
[69]	eval-rmse:57.53290
[70]	eval-rmse:57.49504
[71]	eval-rmse:57.49160
[72]	eval-rmse:57.47122
[73]	eval-rmse:57.22361
[74]	eval-rmse:57.20160
[75]	eval-rmse:57.20227
```

```
[76]	eval-rmse:57.14380
[77]	eval-rmse:57.13302
[78]	eval-rmse:57.10895
[79]	eval-rmse:57.10568
[80]	eval-rmse:57.07434
[81]	eval-rmse:57.07287
[82]	eval-rmse:57.01048
[83]	eval-rmse:56.99133
[84]	eval-rmse:56.99929
[85]	eval-rmse:56.97777
[86]	eval-rmse:56.97313
[87]	eval-rmse:56.94441
[88]	eval-rmse:56.94251
[89]	eval-rmse:56.93324
[90]	eval-rmse:56.89300
[91]	eval-rmse:56.89083
[92]	eval-rmse:56.87757
[93]	eval-rmse:56.85841
[94]	eval-rmse:56.83937
[95]	eval-rmse:56.82865
[96]	eval-rmse:56.82107
[97]	eval-rmse:56.81610
[98]	eval-rmse:56.81557
[99]	eval-rmse:56.81029
```

In [72]:
```
# Make predictions using val data
y_pred_xgb = model_xgb.predict(XGBval)
```

In [73]:
```
# Evaluting the XGB model using mean squared error
mse_xgb = mean_squared_error(y_val, y_pred_xgb)
```

In [74]:
```
# Saving the model for later use
model_xgb.save_model(os.path.join(output_dir, 'xgboost_model.json'))
```

LGB Model

In [75]:
```
lgb_train = lgb.Dataset(X_train, y_train)
lgb_val = lgb.Dataset(X_val, y_val, reference=lgb_train)
```

In [76]:
```
# Hyper parameters for the LGB model
params = {
    'objective': 'regression',
    'metric': 'rmse',
    'boosting_type': 'gbdt',
    'num_leaves': 31,
    'learning_rate': 0.05,
    'feature_fraction': 0.9
}
```

In [77]:
```
# Training the LGB model
model_lgb = lgb.train(params, lgb_train, 100, valid_sets=[lgb_train, lgb_val])
```

```
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing
was 0.001181 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 726
[LightGBM] [Info] Number of data points in the train set: 81188, number of used f
eatures: 5
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Start training from score 8.660716
```

In [78]:
```
# Making predictions using the val data
y_pred_lgb = model_lgb.predict(X_val, num_iteration=model_lgb.best_iteration)
```

In [79]:
```
# Evaluate the LGB model using mean squared error
mse_lgb = mean_squared_error(y_val, y_pred_lgb)
```

In [80]:
```
# Saving the model for later use
model_lgb.save_model(os.path.join(output_dir, 'lightgbm_model.txt'))
```

Out[80]:
```
<lightgbm.basic.Booster at 0x24cec21aac0>
```

LSTM

In [81]:
```
# Convert DataFrames to NumPy arrays
X_train_np = X_train.values
X_val_np = X_val.values

# Reshape for LSTM model input
n_features = X_train_np.shape[1]
X_train_reshaped = X_train_np.reshape((X_train_np.shape[0], 1, n_features))
X_val_reshaped = X_val_np.reshape((X_val_np.shape[0], 1, n_features))
```

In [82]:
```
# Building the LSTM model
model_lstm = Sequential()
model_lstm.add(LSTM(units=50, input_shape=(1, n_features)))
model_lstm.add(Dense(units=1))
```

```
C:\Users\chand\Py_Env\nap\lib\site-packages\keras\src\layers\rnn\rnn.py:204: User
Warning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using
Sequential models, prefer using an `Input(shape)` object as the first layer in th
e model instead.
  super().__init__(**kwargs)
```

In [83]:
```
# Training the LSTM model
model_lstm.compile(optimizer='adam', loss='mse')
history = model_lstm.fit(X_train_reshaped, y_train, epochs=50, batch_size=32, va
```

```
Epoch 1/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 7s 2ms/step - loss: 4946.4199 - val_loss: 6164.289
6
Epoch 2/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 2987.3479 - val_loss: 6162.345
7
Epoch 3/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 2339.7659 - val_loss: 6162.479
0
Epoch 4/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 7013.2588 - val_loss: 6162.768
1
Epoch 5/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 2500.1980 - val_loss: 6162.333
0
Epoch 6/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 2548.6807 - val_loss: 6162.430
7
Epoch 7/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 3802.4062 - val_loss: 6162.408
2
Epoch 8/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 6s 2ms/step - loss: 3189.1250 - val_loss: 6162.232
9
Epoch 9/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 6s 2ms/step - loss: 3681.7754 - val_loss: 6162.352
1
Epoch 10/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 7s 3ms/step - loss: 2303.8928 - val_loss: 6162.249
0
Epoch 11/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 2218.1152 - val_loss: 6162.182
1
Epoch 12/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 3589.4741 - val_loss: 6162.609
9
Epoch 13/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 2355.3018 - val_loss: 6162.206
1
Epoch 14/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 4706.3076 - val_loss: 6162.512
7
Epoch 15/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 2617.5605 - val_loss: 6162.578
6
Epoch 16/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 3259.9814 - val_loss: 6162.689
0
Epoch 17/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 2607.8735 - val_loss: 6162.311
5
Epoch 18/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 2959.8345 - val_loss: 6162.311
5
Epoch 19/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 2643.8201 - val_loss: 6162.362
3
Epoch 20/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 3793.3738 - val_loss: 6162.405
3
```

