Analysis of Perishable Item Sales in Restaurants

This section provides an overview of the dataset used to analyze sales trends of perishable items in restaurants, along with details about preprocessing, decomposition, and data augmentation.

1. Datasets Overview:

We utilize two primary datasets for our analysis:

Pizza Sales Dataset:

- Contains records of daily pizza sales.
- **Date**: Represents the specific day of pizza sales data.
- **Quantity**: Indicates the number of pizzas sold on the respective date.

Bakery Sales Dataset:

- Contains records of daily sales for bakery items.
- **Date**: Represents the specific day of bakery sales data.
- **Quantity**: Indicates the volume of bakery items sold on the respective date.

These datasets not only help in understanding historical sales trends but also serve as a foundation for modeling and prediction.

3. Time Series Decomposition:

Decomposing the time series data provides insights into its various components:

- **Original Series**: Displays the raw sales data.
- **Trend Component**: Shows the underlying trend in sales over time.
- **Seasonal Component**: Represents the regular fluctuations in sales, potentially due to weekly patterns or other recurring events.
- **Residual Component**: Contains the remaining variations in sales after removing the trend and seasonal components.

4. Data Augmentation:

To improve the dataset's coverage and enhance its predictive capabilities, additional data points are generated:

- **Outliers**
- **Backcasting**: Generating past data points using patterns from the existing dataset.
- **Forecasting**: Predicting future data points based on the established trends and patterns.

5. Model Training and Initial Validation:

With the preprocessed and augmented datasets, the model is trained. An initial validation is conducted to assess the model's performance and ensure its reliability before full-scale deployment.

0.1 Import necessary libreries

```
# Standard libraries and data processing
import pandas as pd
import numpy as np
from datetime import datetime, timedelta


# Visualization libraries
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.dates import DateFormatter

# Time series analysis
from statsmodels.tsa.seasonal import STL
from scipy.stats import zscore

# Machine learning and deep learning libraries
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
import tensorflow as tf
from tensorflow.keras.models import Sequential, load_model
from tensorflow.keras.layers import LSTM, Dense, Dropout

# Miscellaneous libraries
import holidays
```

1.1 Pizza Sales Dataset

```
# Load the Excel file
file_path = 'pizza_sales.xlsx'

df = pd.read_excel(file_path)
print('Original Pizza dataframe: ', df)


# Group by order_date and aggregate the quantity and total_price
columns
daily_sales = df.groupby('order_date').agg({
    'quantity': 'sum',

}).reset_index()
```

```
daily_sales = daily_sales.rename(columns={'order_date': 'date'})


print("\n---------------------------------------------------")
print("Cleaned dataframe")
daily_sales
```

```
Original Pizza dataframe:          order_details_id  order_id  
pizza_id  quantity order_date  \
0                     1         1     hawaiian_m         1 2015-01-01

1                     2         2  classic_dlx_m         1 2015-01-01

2                     3         2  five_cheese_l         1 2015-01-01

3                     4         2    ital_supr_l         1 2015-01-01

4                     5         2     mexicana_m         1 2015-01-01

...                 ...       ...            ...       ...         ...

48615             48616     21348  ckn_alfredo_m         1 2015-12-31

48616             48617     21348  four_cheese_l         1 2015-12-31

48617             48618     21348   napolitana_s         1 2015-12-31

48618             48619     21349     mexicana_l         1 2015-12-31

48619             48620     21350      bbq_ckn_s         1 2015-12-31


      order_time  unit_price  total_price pizza_size pizza_category  \
0       11:38:36       13.25        13.25          M        Classic
1       11:57:40       16.00        16.00          M        Classic
2       11:57:40       18.50        18.50          L         Veggie
3       11:57:40       20.75        20.75          L        Supreme
4       11:57:40       16.00        16.00          M         Veggie
...          ...         ...          ...        ...            ...
48615   21:23:10       16.75        16.75          M        Chicken
48616   21:23:10       17.95        17.95          L         Veggie
48617   21:23:10       12.00        12.00          S        Classic
48618   22:09:54       20.25        20.25          L         Veggie
48619   23:02:05       12.75        12.75          S        Chicken

                                       pizza_ingredients  \
0               Sliced Ham, Pineapple, Mozzarella Cheese
1      Pepperoni, Mushrooms, Red Onions, Red Peppers,...
2      Mozzarella Cheese, Provolone Cheese, Smoked Go...
3      Calabrese Salami, Capocollo, Tomatoes, Red Oni...
4      Tomatoes, Red Peppers, Jalapeno Peppers, Red O...
```

```
...                                                     ...
48615  Chicken, Red Onions, Red Peppers, Mushrooms, A...
48616  Ricotta Cheese, Gorgonzola Piccante Cheese, Mo...
48617  Tomatoes, Anchovies, Green Olives, Red Onions,...
48618  Tomatoes, Red Peppers, Jalapeno Peppers, Red O...
48619  Barbecued Chicken, Red Peppers, Green Peppers,...

                       pizza_name
0               The Hawaiian Pizza
1         The Classic Deluxe Pizza
2            The Five Cheese Pizza
3        The Italian Supreme Pizza
4               The Mexicana Pizza
...                            ...
48615    The Chicken Alfredo Pizza
48616        The Four Cheese Pizza
48617         The Napolitana Pizza
48618           The Mexicana Pizza
48619  The Barbecue Chicken Pizza

[48620 rows x 12 columns]

---------------------------------------------------
Cleaned dataframe

          date  quantity
0   2015-01-01       162
1   2015-01-02       165
2   2015-01-03       158
3   2015-01-04       106
4   2015-01-05       125
..         ...       ...
353 2015-12-27        89
354 2015-12-28       102
355 2015-12-29        80
356 2015-12-30        82
357 2015-12-31       178

[358 rows x 2 columns]
```

1.2 Bakery Dataset

```
# Load the data
df_backery = pd.read_csv('bakery_sales.csv')

print('Original Bakery dataframe: ', df_backery)

# Group by the 'date' column and sum the 'Quantity' for each date
df_backery = df_backery.groupby('date').agg({'Quantity':
'sum'}).reset_index()
```

```
# Rename columns for clarity
df_backery.columns = ['date', 'quantity']
df_backery['quantity'] = df_backery['quantity'].astype(int)
df_backery['date'] = pd.to_datetime(df_backery['date'], format='%Y-%m-
%d')

print("\n---------------------------------------------------")
print("Cleaned dataframe")# Display the resulting dataframe

df_backery
```

```
Original Bakery dataframe:          Unnamed: 0        date   time
ticket_number               article  \
0                 0  2021-01-02  08:38       150040.0
BAGUETTE
1                 1  2021-01-02  08:38       150040.0      PAIN AU
CHOCOLAT
2                 4  2021-01-02  09:14       150041.0      PAIN AU
CHOCOLAT
3                 5  2021-01-02  09:14       150041.0
PAIN
4                 8  2021-01-02  09:25       150042.0  TRADITIONAL
BAGUETTE
...             ...         ...    ...            ...
...
234000       511387  2022-09-30  18:52       288911.0
COUPE
234001       511388  2022-09-30  18:52       288911.0            BOULE
200G
234002       511389  2022-09-30  18:52       288911.0
COUPE
234003       511392  2022-09-30  18:55       288912.0  TRADITIONAL
BAGUETTE
234004       511395  2022-09-30  18:56       288913.0  TRADITIONAL
BAGUETTE

        Quantity unit_price
0            1.0     0,90 €
1            3.0     1,20 €
2            2.0     1,20 €
3            1.0     1,15 €
4            5.0     1,20 €
...          ...        ...
234000       1.0     0,15 €
234001       1.0     1,20 €
234002       2.0     0,15 €
234003       1.0     1,30 €
234004       1.0     1,30 €
```

```
[234005 rows x 7 columns]

----------------------------------------------------
Cleaned dataframe

           date  quantity
0   2021-01-02       581
1   2021-01-03       564
2   2021-01-04       315
3   2021-01-05       309
4   2021-01-07       310
..         ...       ...
595 2022-09-26       399
596 2022-09-27       423
597 2022-09-28       357
598 2022-09-29       428
599 2022-09-30       503

[600 rows x 2 columns]
```

