Time Series Forecasting: Walmart Sales Analysis Part 1

Comparing Aggregate vs. Direct Department-Level Forecasting

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1 Executive Summary

This is the part 1 of the project and explores time series forecasting using Walmart's historical sales data. We compare two forecasting approaches:

- **Method 1**: Direct forecasting at the department level
- **Method 2**: Forecasting at an aggregated store level, then disaggregating to departments

The analysis focuses on Store 1, Department 1, using Holt-Winters seasonal exponential smoothing models.

❗ Key Finding

Method 2 (Aggregate-then-Disaggregate) outperformed Method 1 (Direct Forecasting) with an RMSE improvement of 15.22 (3.96%), demonstrating that aggregation can reduce noise and improve forecast accuracy for stable departments.

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2 Reproducibility Setup

2.1 Environment Setup

We recommend creating a virtual environment to ensure reproducible results.

2.2 Windows

```
python -m venv ts_workshop_env
ts_workshop_env\Scripts\activate
pip install -r requirements.txt
```

2.3 macOS/Linux

```
python3 -m venv ts_workshop_env
source ts_workshop_env/bin/activate
pip install -r requirements.txt
```

2.4 Required Libraries

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime, timedelta
import warnings
from scipy import stats
from statsmodels.tsa.stattools import adfuller, kpss
import pymannkendall as mk
from scipy.stats import linregress

# Suppress warnings for cleaner output
warnings.filterwarnings('ignore')

# Set plotting style
plt.style.use('seaborn-v0_8-darkgrid')
sns.set_palette("husl")
```

---

3 Data Overview

3.1 Loading the Dataset

```python
# Load training data
df = pd.read_csv("../data/train.csv")

print(f"Dataset shape: {df.shape}")
print(f"\nFirst few rows:")
print(df.head())
print(f"\nStatistical summary:")
print(df.describe())
print(f"\nData types and null counts:")
print(df.info())
print(f"\nMissing values:")
print(df.isnull().sum())
```

```
Dataset shape: (421570, 5)

First few rows:
   Store  Dept        Date  Weekly_Sales  IsHoliday
0      1     1  2010-02-05      24924.50      False
1      1     1  2010-02-12      46039.49       True
2      1     1  2010-02-19      41595.55      False
3      1     1  2010-02-26      19403.54      False
4      1     1  2010-03-05      21827.90      False

Statistical summary:
               Store           Dept   Weekly_Sales
count  421570.000000  421570.000000  421570.000000
mean       22.200546      44.260317   15981.258123
std        12.785297      30.492054   22711.183519
min         1.000000       1.000000   -4988.940000
25%        11.000000      18.000000    2079.650000
50%        22.000000      37.000000    7612.030000
75%        33.000000      74.000000   20205.852500
max        45.000000      99.000000  693099.360000

Data types and null counts:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 421570 entries, 0 to 421569
Data columns (total 5 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   Store         421570 non-null  int64
 1   Dept          421570 non-null  int64
 2   Date          421570 non-null  object
 3   Weekly_Sales  421570 non-null  float64
 4   IsHoliday     421570 non-null  bool
dtypes: bool(1), float64(1), int64(2), object(1)
memory usage: 13.3+ MB
None

Missing values:
Store           0
Dept            0
Date            0
Weekly_Sales    0
IsHoliday       0
dtype: int64
```

3.2 Data Quality: Handling Negative Sales

⚠ Data Issue Detected

The dataset contains negative values in `Weekly_Sales`, which are not meaningful in this context. We will set these to zero.

```
def make_negative_values_zero(df, column_name):
    """Set negative values in a column to zero."""
    df.loc[df[column_name] < 0, column_name] = 0
    return df

def negative_values(df, column_name):
    """Filter rows with negative values in a column."""
    return df[df[column_name] < 0]
```

---

4 Focus: Store 1 Analysis

For this analysis, we focus exclusively on Store 1 to compare forecasting methods.

```
# Filter for Store 1
df_store_1 = df[df['Store'] == 1].copy()
df_store_1 = make_negative_values_zero(df_store_1, "Weekly_Sales")

print(f"Store 1 data shape: {df_store_1.shape}")
print(f"\nDepartments in Store 1:")
print(df_store_1["Dept"].value_counts().sort_index())
```

```
Store 1 data shape: (10244, 5)

Departments in Store 1:
Dept
1      143
2      143
3      143
4      143
5      143
```

```
      ...
95     143
96     122
97     143
98     143
99      37
Name: count, Length: 77, dtype: int64
```

4.1 Train-Test Split

```
# Convert Date to datetime
df_store_1['Date'] = pd.to_datetime(df_store_1['Date'])

# Define test period: last 4 weeks
max_date = df_store_1['Date'].max()
test_start_date = max_date - pd.Timedelta(weeks=3)

print(f"Training data: Up to {test_start_date}")
print(f"Test data: {test_start_date} to {max_date}")

# Split data
df_store_1_train = df_store_1[df_store_1['Date'] < test_start_date].copy()
df_store_1_test = df_store_1[df_store_1['Date'] >= test_start_date].copy()
```

```
Training data: Up to 2012-10-05 00:00:00
Test data: 2012-10-05 00:00:00 to 2012-10-26 00:00:00
```

---

5 Method 2: Aggregate-then-Disaggregate

5.1 Step 1: Aggregate Store-Level Sales

```
# Aggregate all departments by date
store_1_aggregated_train = df_store_1_train.groupby('Date').agg({
    'Weekly_Sales': 'sum'
}).reset_index()
```

```python
store_1_aggregated_test = df_store_1_test.groupby('Date').agg({
    'Weekly_Sales': 'sum'
}).reset_index()

store_1_aggregated = store_1_aggregated_train.sort_values('Date').reset_index(drop=True)