```
Epoch 21/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 3565.3083 - val_loss: 6162.431
2
Epoch 22/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 2768.4875 - val_loss: 6162.271
5
Epoch 23/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 10s 2ms/step - loss: 5092.7051 - val_loss: 6162.27
20
Epoch 24/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 6s 2ms/step - loss: 2322.5808 - val_loss: 6162.248
0
Epoch 25/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 7s 3ms/step - loss: 3516.3127 - val_loss: 6162.341
3
Epoch 26/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 8s 3ms/step - loss: 2835.6895 - val_loss: 6162.401
9
Epoch 27/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 8s 3ms/step - loss: 4495.9189 - val_loss: 6162.611
8
Epoch 28/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 2812.9744 - val_loss: 6162.350
1
Epoch 29/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 4144.7271 - val_loss: 6162.459
0
Epoch 30/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 6s 2ms/step - loss: 2249.2585 - val_loss: 6162.258
3
Epoch 31/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 7s 3ms/step - loss: 3693.1550 - val_loss: 6162.528
8
Epoch 32/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 6s 2ms/step - loss: 4174.2261 - val_loss: 6162.419
4
Epoch 33/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 3734.6284 - val_loss: 6162.306
6
Epoch 34/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 3280.6672 - val_loss: 6162.571
3
Epoch 35/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 5520.2563 - val_loss: 6162.479
0
Epoch 36/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 7s 3ms/step - loss: 2552.6409 - val_loss: 6162.305
2
Epoch 37/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 7s 3ms/step - loss: 2578.8450 - val_loss: 6162.464
8
Epoch 38/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 4031.4907 - val_loss: 6162.537
6
Epoch 39/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 6001.1680 - val_loss: 6162.442
4
Epoch 40/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 4767.3633 - val_loss: 6162.371
6
```

```
Epoch 41/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 3027.1904 - val_loss: 6162.575
7
Epoch 42/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 2342.3325 - val_loss: 6162.320
3
Epoch 43/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 6s 2ms/step - loss: 2246.2078 - val_loss: 6162.174
8
Epoch 44/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 4037.9202 - val_loss: 6162.360
4
Epoch 45/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 3913.6917 - val_loss: 6162.452
6
Epoch 46/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 6s 3ms/step - loss: 2797.9197 - val_loss: 6162.399
4
Epoch 47/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 6s 2ms/step - loss: 2562.7483 - val_loss: 6162.271
5
Epoch 48/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 3247.6763 - val_loss: 6162.431
6
Epoch 49/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 5s 2ms/step - loss: 2261.3777 - val_loss: 6162.259
3
Epoch 50/50
2538/2538 ━━━━━━━━━━━━━━━━━━━━ 7s 3ms/step - loss: 2883.3115 - val_loss: 6162.286
1
```

In [84]:
```python
# Making predictions using the val data
y_pred_lstm = model_lstm.predict(X_val_reshaped)
```

```
635/635 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step
```

In [85]:
```python
# Evaluate the LSTM model using mean squared error
mse_lstm = mean_squared_error(y_val, y_pred_lstm)
```

In [86]:
```python
# Saving the model for later use
model_lstm.save(os.path.join(output_dir, 'lstm_model.h5'))
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `ker
as.saving.save_model(model)`. This file format is considered legacy. We recommend
using instead the native Keras format, e.g. `model.save('my_model.keras')` or `ke
ras.saving.save_model(model, 'my_model.keras')`.
```

Best Model

In [87]:
```python
# Create a dictionary with MSE values
mse_data = {
    'Model': ['LGBM', 'XGBoost', 'LSTM'],
    'MSE': [mse_lgb, mse_xgb, mse_lstm]
}

# Create a DataFrame
mse_df = pd.DataFrame(mse_data)
print(mse_df)
```

```
     Model          MSE
0     LGBM  3476.089708
1  XGBoost  3227.409424
2     LSTM  6162.284668
```

Testing new data

In [88]:
```
# Creating a directory to save the predictions
output_dir = 'Results'
if not os.path.exists(output_dir):
    os.makedirs(output_dir)
```

In [89]:
```
XGBtest = xgb.DMatrix(test_data[Features])
```

In [90]:
```
# Using the XGBoost model to predict the new test data (unseen data)
predictions = model_xgb.predict(XGBtest)
```

In [91]:
```
# Creating a csv file for saving the predictions
test = pd.read_csv("orgData/test.csv")
predictions_df = pd.DataFrame({
    'date': test['date'],
    'Item Id': test['Item Id'],
    'TARGET': predictions
})

# Saving the predictions to CSV file
predictions_df.to_csv(os.path.join(output_dir, 'predictions.csv'), index=False)
print("Predictions saved to 'predictions.csv'")
```

```
Predictions saved to 'predictions.csv'
```