2.1 Pizza Sales Dataset Time series Decomposition

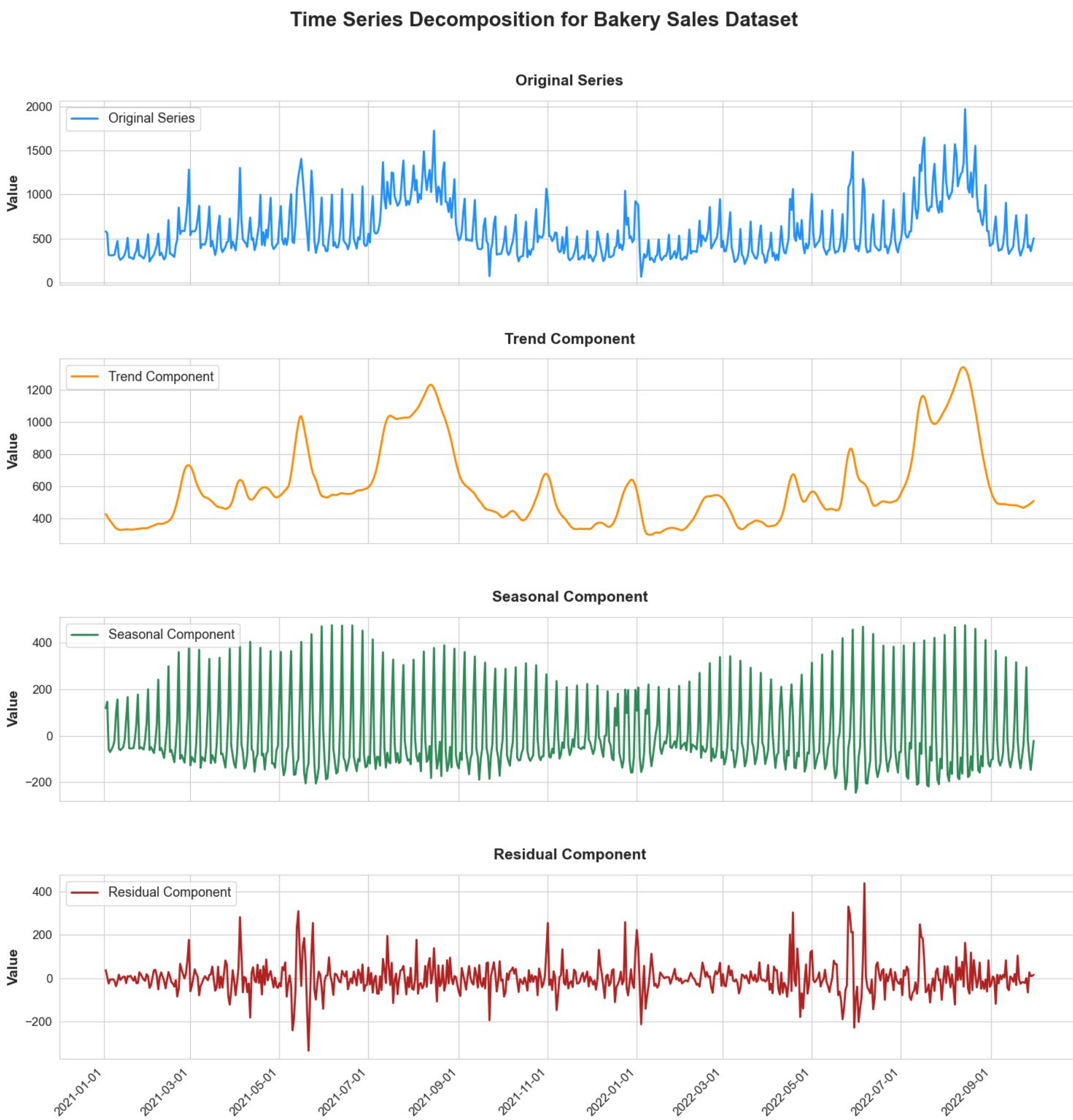
```
# Create a date range for the entire period
complete_date_range = pd.date_range(start=daily_sales["date"].min(),
end=daily_sales["date"].max())

# Identify missing dates
missing_dates =
complete_date_range[~complete_date_range.isin(daily_sales["date"])]

# Fill in the missing dates
daily_sales_filled =
daily_sales.set_index("date").reindex(complete_date_range)
daily_sales_filled.index.name = "date"
daily_sales_filled =
daily_sales_filled.interpolate(method="linear").reset_index()

# STL decomposition with a fixed period of 7 days
stl = STL(daily_sales_filled["quantity"], seasonal=7, period=7)
result_pizza = stl.fit()


# Set seaborn style
sns.set_style("whitegrid")

# Set a consistent color scheme
colors = ["dodgerblue", "darkorange", "seagreen", "firebrick"]

# Create the subplots with more space
fig, axes = plt.subplots(4, 1, figsize=(15, 15), sharex=True)
```

```python
# Plot data
components = [("Original Series", daily_sales_filled["quantity"]),
              ("Trend Component", result_pizza.trend),
              ("Seasonal Component", result_pizza.seasonal),
              ("Residual Component", result_pizza.resid)]

# Plot each component
for (title, data), color, ax in zip(components, colors, axes):
    ax.plot(daily_sales_filled["date"], data, label=title,
color=color, linewidth=2)
    ax.set_title(title, fontsize=15, fontweight='bold', pad=15)
    ax.tick_params(axis='both', which='major', labelsize=12)
    ax.legend(loc="upper left", fontsize=13)
    ax.set_ylabel('Value', fontsize=14, fontweight='semibold')

# Limit the number of ticks on the x-axis and format the ticks
date_form = DateFormatter("%Y-%m-%d")
axes[-1].xaxis.set_major_formatter(date_form)

# Rotate x-axis labels for better visibility
plt.setp(axes[-1].get_xticklabels(), rotation=45, ha="right")

# Set a main title for the entire figure
fig.suptitle('Time Series Decomposition for Pizza Sales Dataset',
fontsize=20, fontweight='bold', y=1.02)

# Adjust the layout
plt.tight_layout()
plt.subplots_adjust(hspace=0.4)

# Display the plot
plt.show()
```

2.2 Bakery sales Time series Decomposition

```
# Create a date range for the entire period
complete_date_range = pd.date_range(start=df_backery["date"].min(),
end=df_backery["date"].max())

# Identify missing dates
missing_dates =
complete_date_range[~complete_date_range.isin(df_backery["date"])]

# Fill in the missing dates
```

```
df_backery = df_backery.set_index("date").reindex(complete_date_range)
df_backery.index.name = "date"
df_backery = df_backery.interpolate(method="linear").reset_index()

# STL decomposition with a fixed period of 7 days
stl = STL(df_backery["quantity"], seasonal=7, period=7)
result_bakery = stl.fit()

# Set seaborn style
sns.set_style("whitegrid")

# Set a consistent color scheme
colors = ["dodgerblue", "darkorange", "seagreen", "firebrick"]

# Create the subplots with more space
fig, axes = plt.subplots(4, 1, figsize=(15, 15), sharex=True)

# Plot data
components = [("Original Series", df_backery["quantity"]),
              ("Trend Component", result_bakery.trend),
              ("Seasonal Component", result_bakery.seasonal),
              ("Residual Component", result_bakery.resid)]

# Plot each component
for (title, data), color, ax in zip(components, colors, axes):
    ax.plot(df_backery["date"], data, label=title, color=color,
linewidth=2)
    ax.set_title(title, fontsize=15, fontweight='bold', pad=15)
    ax.tick_params(axis='both', which='major', labelsize=12)
    ax.legend(loc="upper left", fontsize=13)
    ax.set_ylabel('Value', fontsize=14, fontweight='semibold')

# Limit the number of ticks on the x-axis and format the ticks
date_form = DateFormatter("%Y-%m-%d")
axes[-1].xaxis.set_major_formatter(date_form)

# Rotate x-axis labels for better visibility
plt.setp(axes[-1].get_xticklabels(), rotation=45, ha="right")

# Set a main title for the entire figure
fig.suptitle('Time Series Decomposition for Bakery Sales Dataset',
fontsize=20, fontweight='bold', y=1.02)

# Adjust the layout
plt.tight_layout()
plt.subplots_adjust(hspace=0.4)

# Display the plot
plt.show()
```



3. Data Augmentation and Outlier Management

1. Backcasting and Forecasting:

```
- Using the historical trend and seasonal components extracted from the existing data,
  we can generate data for periods before and after the known data.
- Backcasting involves producing data for earlier periods, and forecasting is for later periods.
```

2. Outlier Detection and Management:

```
- Time series data can often have outliers - values that deviate
significantly from the expected range.
- We calculate the Z-scores for each data point. The Z-score measures
how many standard deviations
  a data point is from the mean.
- We consider data points with Z-scores beyond a threshold (e.g., |Z-
score| > 3) as outliers.
```

3. Visualization:

```
- Visualizing the augmented data helps in understanding the data
structure and identifying any anomalies.
- We plot the data for a specific year and highlight outliers in a
different color to distinguish them easily.
```

4. Outlier Treatment:

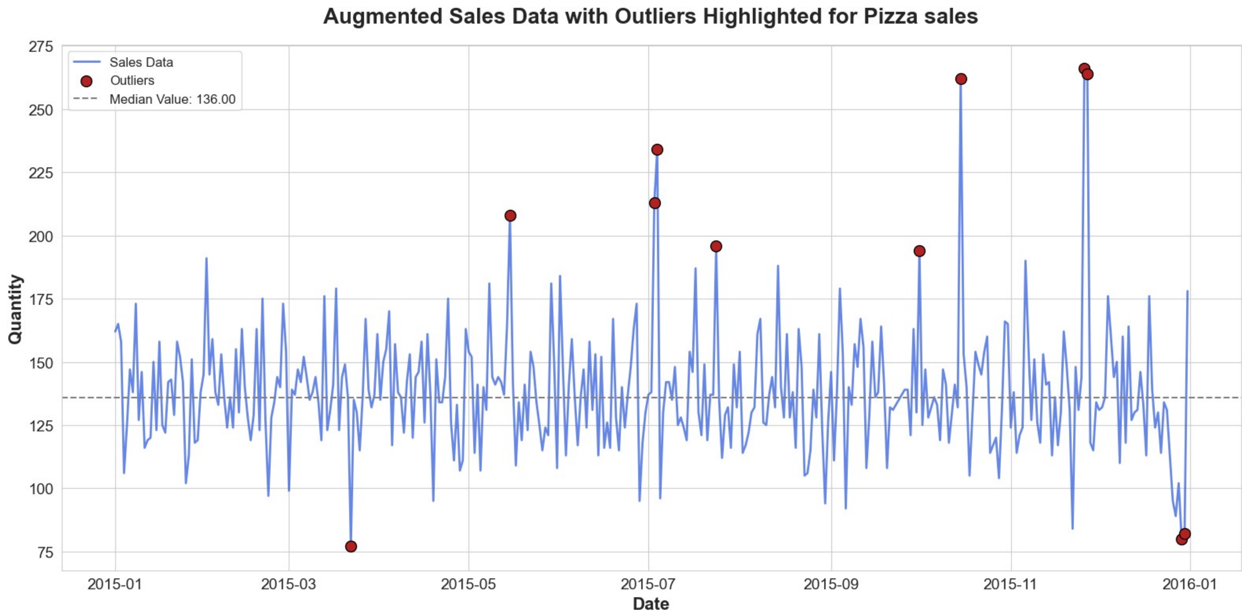
```
- One common method to handle outliers is to replace them with a
measure of central tendency, such as the median.
- We use a rolling window to calculate a localized median around each
outlier
  and then replace the outlier with this median.
```

```
def augment_and_clean_data(data, result, start_date, end_date,
plot_year, title):
    # Define the date ranges to backcast and forecast
    backcast_range = pd.date_range(start=start_date,
end=data["date"].min() - pd.Timedelta(days=1))
    forecast_range = pd.date_range(start=data["date"].max() +
pd.Timedelta(days=1), end=end_date)

    # Backcasting and Forecasting
    backcast_values = [(result.trend.iloc[i % len(result.trend)] +
result.seasonal.iloc[i % len(result.seasonal)]) for i, _ in
enumerate(reversed(backcast_range))]
    forecast_values = [(result.trend.iloc[-(i % len(result.trend)) -
1] + result.seasonal.iloc[i % len(result.seasonal)]) for i, _ in
enumerate(forecast_range)]

    # Combine the backcasted, original, and forecasted data
    augmented_data = pd.DataFrame({
        "date": list(backcast_range) + list(data["date"]) +
list(forecast_range),
        "quantity": backcast_values + list(data["quantity"]) +
forecast_values
    })

    # Detect outliers based on Z-scores
```

```
    augmented_data["zscore"] = zscore(augmented_data["quantity"])
    threshold = 3
    augmented_data["is_outlier"] = augmented_data["zscore"].abs() >
threshold

    # Plotting
    subset_data = augmented_data[augmented_data["date"].dt.year ==
plot_year]
    sns.set_style("whitegrid")
    sns.set_palette("pastel")
    fig, ax = plt.subplots(figsize=(16, 8))
    ax.plot(subset_data["date"], subset_data["quantity"], label="Sales
Data", linewidth=2, color='royalblue', alpha=0.8)
    outliers = subset_data[subset_data["is_outlier"]]
    ax.scatter(outliers["date"], outliers["quantity"],
color="firebrick", s=100, edgecolor='black', zorder=5,
label='Outliers')
    ax.set_title(title, fontsize=20, fontweight='bold', pad=20)
    ax.set_xlabel("Date", fontsize=16, fontweight='semibold')
    ax.set_ylabel("Quantity", fontsize=16, fontweight='semibold')
    ax.tick_params(axis='both', labelsize=14)
    median_val = subset_data["quantity"].median()
    ax.axhline(y=median_val, color='gray', linestyle='--',
label=f"Median Value: {median_val:.2f}")
    ax.legend(fontsize=12, loc="upper left")
    plt.tight_layout()
    plt.show()

    # Handle outliers: replace with the median of surrounding data
points
    window_size = 3
    medians = augmented_data["quantity"].rolling(window=window_size,
center=True).median()
    augmented_data.loc[augmented_data["is_outlier"], "quantity"] =
medians[augmented_data["is_outlier"]]

    return augmented_data[['date', 'quantity']]
```