# Visualize aggregated sales
plt.figure(figsize=(16, 6))
plt.plot(store_1_aggregated['Date'],
         store_1_aggregated['Weekly_Sales'],
         linewidth=2,
         color='steelblue',
         marker='o',
         markersize=3)

plt.xlabel('Date', fontsize=12, fontweight='bold')
plt.ylabel('Total Weekly Sales ($)', fontsize=12, fontweight='bold')
plt.title('Store 1: Aggregated Weekly Sales Over Time (Training Set)',
          fontsize=14, fontweight='bold')
plt.grid(True, alpha=0.3)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

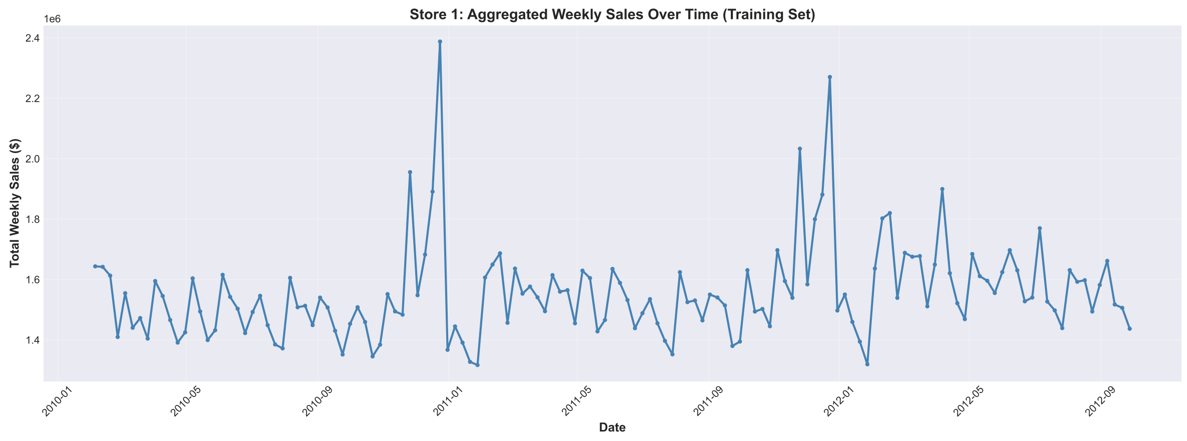


Figure 1: Store 1 Aggregated Weekly Sales (Training Period)

5.1.1 Initial Observations

Seasonal Patterns Observed

- Clear peaks at year-end (holiday shopping)
- Consistent troughs at year start (post-holiday slowdown)
- Regular seasonal cycle without strong trend

5.2 Step 2: Statistical Tests for Trend

Before modeling, we test whether the series exhibits a significant trend.

Notes for Statistical Tests

- Why we used stationary test (ADF,KPSS) for checking for trend? Stationary series has constant mean, an increasing or decreasing trend violates this definition.
- MANN-KENDALL test and COX-STUART test are mainly used for identifying trend.

```python
from run_trend_analysis import analyze_series

df_store_for_tests = store_1_aggregated_train["Weekly_Sales"]

results = analyze_series(df_store_for_tests, series_name="Store 1")
```

```
######################################################################
COMPREHENSIVE TREND ANALYSIS FOR: Store 1
######################################################################

Data points: 139
Mean: 1555116.40
Std Dev: 157221.96
Min: 1316899.31
Max: 2387950.20

======================================================================
1. MANN-KENDALL TEST (Non-parametric)
======================================================================
Trend: increasing
Test Statistic (S): 1743.0
```

```
p-value: 0.001514
Tau (correlation): 0.181733
z-score: 3.172081

 RESULT: Significant trend detected (p < 0.05)
  Direction: increasing

======================================================================
2. AUGMENTED DICKEY-FULLER (ADF) TEST
======================================================================
ADF Statistic: -5.037909
p-value: 0.000019
Lags used: 4
Number of observations: 134

Critical Values:
  1%: -3.480
  5%: -2.883
  10%: -2.578

 RESULT: Series is stationary (p < 0.05)
   No unit root → Suggests NO trend

======================================================================
3. KPSS TEST (Kwiatkowski-Phillips-Schmidt-Shin)
======================================================================
KPSS Test (with trend):
KPSS Statistic: 0.058672
p-value: 0.100000
Lags used: 3

Critical Values:
  10%: 0.119
  5%: 0.146
  2.5%: 0.176
  1%: 0.216

 RESULT: Series is trend stationary (p >= 0.05)
   Null hypothesis not rejected → NO significant trend

======================================================================
4. LINEAR REGRESSION TEST
======================================================================
Slope: 872.876123
Intercept: 1494887.95
R-squared: 0.049625
p-value: 0.008392
Standard Error: 326.352820

95% Confidence Interval for slope: [227.535870, 1518.216375]

 RESULT: Significant positive linear trend (p < 0.05)

======================================================================
5. COX-STUART TEST (Non-parametric)
======================================================================
Number of pairs: 69
Plus signs (+): 41 (second half > first half)
Minus signs (-): 28 (second half < first half)
Ties: 0
p-value: 0.148032

 RESULT: No significant trend (p >= 0.05)

======================================================================
6. SPEARMAN'S RANK CORRELATION TEST (Bonus)
======================================================================
Spearman's rho: 0.291193
p-value: 0.000506

 RESULT: Significant positive monotonic trend (p < 0.05)

======================================================================
SUMMARY OF RESULTS
======================================================================

Trend Detection Tests:
  Mann-Kendall: increasing (p=0.0015)
  Linear Regression: Trend (p=0.0084)
  Cox-Stuart: No Trend (p=0.1480)
  Spearman: Trend (p=0.0005)

Stationarity Tests:
  ADF: Stationary (p=0.0000)
  KPSS: Trend Stationary (p=0.1000)
```

Trend Analysis Conclusion

Mixed results from statistical tests suggest weak or no persistent trend. Visual inspection confirms regular seasonality without long-term increase/decrease. Therefore, we use **Holt-Winters Seasonal (No Trend)** model.