3.1 Pizza dataset outliers

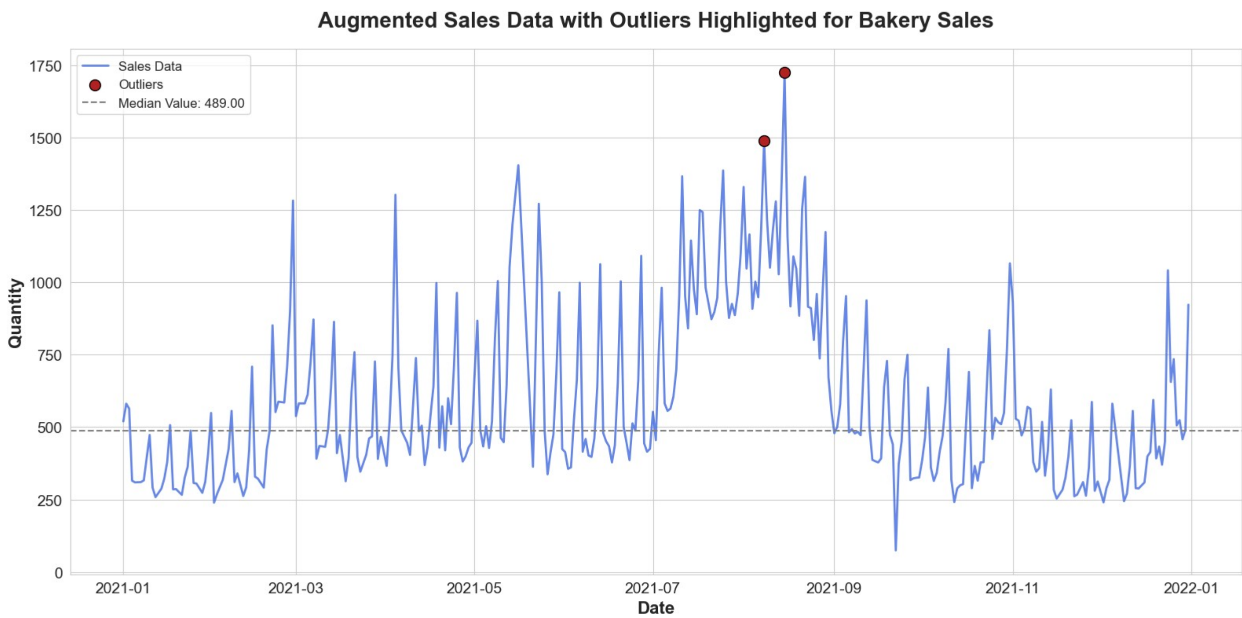
```
df_pizza = augment_and_clean_data(daily_sales_filled, result_pizza,
"2000-01-01", "2020-12-31", 2015, "Augmented Sales Data with Outliers
Highlighted for Pizza sales")
```




```
df_pizza

            date    quantity
0    2000-01-01  170.442315
1    2000-01-02  157.326777
2    2000-01-03  155.744584
3    2000-01-04  108.092598
4    2000-01-05  127.743851
...         ...         ...
7666 2020-12-27  129.366701
7667 2020-12-28  137.656924
7668 2020-12-29  137.656924
7669 2020-12-30  123.733819
7670 2020-12-31  113.458970

[7671 rows x 2 columns]

df_pizza.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7671 entries, 0 to 7670
Data columns (total 2 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   date      7671 non-null   datetime64[ns]
 1   quantity  7671 non-null   float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 120.0 KB
```

3.2 Bakery dataset outliers

```
df_bakery = augment_and_clean_data(df_backery, result_bakery, "2005-01-01", "2023-08-28", 2021, "Augmented Sales Data with Outliers Highlighted for Bakery Sales")
```




```
df_bakery

           date    quantity
0    2005-01-01  544.312674
1    2005-01-02  558.031620
2    2005-01-03  339.790893
3    2005-01-04  315.557867
4    2005-01-05  315.269951
...         ...         ...
6809 2023-08-24  427.181231
6810 2023-08-25  448.042127
6811 2023-08-26  556.063481
6812 2023-08-27  803.470561
6813 2023-08-28  605.219653

[6814 rows x 2 columns]

df_bakery.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6814 entries, 0 to 6813
Data columns (total 2 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   date      6814 non-null   datetime64[ns]
```

```
 1   quantity  6814 non-null   float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 106.6 KB
```

FoodSalesPredictor: Class Overview

The `FoodSalesPredictor` class is designed as a comprehensive solution to predict daily sales of perishable items within a restaurant context, encapsulating everything from features engineering to model training and evaluation.

Dataset Requirements

For this class to function correctly, the input dataset (df) should have the following structure:

- A DataFrame with two columns :
  - `date`: In datetime format.
  - `quantity`: Numeric representation of daily sales or similar metric.

1. Class Description:

This class encapsulates methods to preprocess sales data, build a Long Short-Term Memory (LSTM) model, train the model, and make predictions on test data. It also includes utility functions to handle features such as holidays, weekends, and paydays, which can influence daily sales in restaurants.

2. Feature Processing:

The class focuses on extracting meaningful features from the given sales data:

- **Seasonality**: Based on the month, the data is categorized into 'Winter', 'Spring', 'Summer', or 'Fall'.
- **Holidays**: Leveraging the `holidays` library, the data is annotated with a flag indicating if a day is a public holiday.
- **Weekends**: Days are flagged if they fall on weekends.
- **Paydays**: Days are flagged if they represent month-ends, which could potentially be paydays.
- **Lag Features**: The class creates lag features, indicating sales data from previous days, providing context for the model about recent sales trends.

3. Model Creation:

The choice of model is the LSTM, a type of recurrent neural network (RNN). LSTM is designed to recognize patterns over sequences, making it an optimal choice for time-series forecasting like daily sales predictions.

4. Rationale Behind Model Choice:

LSTMs have the capability to remember past information, which is essential when predicting sequences with fluctuations, like sales data. The LSTM can utilize its internal memory to process sequences of observations. This makes it suitable for our use-case where past sales data can have an influence on future sales.

5. Model Parameters:

- **LSTM Units**: The LSTM layers have units that determine the memory capability and the amount of information they can store.
- **Dropout**: Dropout layers are introduced to prevent overfitting. They randomly set a fraction rate of input units to 0 at each update during training time.
- **Dense Layer**: This is the output layer, which provides the final prediction. It uses a linear activation function.