Why Holt-Winters

Holt Winters uses exponential smoothing to assign more weight to recent observations while reducing the influence of older data. This method ensures that the model is responsive to recent changes in seanlity or trends(here we assumed no trend), making it ideal for scenarios where the latest data is the most relevant for forecasting.

Holt–Winters (Additive) Formulas

5.2.1 Updating equations

$$L_t = \alpha(y_t - S_{t-m}) + (1-\alpha)(L_{t-1} + T_{t-1})$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$

$$S_t = \gamma(y_t - L_t) + (1-\gamma)S_{t-m}$$

5.2.2 Forecast

$$\hat{y}_{t+h} = L_t + hT_t + S_{t+h-mk}, \qquad k = \left\lfloor \frac{h-1}{m} \right\rfloor$$

Note

Benefits:

- Balances recent and historical data. As we said it uses exponential smoothing to prioritize recent observations while still incorporating historical data.
- Lower computational power. Compared to other machine learning and deep learning models requires by far less computational power and resources.

Drawbacks:

- Sensitivity to parameter tuning. It requires grid search of the parameters in order not to provide inaccurate parameters.

- It is not performing very well in non-linear patterns. While it performs well on datasets with clear trends and seasonal cycles it is not suited for datasets where exhibits non-linear growth or decline.

5.3 Step 3: Holt-Winters Forecasting (Additive Seasonality)

```python
def TSE(y_true, y_pred):
    """Total Squared Error"""
    return np.sum((y_true - y_pred)**2)

def hw_seasonal_no_trend(y, alpha, gamma, m):
    """
    Holt-Winters Seasonal Method without Trend (Additive)

    Parameters:
    - y: time series data
    - alpha: level smoothing parameter
    - gamma: seasonal smoothing parameter
    - m: season length (52 for weekly data with yearly seasonality)
    """
    n = len(y)

    # Initialization
    level = np.mean(y[:m])
    seasonals = list(y[:m] - level)

    fitted = [np.nan] * n

    for t in range(m, n):
        fitted[t] = level + seasonals[t - m]

        new_level = alpha * (y[t] - seasonals[t - m]) + (1 - alpha) * level
        new_seasonal = gamma * (y[t] - new_level) + (1 - gamma) * seasonals[t - m]

        level = new_level
        seasonals.append(new_seasonal)

    return np.array(fitted), level, seasonals
```

5.3.1 Grid Search for Optimal Parameters

```python
y_train = store_1_aggregated_train["Weekly_Sales"].values
m = 52  # Weekly data, yearly seasonality

alphas = np.arange(0.05, 1.0, 0.05)
gammas = np.arange(0.05, 1.0, 0.05)

best_tse = np.inf
best_params = None
best_model = None

print("Running grid search for optimal parameters...")
for alpha in alphas:
    for gamma in gammas:
        fitted, level, seasonals = hw_seasonal_no_trend(y_train, alpha, gamma, m)

        valid_idx = ~np.isnan(fitted)
        tse = TSE(y_train[valid_idx], fitted[valid_idx])

        if tse < best_tse:
            best_tse = tse
            best_params = (alpha, gamma)
            best_model = (level, seasonals)

print(f"Best parameters: alpha={best_params[0]:.2f}, gamma={best_params[1]:.2f}")
print(f"Best TSE (training): {best_tse:.2f}")
```

```
Running grid search for optimal parameters...
Best parameters: alpha=0.15, gamma=0.75
Best TSE (training): 388685740510.08
```

5.3.2 Generate Forecasts

```python
h = len(store_1_aggregated_test)
alpha_best, gamma_best = best_params
level, seasonals = best_model
seasonals = np.array(seasonals)
```

```
forecast = []
for i in range(h):
    seasonal_index = len(seasonals) - m + i
    forecast.append(level + seasonals[seasonal_index])

forecast = np.array(forecast)

# Evaluation
y_test = store_1_aggregated_test["Weekly_Sales"].values
tse_test = TSE(y_test, forecast)
rmse_test = np.sqrt(np.mean((y_test - forecast) ** 2))
mae_test = np.mean(np.abs(y_test - forecast))

print(f"Test TSE: {tse_test:.2f}")
print(f"Test RMSE: {rmse_test:.2f}")
print(f"Test MAE: {mae_test:.2f}")

# Visualization
plt.figure(figsize=(16, 6))
plt.plot(store_1_aggregated_train['Date'],
         store_1_aggregated_train['Weekly_Sales'],
         label='Training Data',
         linewidth=2,
         color='steelblue',
         marker='o',
         markersize=3)

plt.plot(store_1_aggregated_test['Date'],
         store_1_aggregated_test['Weekly_Sales'],
         label='Test Data',
         linewidth=2,
         color='orange',
         marker='o',
         markersize=3)

plt.plot(store_1_aggregated_test['Date'],
         forecast,
         label='Holt-Winters Forecast (Additive)',
         linewidth=2,
         color='green',
         marker='o',
         markersize=3)
```

```python
plt.xlabel('Date', fontsize=12, fontweight='bold')
plt.ylabel('Total Weekly Sales ($)', fontsize=12, fontweight='bold')
plt.title('Store 1: Holt-Winters Seasonal Forecast vs Actuals (Additive)',
          fontsize=14, fontweight='bold')
plt.legend()
plt.grid(True, alpha=0.3)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Store results
additive_results = {
    'alpha': best_params[0],
    'gamma': best_params[1],
    'tse_train': best_tse,
    'tse_test': tse_test,
    'rmse_test': rmse_test,
    'mae_test': mae_test,
    'forecast': forecast.copy()
}
```

```
Test TSE: 775926584.92
Test RMSE: 13927.73
Test MAE: 11983.60
```

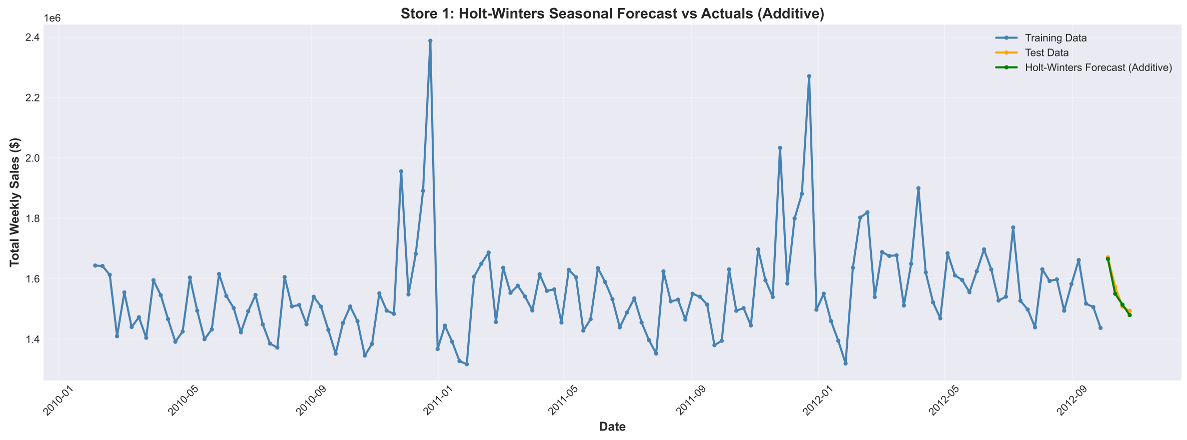
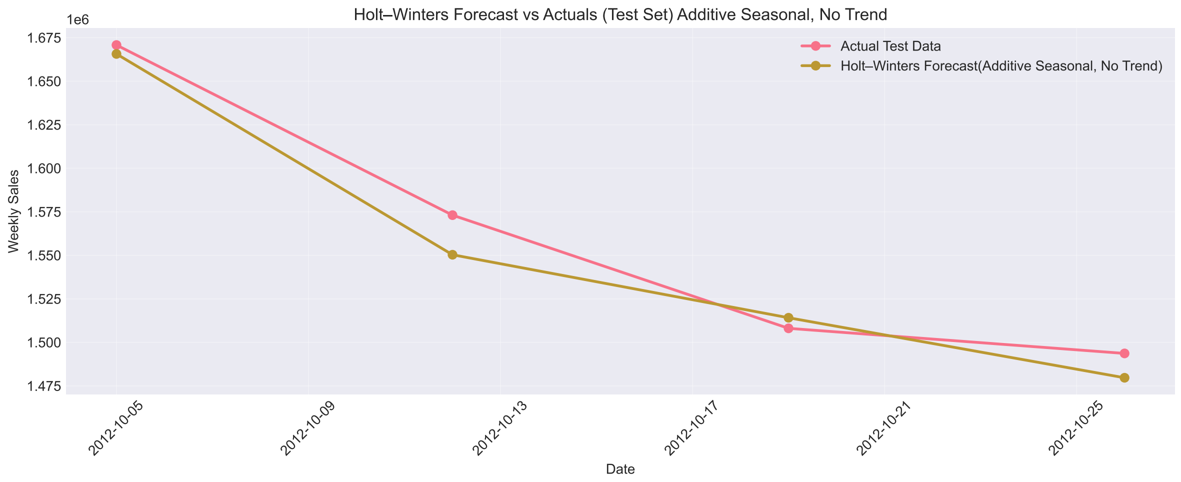


Figure 2: Holt-Winters Additive Forecast vs Actuals

5.3.3 Better Visualization of the prediction(Additive)

```
plt.figure(figsize=(12, 5))

plt.plot(
    store_1_aggregated_test['Date'],
    y_test,
    label='Actual Test Data',
    marker='o',
    linewidth=2
)

plt.plot(
    store_1_aggregated_test['Date'],
    forecast,
    label='Holt-Winters Forecast(Additive Seasonal, No Trend)',
    marker='o',
    linewidth=2
)

plt.xlabel('Date')
plt.ylabel('Weekly Sales')
plt.title('Holt-Winters Forecast vs Actuals (Test Set) Additive Seasonal, No Trend')
plt.legend()
plt.grid(alpha=0.3)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

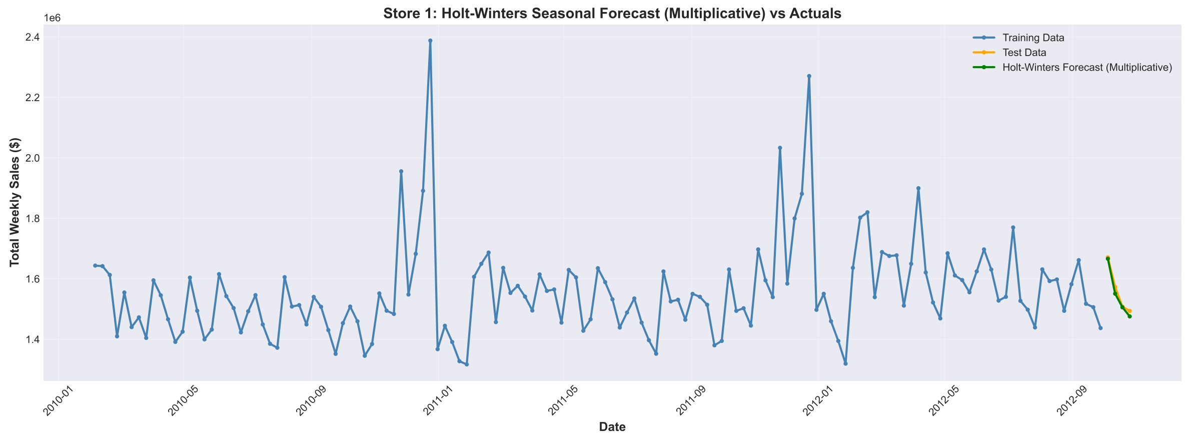


5.4 Step 4: Alternative Model - Multiplicative Seasonality