In essence, the `FoodSalesPredictor` serves as a one-stop solution for building a robust perishable item sales forecasting system.

```
class FoodSalesPredictor:
    def __init__(self, df):
        self.df = df.copy()
        self.quantity_scaler = MinMaxScaler(feature_range=(0, 1))
        self.scaler = MinMaxScaler(feature_range=(0, 1))
        self.look_back = 20
        self.model = None

    def get_season(self, date):
        """ get season feature for the df"""

        if date.month in [12, 1, 2]:
            return 'Winter'
        elif date.month in [3, 4, 5]:
            return 'Spring'
        elif date.month in [6, 7, 8]:
            return 'Summer'
        else:
            return 'Fall'

    def preprocess_data(self):
        """Process the df extracting new features splitting the df in
90% train and 10% test"""

        us_holidays =
holidays.US(years=self.df['date'].dt.year.unique())
        self.df['is_holiday'] = self.df['date'].apply(lambda x: 1 if x
in us_holidays else 0)
        self.df['is_weekend'] = self.df['date'].apply(lambda x: 1 if
x.weekday() >= 5 else 0)
        self.df['is_paycheck'] = self.df['date'].apply(lambda x: 1 if
```

```
x.is_month_end else 0)
        self.df['season'] = self.df['date'].apply(self.get_season)

        # Create lag features
        n_lags = 7
        for i in range(1, n_lags + 1):
            self.df[f'lag_{i}'] = self.df['quantity'].shift(i)

        self.df.dropna(inplace=True)
        self.df = pd.get_dummies(self.df, columns=['season'])

        # Scale the 'quantity' column
        self.df['quantity'] =
self.quantity_scaler.fit_transform(self.df[['quantity']])

        # Normalize the entire dataframe
        scaled_data =
self.scaler.fit_transform(self.df.drop(columns='date'))

        # Determine the correct index for 'quantity' column after one-
hot encoding
        quantity_col_index = list(self.df.columns).index('quantity')

        X, Y = [], []
        for i in range(len(scaled_data)-self.look_back):
            X.append(scaled_data[i:(i+self.look_back), :-1])
            Y.append(scaled_data[i + self.look_back,
quantity_col_index-1])

        self.X = np.array(X)
        self.Y = np.array(Y)

        train_size = int(len(self.X) * 0.90)
        test_size = len(self.X) - train_size

        self.X_train, self.X_test = self.X[0:train_size],
self.X[train_size:len(X)]
        self.Y_train, self.Y_test = self.Y[0:train_size],
self.Y[train_size:len(Y)]



    def preprocess_all_data(self):
        """Process the df extracting new features without splitting
the df for training"""

        us_holidays =
holidays.US(years=self.df['date'].dt.year.unique())
        self.df['is_holiday'] = self.df['date'].apply(lambda x: 1 if x
in us_holidays else 0)
```

```
        self.df['is_weekend'] = self.df['date'].apply(lambda x: 1 if
x.weekday() >= 5 else 0)
        self.df['is_paycheck'] = self.df['date'].apply(lambda x: 1 if
x.is_month_end else 0)
        self.df['season'] = self.df['date'].apply(self.get_season)

        # Create lag features
        n_lags = 7
        for i in range(1, n_lags + 1):
            self.df[f'lag_{i}'] = self.df['quantity'].shift(i)

        self.df.dropna(inplace=True)

        # Create one-hot encoded columns for all seasons manually
        seasons = ['Winter', 'Spring', 'Summer', 'Fall']
        for season in seasons:
            self.df[f'season_{season}'] =
self.df['season'].apply(lambda x: 1 if x == season else 0)

        self.df.drop(columns=['season'], inplace=True)

        # Scale the 'quantity' column
        self.df['quantity'] =
self.quantity_scaler.fit_transform(self.df[['quantity']])

        scaled_data =
self.scaler.fit_transform(self.df.drop(columns='date'))

        # Determine the correct index for 'quantity' column after one-
hot encoding
        quantity_col_index = list(self.df.columns).index('quantity')

        X, Y = [], []
        for i in range(len(scaled_data)-self.look_back):
            X.append(scaled_data[i:(i+self.look_back), :-1])
            Y.append(scaled_data[i + self.look_back,
quantity_col_index-1])


        self.X = np.array(X)
        self.Y = np.array(Y)

    def build_model(self, lstm_units=50):
        """Build simplified LSTM model with fewer dense layers"""

        self.model = Sequential()
        input_shape = self.X_train.shape if hasattr(self, 'X_train')
else self.X.shape

        self.model.add(LSTM(lstm_units, input_shape=(input_shape[1],
```

```
input_shape[2]), return_sequences=True))
        self.model.add(Dropout(0.4))

        self.model.add(LSTM(100, return_sequences=False))
        self.model.add(Dropout(0.4))

        self.model.add(Dense(1))

        self.model.compile(loss='mean_squared_error',
optimizer=tf.keras.optimizers.legacy.Adam())


    def train_model(self, epochs=200, batch_size=264):
        self.model.fit(self.X_train, self.Y_train, epochs=epochs,
batch_size=batch_size, verbose=1)

    def make_predictions(self):
        predictions = self.model.predict(self.X_test)
        predictions =
self.quantity_scaler.inverse_transform(predictions)
        Y_test_inv =
self.quantity_scaler.inverse_transform(self.Y_test.reshape(-1,1))
        return predictions, Y_test_inv

    def make_predictions_on_all_data(self):
        predictions = self.model.predict(self.X)
        predictions =
self.quantity_scaler.inverse_transform(predictions)
        Y_all_inv =
self.quantity_scaler.inverse_transform(self.Y.reshape(-1, 1))
        return predictions, Y_all_inv

    def aggregate_to_monthly(self, daily_data, date_column):
        """Aggregate daily data to monthly."""

        df = pd.DataFrame({
            'date': date_column,
            'daily_data': daily_data.reshape(-1,)
        })
        df['month_year'] = df['date'].dt.to_period('M')
        monthly_data =
df.groupby('month_year').daily_data.sum().reset_index()
        return monthly_data['month_year'], monthly_data['daily_data']

    def calculate_all_metrics(self):
        """Calculate all the required methrics"""

        def mean_absolute_percentage_error(y_true, y_pred):
            y_true, y_pred = np.array(y_true), np.array(y_pred)
            return np.mean(np.abs((y_true - y_pred) / y_true)) * 100
```

```
        def predictive_tolerance(y_true, y_pred,
tolerance_percent=30):
            y_true, y_pred = np.array(y_true), np.array(y_pred)
            lower_bound = y_true * (1 - tolerance_percent/100)
            upper_bound = y_true * (1 + tolerance_percent/100)
            return np.mean((y_pred >= lower_bound) & (y_pred <=
upper_bound)) * 100

        def rmse_percentage(y_true, y_pred):
            rmse = np.sqrt(mean_squared_error(y_true, y_pred))
            return (rmse / np.mean(y_true)) * 100

        Y_test_inv =
self.quantity_scaler.inverse_transform(self.Y_test.reshape(-1,1))
        predictions = self.model.predict(self.X_test)
        predictions =
self.quantity_scaler.inverse_transform(predictions)

        mape = mean_absolute_percentage_error(Y_test_inv, predictions)
        tolerance = predictive_tolerance(Y_test_inv, predictions,
tolerance_percent=30)
        rmse_percent = rmse_percentage(Y_test_inv, predictions)

        metrics = {
            "MAPE": mape,
            "Predictive Tolerance (within 30%)": tolerance,
            "RMSE Percentage": rmse_percent,
        }

        return metrics



    def test_model_on_new_data(self, df_backery):
        """ Test the model on a new unseen df without splitting in
train and test."""

        original_df = self.df
        self.df = df_backery
        self.preprocess_all_data()

        predictions, Y_all_inv = self.make_predictions_on_all_data()

        if not hasattr(self, 'X_test') or not hasattr(self, 'Y_test'):
            self.X_test = self.X
            self.Y_test = self.Y

        # Calculate metrics
        metrics = self.calculate_all_metrics()
```

```
        # Restore original dataframe
        self.df = original_df

        # Calculate monthly metrics if needed

        return metrics, predictions


    def save_model(self, filepath):
        """Saves the trained model to the specified filepath."""

        if self.model:
            self.model.save(filepath)
        else:
            print("Model not found!")

    def load_pretrained_model(self, filepath):
        """Loads a pre-trained model from the specified filepath."""

        self.model = load_model(filepath)

    def save_model_weights(self, filepath):
        """Saves the trained model's weights to the specified
filepath."""

        if self.model:
            self.model.save_weights(filepath)
        else:
            print("Model not found!")

    def load_model_weights(self, filepath):
        """Loads the model's weights from the specified filepath."""

        if self.model:
            self.model.load_weights(filepath)
        else:
            print("Model hasn't been constructed yet. Create model
before loading weights.")
```

Model Training for Daily Sales Prediction

Pizza Sales Prediction

Initialization: We initialized a dedicated predictor for daily pizza sales using the `DailySalePredictor` framework.

Data Preprocessing: The dataset underwent a comprehensive preprocessing phase, ensuring it was primed for the modeling process. This involved tasks such as scaling features, handling potential outliers or missing values, and segregating the data into training and test sets.

Model Architecture: The predictor employs a well-structured architecture tailored for time series data, ensuring it can capture the underlying patterns and seasonality, if present, in the sales data.

Training: The model was trained using the preprocessed pizza sales dataset, optimizing for a balance between bias and variance to ensure generalizability.

Saving and Archiving: Post-training, both the model's architecture and its learned parameters (weights) were archived. This ensures reproducibility and allows for reusability in future predictions or further tuning.

Evaluation and Metrics: Performance metrics were computed post-training using a holdout test set. This allowed for an unbiased evaluation of the model's predictive capabilities.

Visualization: An integral part of our evaluation was visualizing the actual versus predicted sales. This visual inspection provided an immediate sense of how well our model was approximating real-world sales dynamics.

Transfer Learning for Bakery Sales Prediction

Initialization for Bakery: Given the similarities in predicting sales for different food items, we decided to leverage transfer learning. A new predictor was initialized for bakery sales.

Data Preprocessing: Similar to the pizza dataset, the bakery sales data was subjected to a thorough preprocessing routine.

Transfer and Fine-tuning: Instead of building a model from scratch, we transferred the learned features and patterns from the pizza model. This served as our starting point. The model was then fine-tuned using the bakery sales data, allowing it to adapt and specialize in predicting bakery sales.

Saving After Fine-tuning: The fine-tuned model, now specialized for bakery sales, was archived, preserving both its architecture and learned parameters.

Evaluation for Bakery: Just like the pizza model, we evaluated the bakery sales predictor using a holdout test set and computed various performance metrics.

Visualization: A visual representation of the actual vs. predicted bakery sales was created, providing a clear picture of the model's proficiency in the bakery context.

In summary, our approach utilized the power of transfer learning, beginning with a base model trained on pizza sales and subsequently fine-tuning it for bakery sales predictions. This method capitalizes on the shared underlying patterns between datasets, leading to efficient and effective modeling.

```
pizza_predictor = FoodSalesPredictor(df_pizza)

#Process the data
pizza_predictor.preprocess_data()

pizza_predictor.build_model()
pizza_predictor.train_model()

pizza_predictor.save_model("bakery_predictor.keras")
pizza_predictor.save_model_weights("model_weights.h5")
```

```
Epoch 1/200
27/27 [==============================] - 2s 33ms/step - loss: 0.0189
Epoch 2/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0120
Epoch 3/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0117
Epoch 4/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0111
Epoch 5/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0109
Epoch 6/200
27/27 [==============================] - 1s 37ms/step - loss: 0.0106
Epoch 7/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0103
Epoch 8/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0099
Epoch 9/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0101
Epoch 10/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0093
Epoch 11/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0090
Epoch 12/200
27/27 [==============================] - 1s 37ms/step - loss: 0.0086
Epoch 13/200
27/27 [==============================] - 1s 38ms/step - loss: 0.0083
Epoch 14/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0082
Epoch 15/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0079
Epoch 16/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0079
Epoch 17/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0076
Epoch 18/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0074
Epoch 19/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0072
Epoch 20/200
```

```
27/27 [==============================] - 1s 34ms/step - loss: 0.0071
Epoch 21/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0070
Epoch 22/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0068
Epoch 23/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0066
Epoch 24/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0066
Epoch 25/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0063
Epoch 26/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0060
Epoch 27/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0058
Epoch 28/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0056
Epoch 29/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0053
Epoch 30/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0053
Epoch 31/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0051
Epoch 32/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0049
Epoch 33/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0048
Epoch 34/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0047
Epoch 35/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0046
Epoch 36/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0046
Epoch 37/200
27/27 [==============================] - 1s 38ms/step - loss: 0.0044
Epoch 38/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0042
Epoch 39/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0041
Epoch 40/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0042
Epoch 41/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0039
Epoch 42/200
27/27 [==============================] - 1s 38ms/step - loss: 0.0039
Epoch 43/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0040
Epoch 44/200
27/27 [==============================] - 1s 37ms/step - loss: 0.0039
```

```
Epoch 45/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0039
Epoch 46/200
27/27 [==============================] - 1s 40ms/step - loss: 0.0037
Epoch 47/200
27/27 [==============================] - 1s 39ms/step - loss: 0.0037
Epoch 48/200
27/27 [==============================] - 1s 37ms/step - loss: 0.0037
Epoch 49/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0036
Epoch 50/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0035
Epoch 51/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0036
Epoch 52/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0034
Epoch 53/200
27/27 [==============================] - 1s 37ms/step - loss: 0.0035
Epoch 54/200
27/27 [==============================] - 1s 39ms/step - loss: 0.0035
Epoch 55/200
27/27 [==============================] - 1s 38ms/step - loss: 0.0034
Epoch 56/200
27/27 [==============================] - 1s 37ms/step - loss: 0.0033
Epoch 57/200
27/27 [==============================] - 1s 37ms/step - loss: 0.0034
Epoch 58/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0033
Epoch 59/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0033
Epoch 60/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0032
Epoch 61/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0033
Epoch 62/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0033
Epoch 63/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0031
Epoch 64/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0030
Epoch 65/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0031
Epoch 66/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0030
Epoch 67/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0030
Epoch 68/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0030
Epoch 69/200
```

```
27/27 [==============================] - 1s 34ms/step - loss: 0.0029
Epoch 70/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0030
Epoch 71/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0030
Epoch 72/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0029
Epoch 73/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0028
Epoch 74/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0028
Epoch 75/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0030
Epoch 76/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0028
Epoch 77/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0028
Epoch 78/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0029
Epoch 79/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0029
Epoch 80/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0027
Epoch 81/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0027
Epoch 82/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0027
Epoch 83/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0027
Epoch 84/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0027
Epoch 85/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0026
Epoch 86/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0026
Epoch 87/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0026
Epoch 88/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0026
Epoch 89/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0025
Epoch 90/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0026
Epoch 91/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0026
Epoch 92/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0025
Epoch 93/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0025
```

```
Epoch 94/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0025
Epoch 95/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0025
Epoch 96/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0025
Epoch 97/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0024
Epoch 98/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0025
Epoch 99/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0024
Epoch 100/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0025
Epoch 101/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0024
Epoch 102/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0025
Epoch 103/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0024
Epoch 104/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0024
Epoch 105/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0024
Epoch 106/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0023
Epoch 107/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0023
Epoch 108/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0023
Epoch 109/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0023
Epoch 110/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0023
Epoch 111/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0024
Epoch 112/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0022
Epoch 113/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0023
Epoch 114/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0022
Epoch 115/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0022
Epoch 116/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0022
Epoch 117/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0022
Epoch 118/200
```