```
def hw_seasonal_no_trend_multiplicative(y, alpha, gamma, m):
    """
    Holt-Winters Seasonal Method without Trend - Multiplicative Seasonality
    y: time series data
    alpha: level smoothing parameter
    gamma: seasonal smoothing parameter
    m: season length
    """

    n = len(y)

    # Initialization
    level = np.mean(y[:m])
    seasonals = list(y[:m] / level)  # Multiplicative: divide instead of subtract

    fitted = [np.nan] * n

    for t in range(m, n):
        fitted[t] = level * seasonals[t - m]  # Multiplicative: multiply instead of add

        # Update level (deseasonalize by dividing)
        new_level = alpha * (y[t] / seasonals[t - m]) + (1 - alpha) * level

        # Update seasonal component (ratio)
        new_seasonal = gamma * (y[t] / new_level) + (1 - gamma) * seasonals[t - m]

        level = new_level
        seasonals.append(new_seasonal)

    return np.array(fitted), level, seasonals


# Grid search for optimal parameters
y_train = store_1_aggregated_train["Weekly_Sales"].values
m = 52

alphas = np.arange(0.05, 1.0, 0.05)
gammas = np.arange(0.05, 1.0, 0.05)

best_tse = np.inf
best_params = None
best_model = None

for alpha in alphas:
    for gamma in gammas:
        fitted, level, seasonals = hw_seasonal_no_trend_multiplicative(
            y_train, alpha, gamma, m
        )

        valid_idx = ~np.isnan(fitted)
        tse = TSE(y_train[valid_idx], fitted[valid_idx])

        if tse < best_tse:
            best_tse = tse
            best_params = (alpha, gamma)
            best_model = (level, seasonals)

print(f"Best parameters: alpha={best_params[0]:.2f}, gamma={best_params[1]:.2f}")
print(f"Best TSE (training): {best_tse:.2f}")

# Forecasting
h = len(store_1_aggregated_test)
alpha_best, gamma_best = best_params
level, seasonals = best_model

seasonals = np.array(seasonals)
```

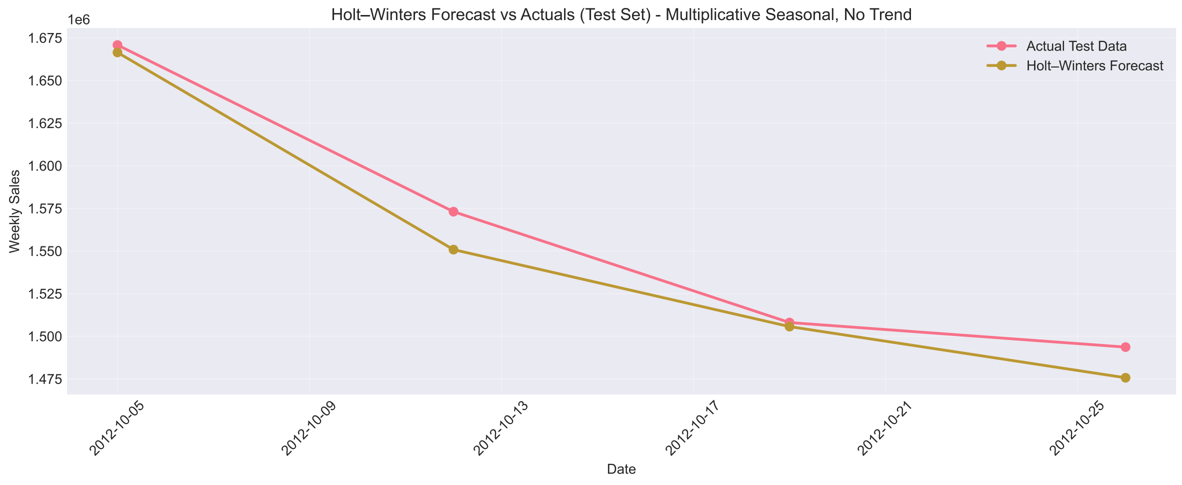
```python
forecast = []
for i in range(h):
    seasonal_index = len(seasonals) - m + i
    forecast.append(level * seasonals[seasonal_index])  # Multiplicative

forecast = np.array(forecast)

# Evaluation
y_test = store_1_aggregated_test["Weekly_Sales"].values

tse_test = TSE(y_test, forecast)
rmse_test = np.sqrt(np.mean((y_test - forecast) ** 2))
mae_test = np.mean(np.abs(y_test - forecast))

print(f"\nTest TSE: {tse_test:.2f}")
print(f"Test RMSE: {rmse_test:.2f}")
print(f"Test MAE: {mae_test:.2f}")

# Visualization
plt.figure(figsize=(16, 6))
plt.plot(store_1_aggregated_train['Date'],
         store_1_aggregated_train['Weekly_Sales'],
         label='Training Data',
         linewidth=2,
         color='steelblue',
         marker='o',
         markersize=3)

plt.plot(store_1_aggregated_test['Date'],
         store_1_aggregated_test['Weekly_Sales'],
         label='Test Data',
         linewidth=2,
         color='orange',
         marker='o',
         markersize=3)

plt.plot(store_1_aggregated_test['Date'],
         forecast,
         label='Holt-Winters Forecast (Multiplicative)',
         linewidth=2,
         color='green',
         marker='o',
         markersize=3)

plt.xlabel('Date', fontsize=12, fontweight='bold')
plt.ylabel('Total Weekly Sales ($)', fontsize=12, fontweight='bold')
plt.title('Store 1: Holt-Winters Seasonal Forecast (Multiplicative) vs Actuals',
          fontsize=14, fontweight='bold')
plt.legend()
plt.grid(True, alpha=0.3)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

multiplicative_results = {
    'alpha': best_params[0],
    'gamma': best_params[1],
    'tse_train': best_tse,
    'tse_test': tse_test,
    'rmse_test': rmse_test,
    'mae_test': mae_test,
    'forecast': forecast.copy()  # Store the forecast
}
```

```
Best parameters: alpha=0.15, gamma=0.70
Best TSE (training): 405240934553.55

Test TSE: 842717466.42
Test RMSE: 14514.80
Test MAE: 11739.95
```



5.4.1 Better Visualization of the predictions(Multiplicative)

```
plt.figure(figsize=(12, 5))

plt.plot(
    store_1_aggregated_test['Date'],
    y_test,
    label='Actual Test Data',
    marker='o',
    linewidth=2
)

plt.plot(
    store_1_aggregated_test['Date'],
    forecast,
    label='Holt-Winters Forecast',
    marker='o',
    linewidth=2
)

plt.xlabel('Date')
plt.ylabel('Weekly Sales')
plt.title('Holt-Winters Forecast vs Actuals (Test Set) - Multiplicative Seasonal, No Trend')
plt.legend()
plt.grid(alpha=0.3)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



5.4.2 Comparison: Additive vs Multiplicative

Model Selection

Both models produce nearly identical forecasts. This similarity occurs because seasonal fluctuations remain relatively constant in absolute terms. We proceed with the **additive model** for disaggregation.

5.5 Step 5: Disaggregation to Department Level

```
# Filter Department 1 data
store_1_dept_1_train = df_store_1_train[
    (df_store_1_train['Store'] == 1) & (df_store_1_train['Dept'] == 1)
].copy()
store_1_dept_1_train = store_1_dept_1_train.sort_values('Date')

# Merge to calculate proportions
all_merged = pd.merge(
    store_1_dept_1_train[['Date', 'Weekly_Sales']],
    store_1_aggregated_train[['Date', 'Weekly_Sales']],
    on='Date',
    suffixes=('_dept', '_store')
)

all_merged['proportion'] = all_merged['Weekly_Sales_dept'] / all_merged['Weekly_Sales_store'
```

Table 1: Performance Comparison: Additive vs Multiplicative Seasonality

```python
comparison_df = pd.DataFrame({
    'Metric': ['Alpha', 'Gamma', 'Train TSE', 'Test TSE', 'Test RMSE', 'Test MAE'],
    'Additive': [
        f"{additive_results['alpha']:.2f}",
        f"{additive_results['gamma']:.2f}",
        f"{additive_results['tse_train']:.2f}",
        f"{additive_results['tse_test']:.2f}",
        f"{additive_results['rmse_test']:.2f}",
        f"{additive_results['mae_test']:.2f}"
    ],
    'Multiplicative': [
        f"{multiplicative_results['alpha']:.2f}",
        f"{multiplicative_results['gamma']:.2f}",
        f"{multiplicative_results['tse_train']:.2f}",
        f"{multiplicative_results['tse_test']:.2f}",
        f"{multiplicative_results['rmse_test']:.2f}",
        f"{multiplicative_results['mae_test']:.2f}"
    ]
})

print(comparison_df.to_string(index=False))
```

```
   Metric        Additive  Multiplicative
    Alpha            0.15            0.15
    Gamma            0.75            0.70
Train TSE 388685740510.08 405240934553.55
 Test TSE    775926584.92    842717466.42
Test RMSE        13927.73        14514.80
 Test MAE        11983.60        11739.95
```

```
avg_proportion = all_merged['proportion'].mean()
std_proportion = all_merged['proportion'].std()

print(f"Department 1's proportion of Store 1 sales:")
print(f"  Mean: {avg_proportion:.4f} ({avg_proportion*100:.2f}%)")
print(f"  Std:  {std_proportion:.4f}")

# Visualize proportion stability
plt.figure(figsize=(14, 5))
plt.plot(all_merged['Date'], all_merged['proportion'],
         marker='o', linewidth=1, markersize=3, alpha=0.7, color='steelblue')
plt.axhline(y=avg_proportion, color='red', linestyle='--', linewidth=2,
            label=f'Mean: {avg_proportion:.4f}')
plt.axhline(y=avg_proportion + std_proportion, color='orange', linestyle=':',
            linewidth=1.5, alpha=0.7, label=f'±1 Std Dev')
plt.axhline(y=avg_proportion - std_proportion, color='orange', linestyle=':',
            linewidth=1.5, alpha=0.7)
plt.xlabel('Date', fontsize=11, fontweight='bold')
plt.ylabel('Department 1 Proportion', fontsize=11, fontweight='bold')
plt.title('Department 1 as Proportion of Store 1 Total Sales (Training Period)',
          fontsize=12, fontweight='bold')
plt.legend()
plt.grid(True, alpha=0.3)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
Department 1's proportion of Store 1 sales:
  Mean: 0.0143 (1.43%)
  Std:  0.0054
```