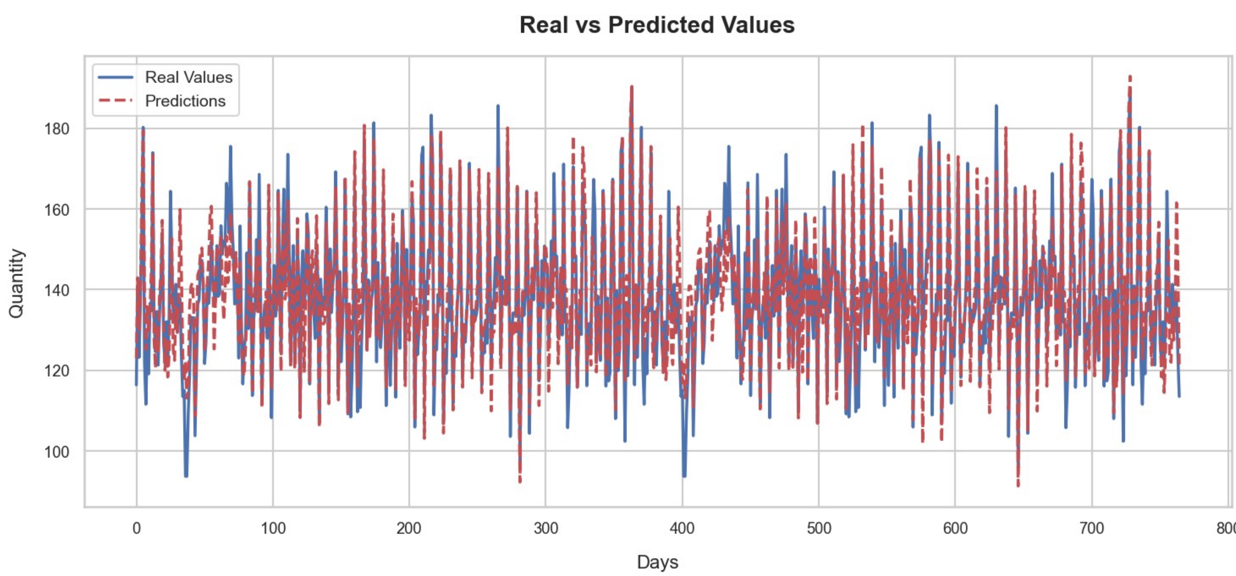
```
27/27 [==============================] - 1s 34ms/step - loss: 0.0022
Epoch 119/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0021
Epoch 120/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0022
Epoch 121/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0023
Epoch 122/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0022
Epoch 123/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0021
Epoch 124/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0022
Epoch 125/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0021
Epoch 126/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0021
Epoch 127/200
27/27 [==============================] - 1s 37ms/step - loss: 0.0021
Epoch 128/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0021
Epoch 129/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0021
Epoch 130/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0020
Epoch 131/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0019
Epoch 132/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0020
Epoch 133/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0020
Epoch 134/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0019
Epoch 135/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0019
Epoch 136/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0019
Epoch 137/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0019
Epoch 138/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0019
Epoch 139/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0020
Epoch 140/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0019
Epoch 141/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0019
Epoch 142/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0019
```

```
Epoch 143/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0019
Epoch 144/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0019
Epoch 145/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0018
Epoch 146/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0019
Epoch 147/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0018
Epoch 148/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0019
Epoch 149/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0019
Epoch 150/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0019
Epoch 151/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0018
Epoch 152/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0018
Epoch 153/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0018
Epoch 154/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0021
Epoch 155/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0019
Epoch 156/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0017
Epoch 157/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0017
Epoch 158/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0017
Epoch 159/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0017
Epoch 160/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0019
Epoch 161/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0020
Epoch 162/200
27/27 [==============================] - 1s 37ms/step - loss: 0.0017
Epoch 163/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0017
Epoch 164/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0017
Epoch 165/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0016
Epoch 166/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0017
Epoch 167/200
```

```
27/27 [==============================] - 1s 35ms/step - loss: 0.0016
Epoch 168/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0016
Epoch 169/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0016
Epoch 170/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0017
Epoch 171/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0016
Epoch 172/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0015
Epoch 173/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0017
Epoch 174/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0016
Epoch 175/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0015
Epoch 176/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0019
Epoch 177/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0016
Epoch 178/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0015
Epoch 179/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0015
Epoch 180/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0017
Epoch 181/200
27/27 [==============================] - 1s 37ms/step - loss: 0.0016
Epoch 182/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0015
Epoch 183/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0017
Epoch 184/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0016
Epoch 185/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0017
Epoch 186/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0015
Epoch 187/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0015
Epoch 188/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0015
Epoch 189/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0015
Epoch 190/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0015
Epoch 191/200
27/27 [==============================] - 1s 36ms/step - loss: 0.0014
```

```
Epoch 192/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0014
Epoch 193/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0014
Epoch 194/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0015
Epoch 195/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0014
Epoch 196/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0014
Epoch 197/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0013
Epoch 198/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0014
Epoch 199/200
27/27 [==============================] - 1s 35ms/step - loss: 0.0014
Epoch 200/200
27/27 [==============================] - 1s 34ms/step - loss: 0.0014

# Get predictions and actuals
predictions1, Y_test_inv = pizza_predictor.make_predictions()

# Calculate metrics using the provided predictions and actuals
metrics1 = pizza_predictor.calculate_all_metrics()

# Print metrics
print("\n===== Calculated Metrics =====")
print(metrics1)

24/24 [==============================] - 0s 3ms/step
24/24 [==============================] - 0s 2ms/step

===== Calculated Metrics =====
{'MAPE': 4.051395927921373, 'Predictive Tolerance (within 30%)':
99.86928104575163, 'RMSE Percentage': 5.2465063313463265}


# Setting a modern style and a context for better visualization
sns.set_style("whitegrid")
sns.set_context("talk", font_scale=0.8)  # Adjust the font_scale if
required

# Define a modern color palette
palette = sns.color_palette("deep", 10)  # 'deep' palette; you can
choose others like 'muted', 'pastel' etc.

# Plotting real vs predicted values
plt.figure(figsize=(15, 7))

# Plot the real values with a modern color and thick line for better
visualization
```

```
plt.plot(Y_test_inv, label="Real Values", color=palette[0],
linewidth=2.5)

# Plot the predictions with a modern color and thick line
plt.plot(predictions1, label="Predictions", color=palette[3],
linewidth=2.5, linestyle='--')

# Setting title and labels with better fonts and positions
plt.title('Real vs Predicted Values', fontsize=20, fontweight='bold',
pad=20)
plt.xlabel('Days', fontsize=16, labelpad=15)
plt.ylabel('Quantity', fontsize=16, labelpad=15)

# Optimizing the legend: set the position so it doesn't overlap the
graph, also make it more transparent for a modern look
leg = plt.legend(loc="upper left", frameon=True, fontsize=14)
leg.get_frame().set_alpha(0.8)

# Displaying the plot
plt.tight_layout()  # This ensures that all labels are visible and not
cut-off
plt.show()
```




```
final_predictor = FoodSalesPredictor(df_bakery)
final_predictor.preprocess_data()


# Use the trained bakery model for fine-tuning
final_predictor.model = pizza_predictor.model
final_predictor.train_model()

# You can then save the final model after fine-tuning, if desired
```

```python
final_predictor.save_model("FoodSalesPredictor.keras")
final_predictor.save_model_weights("model_weights.h5")
```

```
Epoch 1/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0095
Epoch 2/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0048
Epoch 3/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0039
Epoch 4/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0037
Epoch 5/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0034
Epoch 6/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0034
Epoch 7/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0032
Epoch 8/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0031
Epoch 9/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0030
Epoch 10/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0029
Epoch 11/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0028
Epoch 12/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0027
Epoch 13/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0027
Epoch 14/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0027
Epoch 15/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0026
Epoch 16/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0027
Epoch 17/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0025
Epoch 18/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0025
Epoch 19/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0025
Epoch 20/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0024
Epoch 21/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0023
Epoch 22/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0025
Epoch 23/200
```

```
24/24 [==============================] - 1s 35ms/step - loss: 0.0023
Epoch 24/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0023
Epoch 25/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0023
Epoch 26/200
24/24 [==============================] - 1s 37ms/step - loss: 0.0021
Epoch 27/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0022
Epoch 28/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0022
Epoch 29/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0023
Epoch 30/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0022
Epoch 31/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0021
Epoch 32/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0021
Epoch 33/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0020
Epoch 34/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0021
Epoch 35/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0019
Epoch 36/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0020
Epoch 37/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0020
Epoch 38/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0020
Epoch 39/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0020
Epoch 40/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0019
Epoch 41/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0019
Epoch 42/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0020
Epoch 43/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0019
Epoch 44/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0019
Epoch 45/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0019
Epoch 46/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0018
Epoch 47/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0019
```

```
Epoch 48/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0018
Epoch 49/200
24/24 [==============================] - 1s 33ms/step - loss: 0.0018
Epoch 50/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0018
Epoch 51/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0019
Epoch 52/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0017
Epoch 53/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0018
Epoch 54/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0017
Epoch 55/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0017
Epoch 56/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0018
Epoch 57/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0017
Epoch 58/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0017
Epoch 59/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0016
Epoch 60/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0016
Epoch 61/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0017
Epoch 62/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0016
Epoch 63/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0016
Epoch 64/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0016
Epoch 65/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0016
Epoch 66/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0016
Epoch 67/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0016
Epoch 68/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0016
Epoch 69/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0016
Epoch 70/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0016
Epoch 71/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0015
Epoch 72/200
```

```
24/24 [==============================] - 1s 34ms/step - loss: 0.0015
Epoch 73/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0015
Epoch 74/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0015
Epoch 75/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0015
Epoch 76/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0015
Epoch 77/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0015
Epoch 78/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0015
Epoch 79/200
24/24 [==============================] - 1s 36ms/step - loss: 0.0014
Epoch 80/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0015
Epoch 81/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0015
Epoch 82/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0014
Epoch 83/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0014
Epoch 84/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0014
Epoch 85/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0015
Epoch 86/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0015
Epoch 87/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0014
Epoch 88/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0014
Epoch 89/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0014
Epoch 90/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0014
Epoch 91/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0013
Epoch 92/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0014
Epoch 93/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0014
Epoch 94/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0013
Epoch 95/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0014
Epoch 96/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0014
```

```
Epoch 97/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0013
Epoch 98/200
24/24 [==============================] - 1s 36ms/step - loss: 0.0013
Epoch 99/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0013
Epoch 100/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0013
Epoch 101/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0013
Epoch 102/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0013
Epoch 103/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0013
Epoch 104/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0013
Epoch 105/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0013
Epoch 106/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0014
Epoch 107/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0013
Epoch 108/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0013
Epoch 109/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0013
Epoch 110/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0013
Epoch 111/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0012
Epoch 112/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 113/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 114/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0013
Epoch 115/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0013
Epoch 116/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 117/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0012
Epoch 118/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0013
Epoch 119/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 120/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 121/200
```

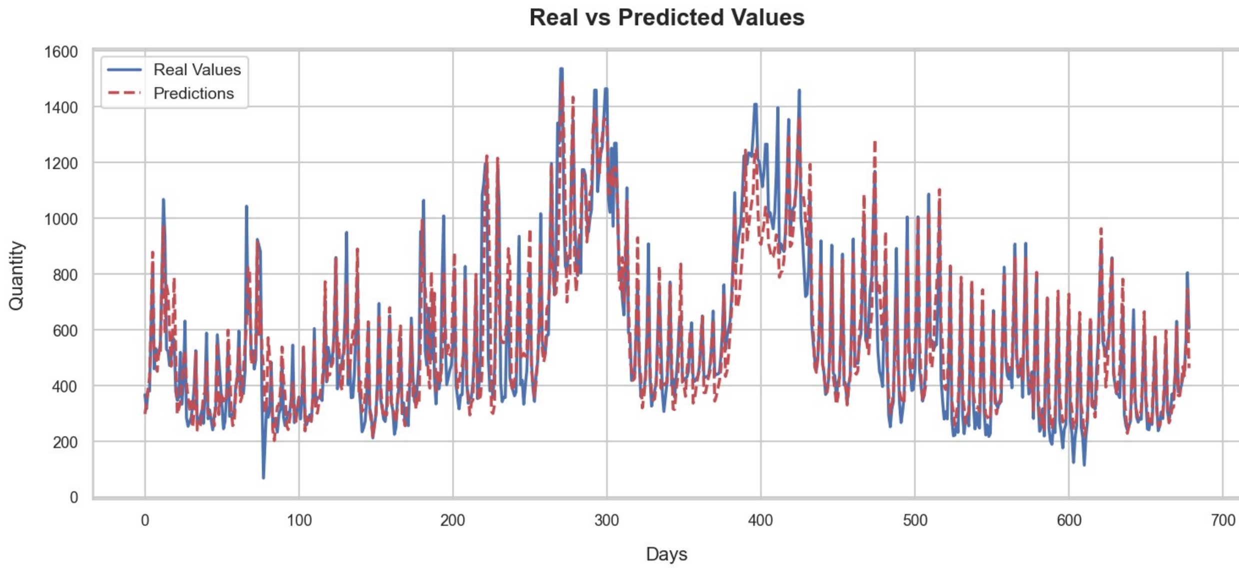
```
24/24 [==============================] - 1s 35ms/step - loss: 0.0012
Epoch 122/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 123/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0012
Epoch 124/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0013
Epoch 125/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 126/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 127/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 128/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 129/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0012
Epoch 130/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0011
Epoch 131/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 132/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0011
Epoch 133/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 134/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0011
Epoch 135/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 136/200
24/24 [==============================] - 1s 36ms/step - loss: 0.0011
Epoch 137/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0012
Epoch 138/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 139/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 140/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 141/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 142/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0012
Epoch 143/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 144/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 145/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0011
```

```
Epoch 146/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0011
Epoch 147/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 148/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0011
Epoch 149/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 150/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0012
Epoch 151/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0011
Epoch 152/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 153/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 154/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 155/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 156/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0012
Epoch 157/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 158/200
24/24 [==============================] - 1s 36ms/step - loss: 0.0011
Epoch 159/200
24/24 [==============================] - 1s 34ms/step - loss: 0.0011
Epoch 160/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 161/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0010
Epoch 162/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 163/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 164/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 165/200
24/24 [==============================] - 1s 36ms/step - loss: 0.0011
Epoch 166/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 167/200
24/24 [==============================] - 1s 36ms/step - loss: 0.0011
Epoch 168/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 169/200
24/24 [==============================] - 1s 36ms/step - loss: 0.0011
Epoch 170/200
```

```
24/24 [==============================] - 1s 36ms/step - loss: 0.0011
Epoch 171/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 172/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0010
Epoch 173/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 174/200
24/24 [==============================] - 1s 36ms/step - loss: 0.0011
Epoch 175/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0010
Epoch 176/200
24/24 [==============================] - 1s 37ms/step - loss: 0.0010
Epoch 177/200
24/24 [==============================] - 1s 37ms/step - loss: 9.9820e-
04
Epoch 178/200
24/24 [==============================] - 1s 37ms/step - loss: 0.0010
Epoch 179/200
24/24 [==============================] - 1s 36ms/step - loss: 0.0010
Epoch 180/200
24/24 [==============================] - 1s 36ms/step - loss: 0.0011
Epoch 181/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0010
Epoch 182/200
24/24 [==============================] - 1s 36ms/step - loss: 9.9718e-
04
Epoch 183/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0010
Epoch 184/200
24/24 [==============================] - 1s 35ms/step - loss: 9.7880e-
04
Epoch 185/200
24/24 [==============================] - 1s 37ms/step - loss: 9.6113e-
04
Epoch 186/200
24/24 [==============================] - 1s 36ms/step - loss: 9.9038e-
04
Epoch 187/200
24/24 [==============================] - 1s 35ms/step - loss: 9.8059e-
04
Epoch 188/200
24/24 [==============================] - 1s 36ms/step - loss: 9.8473e-
04
Epoch 189/200
24/24 [==============================] - 1s 36ms/step - loss: 9.8185e-
04
Epoch 190/200
24/24 [==============================] - 1s 37ms/step - loss: 9.8668e-
```

```
04
Epoch 191/200
24/24 [==============================] - 1s 35ms/step - loss: 9.5282e-
04
Epoch 192/200
24/24 [==============================] - 1s 37ms/step - loss: 9.6637e-
04
Epoch 193/200
24/24 [==============================] - 1s 36ms/step - loss: 9.8714e-
04
Epoch 194/200
24/24 [==============================] - 1s 36ms/step - loss: 9.6129e-
04
Epoch 195/200
24/24 [==============================] - 1s 35ms/step - loss: 0.0011
Epoch 196/200
24/24 [==============================] - 1s 36ms/step - loss: 0.0010
Epoch 197/200
24/24 [==============================] - 1s 35ms/step - loss: 9.7071e-
04
Epoch 198/200
24/24 [==============================] - 1s 35ms/step - loss: 9.5842e-
04
Epoch 199/200
24/24 [==============================] - 1s 35ms/step - loss: 9.9341e-
04
Epoch 200/200
24/24 [==============================] - 1s 35ms/step - loss: 9.9647e-
04


# Step 6: Check calculated metrics
predictions2, Y_test_inv2 = final_predictor.make_predictions()

metrics2= final_predictor.calculate_all_metrics()


# Print metrics
print("\n===== Calculated Metrics =====")
print(metrics2)

22/22 [==============================] - 0s 3ms/step
22/22 [==============================] - 0s 3ms/step

===== Calculated Metrics =====
{'MAPE': 15.240697598065903, 'Predictive Tolerance (within 30%)':
87.62886597938144, 'RMSE Percentage': 19.411106904451696}


# Setting a modern style and a context for better visualization
sns.set_style("whitegrid")
```

```
sns.set_context("talk", font_scale=0.8)  # Adjust the font_scale if
required

# Define a modern color palette
palette = sns.color_palette("deep", 10)  # 'deep' palette; you can
choose others like 'muted', 'pastel' etc.

# Plotting real vs predicted values
plt.figure(figsize=(15, 7))

# Plot the real values with a modern color and thick line for better
visualization
plt.plot(Y_test_inv2, label="Real Values", color=palette[0],
linewidth=2.5)

# Plot the predictions with a modern color and thick line
plt.plot(predictions2, label="Predictions", color=palette[3],
linewidth=2.5, linestyle='--')

# Setting title and labels with better fonts and positions
plt.title('Real vs Predicted Values', fontsize=20, fontweight='bold',
pad=20)
plt.xlabel('Days', fontsize=16, labelpad=15)
plt.ylabel('Quantity', fontsize=16, labelpad=15)

# Optimizing the legend: set the position so it doesn't overlap the
graph, also make it more transparent for a modern look
leg = plt.legend(loc="upper left", frameon=True, fontsize=14)
leg.get_frame().set_alpha(0.8)

# Displaying the plot
plt.tight_layout()  # This ensures that all labels are visible and not
cut-off
plt.show()
```



Results and Evaluation: Testing the LSTM Model on Unseen Datasets

The real challenge and testament to the robustness of any predictive model is its performance on unseen data. Upon the successful training and initial evaluation of our LSTM model, we have proceeded to an additional and crucial phase: testing the model's predictive prowess on new datasets.