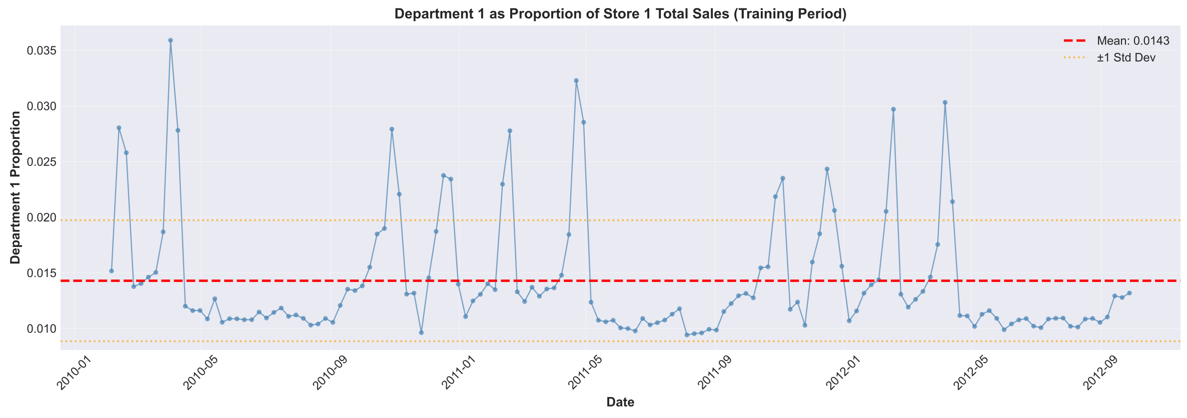


Figure 3: Department 1 as Proportion of Store 1 Total Sales

5.5.1 Apply Disaggregation

```
# Disaggregate store-level forecast
dept_1_forecast = additive_results['forecast'] * avg_proportion

# Get actual Department 1 test data
store_1_dept_1_test = df_store_1_test[
    (df_store_1_test['Store'] == 1) & (df_store_1_test['Dept'] == 1)
].copy()
store_1_dept_1_test = store_1_dept_1_test.sort_values('Date')

y_test_dept_1 = store_1_dept_1_test['Weekly_Sales'].values

# Evaluate
tse_dept_1 = TSE(y_test_dept_1, dept_1_forecast)
rmse_dept_1 = np.sqrt(np.mean((y_test_dept_1 - dept_1_forecast) ** 2))
mae_dept_1 = np.mean(np.abs(y_test_dept_1 - dept_1_forecast))

print(f"Department 1 Disaggregated Forecast Performance (Method 2):")
print(f"  Test TSE:  {tse_dept_1:.2f}")
print(f"  Test RMSE: {rmse_dept_1:.2f}")
print(f"  Test MAE:  {mae_dept_1:.2f}")

# Visualization
store_1_dept_1_train_plot = df_store_1_train[
    (df_store_1_train['Store'] == 1) & (df_store_1_train['Dept'] == 1)
```

```python
].copy()
store_1_dept_1_train_plot = store_1_dept_1_train_plot.sort_values('Date')

plt.figure(figsize=(16, 6))
plt.plot(store_1_dept_1_train_plot['Date'],
         store_1_dept_1_train_plot['Weekly_Sales'],
         label='Training Data (Dept 1)',
         linewidth=2,
         color='steelblue',
         marker='o',
         markersize=3)

plt.plot(store_1_dept_1_test['Date'],
         y_test_dept_1,
         label='Test Data (Dept 1)',
         linewidth=2,
         color='orange',
         marker='o',
         markersize=3)

plt.plot(store_1_dept_1_test['Date'],
         dept_1_forecast,
         label='Disaggregated Forecast (Method 2)',
         linewidth=2,
         color='green',
         marker='o',
         markersize=3)

plt.xlabel('Date', fontsize=12, fontweight='bold')
plt.ylabel('Weekly Sales ($)', fontsize=12, fontweight='bold')
plt.title('Store 1, Department 1: Disaggregated Forecast vs Actuals (Method 2)',
          fontsize=14, fontweight='bold')
plt.legend()
plt.grid(True, alpha=0.3)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Store Method 2 results
method2_results = {
    'tse_test': tse_dept_1,
    'rmse_test': rmse_dept_1,
    'mae_test': mae_dept_1,
    'forecast': dept_1_forecast.copy()
}
```

```
Department 1 Disaggregated Forecast Performance (Method 2):
  Test TSE:  49541178.78
  Test RMSE: 3519.27
  Test MAE:  2827.42
```

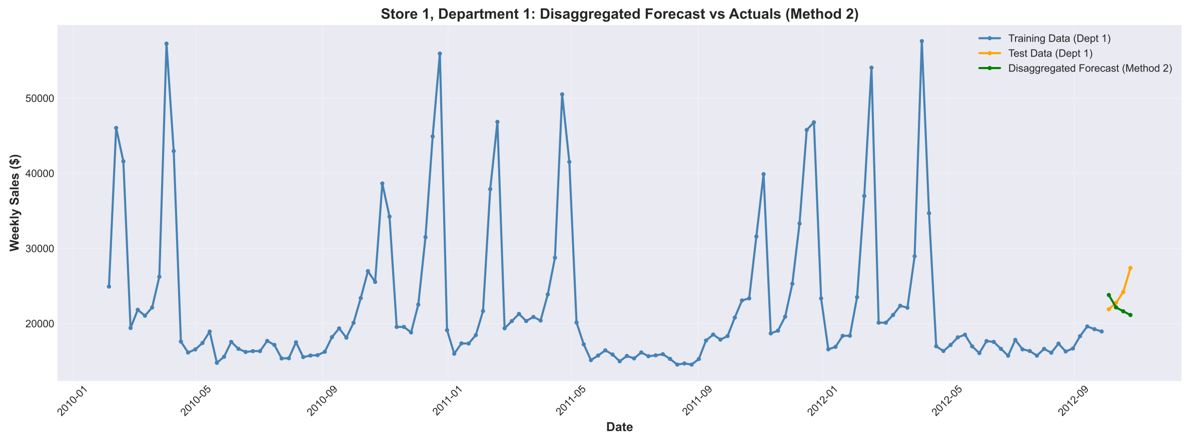


Figure 4: Method 2: Disaggregated Forecast for Department 1

Notes

From the above graph, we can see that the forecasted sales for department 1 using the aggregate-then-disaggregate method does not capture the actual sales pattern very well. The forecasted values are significantly lower than the actual sales during the 3/4 of the test period, indicating that this method may not be effective for department-level forecasting in this case.