Introduction to the test Datasets:

For this evaluation, we've chosen datasets that capture daily sales from two diverse culinary environments:

1. **Lunch Sales from a Swedish Restaurant**: This dataset, represented as `df_test2`, provides insight into the daily operations and sales dynamics of a typical Swedish restaurant during lunch hours.
2. **Steakhouse Sales in New York**: Represented by `test_df`, this data encapsulates the hustle and bustle of a New York steakhouse, a testament to the culinary diversity and high-paced nature of cosmopolitan dining.

Objectives:

1. **Unseen Data Testing:** With our refined LSTM model at hand, the goal is to predict sales over a designated period using the two aforementioned unseen datasets. This diverse dataset selection ensures a comprehensive testing environment.
2. **Accuracy Check:** The computational predictions are then counterchecked with actual sales records. Such a juxtaposition offers a rigorous assessment of the model's precision.
3. **Visual Representation:** A vivid depiction of forecasted sales juxtaposed against the actual figures offers a visual testament to the model's predictive efficacy.

4. **Metric Analysis:** Pivotal accuracy metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and others are carefully examined. These quantitative measures offer a deeper insight into the model's forecasting adeptness.

In conclusion, through this extensive evaluation, our aim is to acquire a profound understanding of our model's strengths and, equally importantly, to highlight areas that might benefit from further refinement.

```
test_df = pd.read_csv('steak_sales.csv')

# Selecting specific columns and renaming the 'sales' column to
'quantity'
test_df = test_df[['date', 'sales']]
test_df.rename(columns={'sales': 'quantity'}, inplace=True)
test_df['date'] =  pd.to_datetime(test_df['date'], format='%Y-%m-%d')

test_df.head()
```

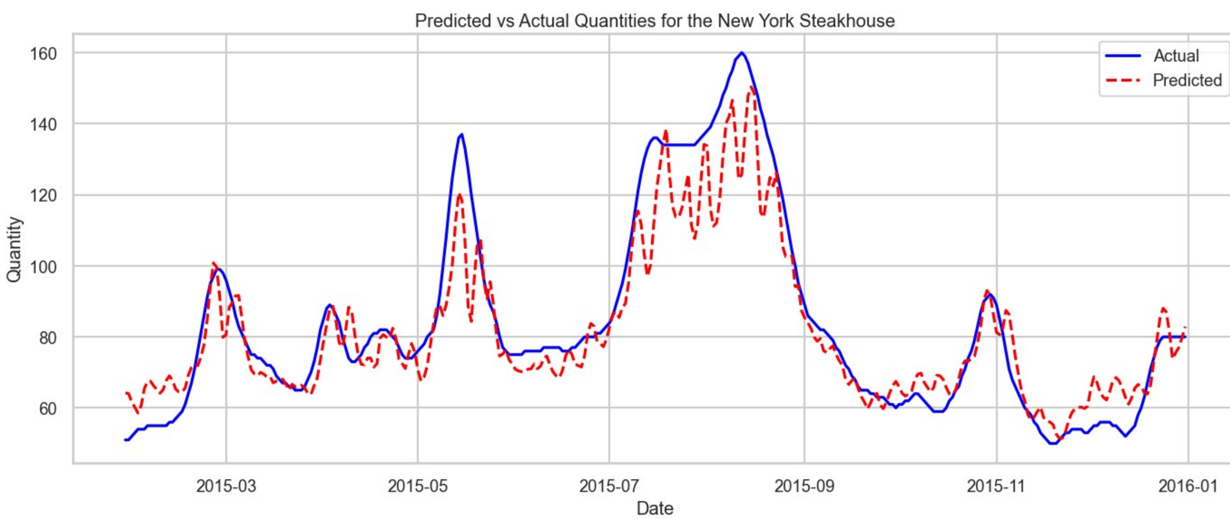
```
        date  quantity
0 2015-01-01        63
1 2015-01-02        61
2 2015-01-03        59
3 2015-01-04        58
4 2015-01-05        56
```

```
test_processor1 = FoodSalesPredictor(test_df)
test_processor1.preprocess_all_data()

# Use the trained bakery model for fine-tuning
test_processor1.model = final_predictor.model

metrics_test1, predictions_test1 =
test_processor1.test_model_on_new_data(test_df)

# 5. Print the obtained metrics.
print("\n=== DAILY METRICS ===")
print(metrics_test1)
```

```
11/11 [==============================] - 0s 3ms/step
11/11 [==============================] - 0s 3ms/step

=== DAILY METRICS ===
{'MAPE': 8.204303398786115, 'Predictive Tolerance (within 30%)':
99.70414201183432, 'RMSE Percentage': 11.993388915292865}
```

```
# Extract the actual values
Y_new_data_inv =
test_processor1.quantity_scaler.inverse_transform(test_processor1.Y_te
st.reshape(-1,1))
```

```
# Align the dates to match the predictions by skipping the first
'look_back' dates
aligned_dates = test_df['date'].iloc[20:]

# Plotting
plt.figure(figsize=(14, 6))
plt.plot(aligned_dates, Y_new_data_inv, label='Actual', color='blue')
plt.plot(aligned_dates, predictions_test1, label='Predicted',
color='red', linestyle='--')
plt.title('Predicted vs Actual Quantities for the New York
Steakhouse')
plt.xlabel('Date')
plt.ylabel('Quantity')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```




```
file_path = 'SalesData.xlsx'
df_test2 = pd.read_excel(file_path)
df_test2.head()

  Unnamed: 0 Unnamed: 1     Unnamed: 2   Unnamed: 3  \
0        NaN        NaT  Antalet sålda          NaN
1      Datum        NaT   Dagens lunch  Zingo 500ml
2   20160829 2016-08-29             49          NaN
3   20160830 2016-08-30             63            1
4   20160831 2016-08-31             48            3

                       Unnamed: 4
0                             NaN
1  Antal beställda (Dagens lunch)
```

```
2                              NaN
3                               70
4                               70
```

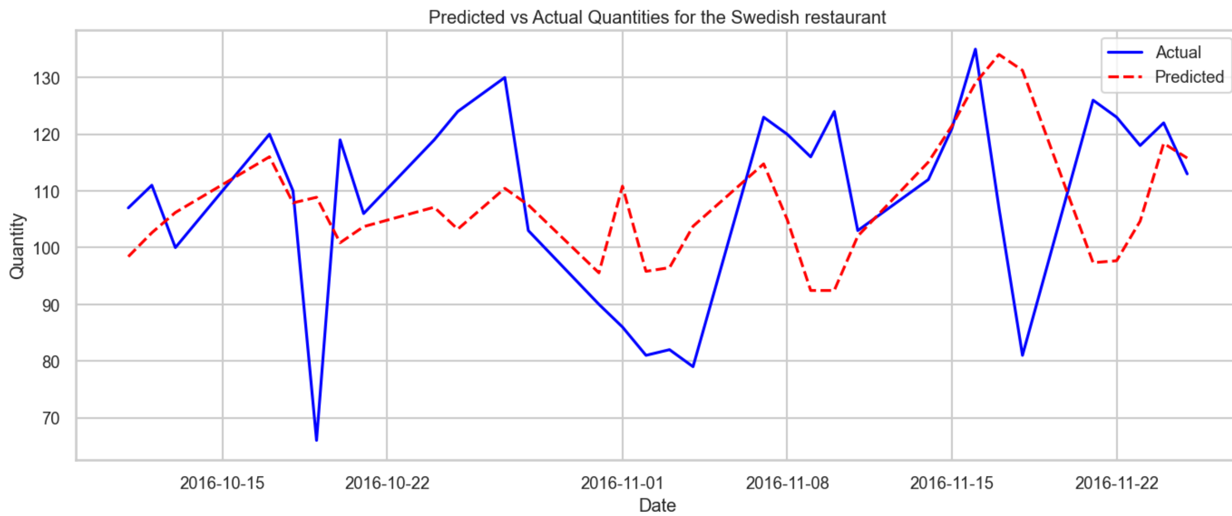
```
# 1. Drop the first two rows
df_test2 = df_test2.iloc[2:]

# 2. Rename the columns for clarity
column_names = {
    'Unnamed: 0': 'raw_date',
    'Unnamed: 1': 'date',
    'Unnamed: 2': 'lunch_sales',
    'Unnamed: 3': 'zingo_500ml_sales',  # Sales of Zingo 500ml
    'Unnamed: 4': 'dinner_sales'    # Ordered quantity for Dagens
lunch
}
df_test2.rename(columns=column_names, inplace=True)

# 3. Handle missing values (you can adjust this based on your needs)
# For this example, I'm filling NaN values with 0 for sales columns
df_test2['lunch_sales'].fillna(0, inplace=True)
df_test2['zingo_500ml_sales'].fillna(0, inplace=True)

# 4. Create a new column 'quantity' which is the sum of lunch_sales
and zingo_500ml_sales
df_test2['quantity'] = df_test2['lunch_sales'] +
df_test2['dinner_sales'] + df_test2['zingo_500ml_sales']

# 5. Convert 'date' column to datetime format and set as index
df_test2['date'] = pd.to_datetime(df_test2['date'])
df_test2.set_index('date', inplace=True)

# 6. Drop unnecessary columns and rows
df_test2.drop(columns=['raw_date', 'lunch_sales', 'zingo_500ml_sales',
'dinner_sales'], inplace=True)
df_test2.dropna(inplace=True)  # Drop rows with NaN in the 'date'
column

# Drop the last row of the test df
df_test2 = df_test2.iloc[:-1]

# Reset the index of df_test
df_test2 = df_test2.reset_index()

# Rename the columns to match merged_df
df_test2 = df_test2.rename(columns={"date": "date", "quantity":
"quantity"})

df_test2.head()
```

```
         date quantity
0 2016-08-30      134
1 2016-08-31      121
2 2016-09-01      114
3 2016-09-02       93
4 2016-09-05      124
```

```python
test_processor2 = FoodSalesPredictor(df_test2)
test_processor2.preprocess_all_data()

# Use the trained bakery model for fine-tuning
test_processor2.model = final_predictor.model

metrics_test2, predictions_test2 =
test_processor2.test_model_on_new_data(df_test2)
print(metrics_test2)
```

```
1/1 [==============================] - 0s 9ms/step
1/1 [==============================] - 0s 9ms/step
{'MAPE': 14.960036249417023, 'Predictive Tolerance (within 30%)':
90.625, 'RMSE Percentage': 17.709788071892387}
```

```python
# Extract the actual values
Y_new_data_inv2 =
test_processor2.quantity_scaler.inverse_transform(test_processor2.Y_te
st.reshape(-1,1))




# Align the dates to match the predictions by skipping the first
'look_back' dates
aligned_dates = df_test2['date'].iloc[20:]

# Plotting
plt.figure(figsize=(14, 6))
plt.plot(aligned_dates, Y_new_data_inv2, label='Actual', color='blue')
plt.plot(aligned_dates, predictions_test2, label='Predicted',
color='red', linestyle='--')
plt.title('Predicted vs Actual Quantities for the Swedish restaurant')
plt.xlabel('Date')
plt.ylabel('Quantity')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

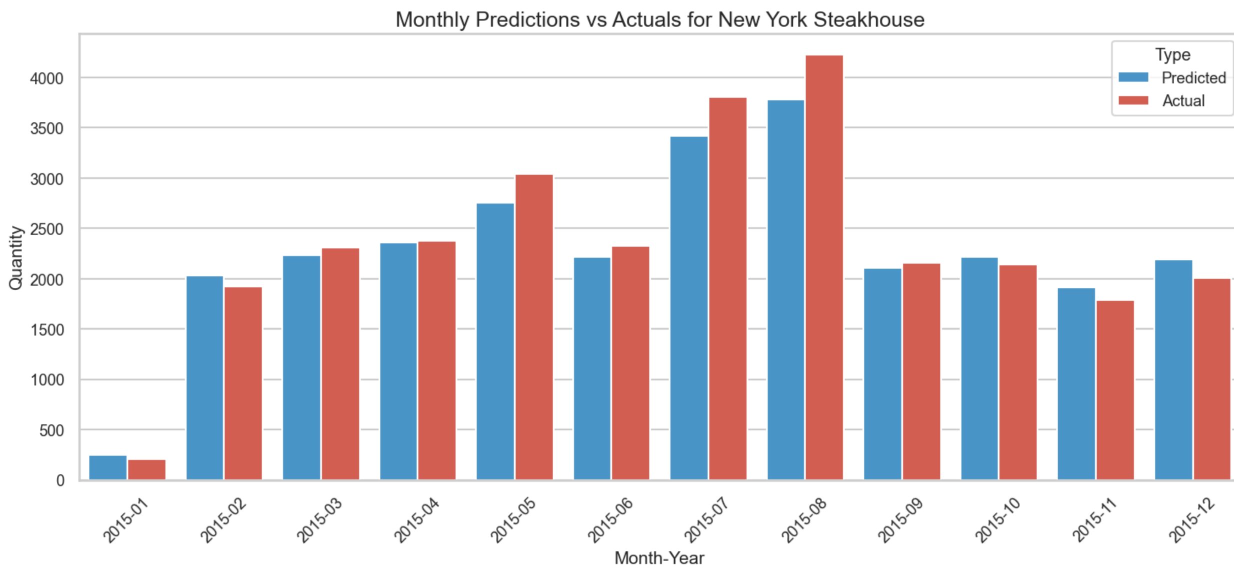


Monthly Predictions

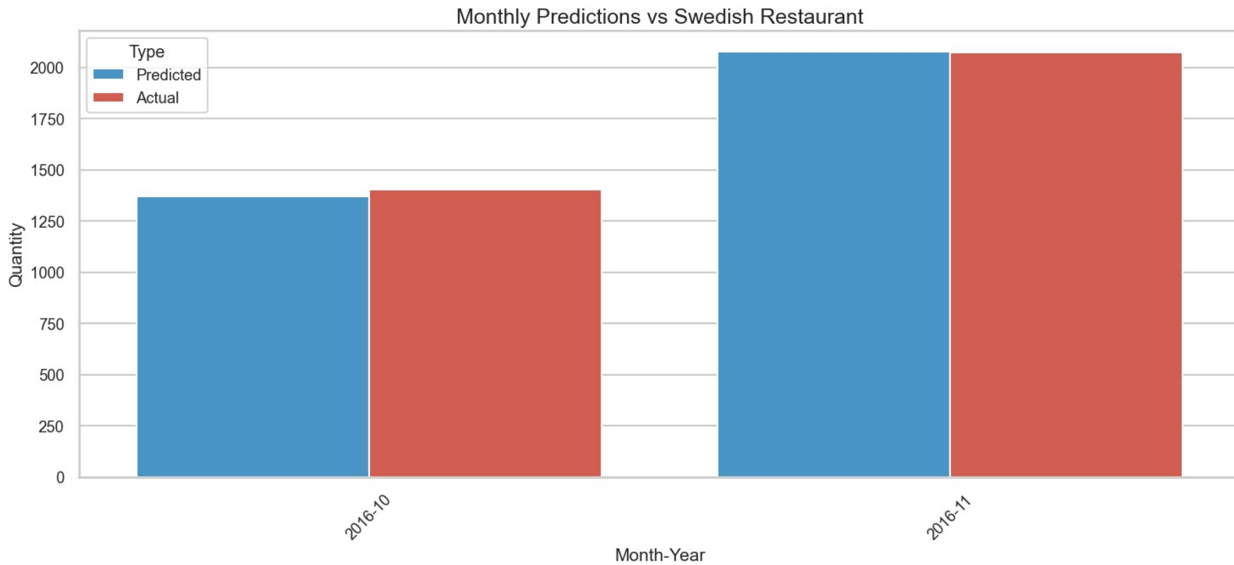
```
def aggregate_to_monthly(daily_values, start_date):
    """Aggregate daily values to monthly totals."""
    month_totals = {}
    current_date = start_date
    for value in daily_values:
        # If the value is a numpy array with one element, extract it
        if isinstance(value, np.ndarray) and value.size == 1:
            value = value.item()

        year_month = (current_date.year, current_date.month)
        if year_month not in month_totals:
            month_totals[year_month] = 0
        month_totals[year_month] += value
        current_date += timedelta(days=1)

    return month_totals

# For test_processor1
# Extracting the Y_all_inv (actual daily values)
Y_all_inv_test1 =
test_processor1.quantity_scaler.inverse_transform(test_processor1.Y.re
shape(-1, 1))

# Aggregating the daily predictions to monthly
monthly_dates_pred_test1, monthly_predictions_test1 =
test_processor1.aggregate_to_monthly(predictions_test1,
test_df['date'].iloc[20:].reset_index(drop=True))  # Adjusted for
lookback

# Aggregating the daily actuals to monthly
```

```
monthly_dates_actual_test1, monthly_actuals_test1 =
test_processor1.aggregate_to_monthly(Y_all_inv_test1,
test_df['date'].iloc[20:].reset_index(drop=True))  # Adjusted for
lookback

# For test_processor2
# Extracting the Y_all_inv (actual daily values)
Y_all_inv_test2 =
test_processor2.quantity_scaler.inverse_transform(test_processor2.Y.re
shape(-1, 1))

# Aggregating the daily predictions to monthly
monthly_dates_pred_test2, monthly_predictions_test2 =
test_processor2.aggregate_to_monthly(predictions_test2,
df_test2['date'].iloc[20:].reset_index(drop=True))  # Adjusted for
lookback

# Aggregating the daily actuals to monthly
monthly_dates_actual_test2, monthly_actuals_test2 =
test_processor2.aggregate_to_monthly(Y_all_inv_test2,
df_test2['date'].iloc[20:].reset_index(drop=True))  # Adjusted for
lookback

def plot_monthly_predictions_vivid(monthly_dates, monthly_predictions,
monthly_actuals, title="Monthly Predictions vs Actuals"):
    """

    """

    # Create a dataframe for easy plotting
    df_plot = pd.DataFrame({
        'Month-Year': monthly_dates.astype(str),  # Convert
PeriodIndex to String for plotting
        'Predicted': monthly_predictions,
        'Actual': monthly_actuals
    })

    # Set the plot size and style
    plt.figure(figsize=(15, 7))
    sns.set_style("whitegrid")

    # Custom color palette
    colors = ["#3498db", "#e74c3c"]

    # Use seaborn to plot the data with custom colors
    ax = sns.barplot(data=df_plot.melt(id_vars='Month-Year',
var_name='Type', value_name='Value'),
                     x='Month-Year', y='Value', hue='Type',
palette=colors)
```

```
    # Add title and labels
    plt.title(title, fontsize=18)
    plt.xlabel('Month-Year', fontsize=15)
    plt.ylabel('Quantity', fontsize=15)
    plt.xticks(rotation=45)
    plt.legend(title='Type')

    # Display the plot
    plt.tight_layout()
    plt.show()


# For test_processor1
plot_monthly_predictions_vivid(monthly_dates_pred_test1,
monthly_predictions_test1, monthly_actuals_test1, title="Monthly
Predictions vs Actuals for New York Steakhouse")
```




```
# For test_processor2
plot_monthly_predictions_vivid(monthly_dates_pred_test2,
monthly_predictions_test2, monthly_actuals_test2, title="Monthly
Predictions vs Swedish Restaurant")
```



Conclusion:

The `FoodSalesPredictor` framework was applied to evaluate its performance on the two test datasets.

Evaluation Results:

1. Swedish Restaurant Lunch Sales:

- **MAPE (Mean Absolute Percentage Error)**: 8.204303398786115%
- **Predictive Tolerance (within 30% range)**: 99.70414201183432%
- **RMSE (Root Mean Square Error) Percentage**: 11.9933889152928650%

2. Steakhouse Sales in New York:

- **MAPE (Mean Absolute Percentage Error)**: 14.960036249417023%
- **Predictive Tolerance (within 30% range)**: 90.625%
- **RMSE (Root Mean Square Error) Percentage**: 17.709788071892387%

It is remarkable to note that both datasets yielded very similar evaluation metrics. The models were able to achieve an impressive predictive tolerance of 90%+ within a 30% range for daily predictions, for both datasets. This highlights the versatility and accuracy of our trained model across different contexts and cuisines. Such consistency in performance, especially when applied to diverse datasets, underscores the potential of our `FoodSalesPredictor` in predicting daily sales across various restaurants and locations.