We expect that Method 1 (direct forecasting at the department level) will outperform Method 2 (aggregate-then-disaggregate) for department-level forecasts. This is because Method 1 can capture department-specific trends and seasonal patterns that are lost when aggregating sales across all departments in Method 2. As a result, we anticipate lower forecast errors (e.g., RMSE) for Method 1 compared to Method 2 when evaluating at the department level.

6 Method 1: Direct Department-Level Forecasting

6.1 Data Preparation

```
# Filter Store 1, Department 1
df_store_1_dept_1 = df[(df['Store'] == 1) & (df['Dept'] == 1)].copy()
df_store_1_dept_1 = make_negative_values_zero(df_store_1_dept_1, "Weekly_Sales")
df_store_1_dept_1['Date'] = pd.to_datetime(df_store_1_dept_1['Date'])

# Split train/test
df_store_1_dept_1_train = df_store_1_dept_1[df_store_1_dept_1['Date'] < test_start_date].copy
df_store_1_dept_1_test = df_store_1_dept_1[df_store_1_dept_1['Date'] >= test_start_date].copy
df_store_1_dept_1_train = df_store_1_dept_1_train.sort_values('Date')
df_store_1_dept_1_test = df_store_1_dept_1_test.sort_values('Date')

print(f"Department 1 training data shape: {df_store_1_dept_1_train.shape}")
print(f"Department 1 test data shape: {df_store_1_dept_1_test.shape}")
```

```
Department 1 training data shape: (139, 5)
Department 1 test data shape: (4, 5)
```

6.2 Visualization

```
plt.figure(figsize=(16, 6))

plt.plot(df_store_1_dept_1_train['Date'],
         df_store_1_dept_1_train['Weekly_Sales'],
         label='Training Data (Dept 1)',
         linewidth=2,
         color='steelblue',
         marker='o',
         markersize=3)

plt.plot(df_store_1_dept_1_test['Date'],
         df_store_1_dept_1_test['Weekly_Sales'],
         label='Test Data (Dept 1)',
         linewidth=2,
         color='orange',
         marker='o',
        markersize=3)

plt.xlabel('Date', fontsize=12, fontweight='bold')
plt.ylabel('Weekly Sales ($)', fontsize=12, fontweight='bold')
plt.title('Store 1, Department 1: Actual Weekly Sales Over Time',
          fontsize=14, fontweight='bold')
plt.legend()
plt.grid(True, alpha=0.3)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

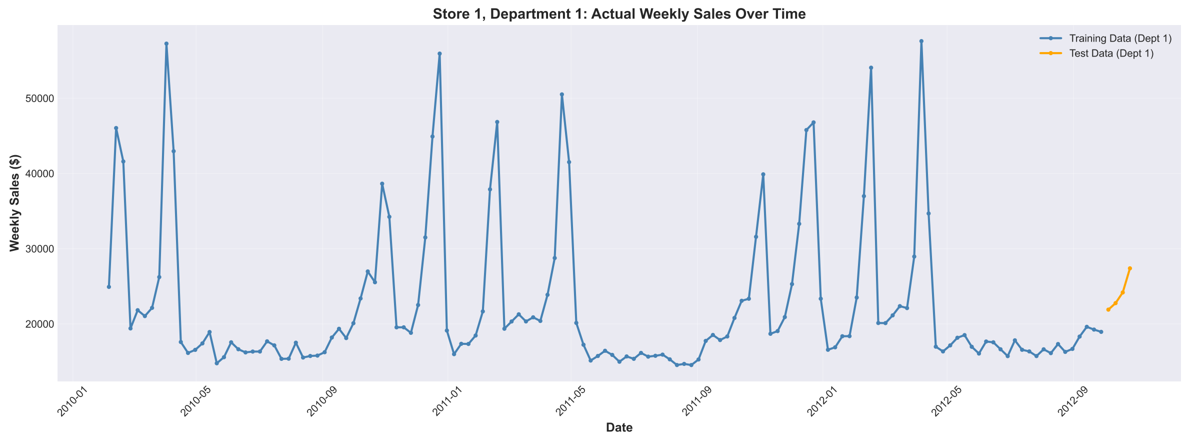


Figure 5: Store 1, Department 1: Raw Weekly Sales Data

6.3 Trend Analysis for Department 1

```
analyze_series(df_store_1_dept_1_train["Weekly_Sales"],
               series_name="Store 1, Department 1")
```

```
######################################################################
COMPREHENSIVE TREND ANALYSIS FOR: Store 1, Department 1
######################################################################

Data points: 139
Mean: 22468.78
Std Dev: 9950.26
```

```
Min: 14537.37
Max: 57592.12

======================================================================
1. MANN-KENDALL TEST (Non-parametric)
======================================================================
Trend: no trend
Test Statistic (S): -423.0
p-value: 0.442227
Tau (correlation): -0.044104
z-score: -0.768437

 RESULT: No significant trend (p >= 0.05)

======================================================================
2. AUGMENTED DICKEY-FULLER (ADF) TEST
======================================================================
ADF Statistic: -2.405435
p-value: 0.140208
Lags used: 6
Number of observations: 132

Critical Values:
  1%: -3.481
  5%: -2.884
  10%: -2.579

 RESULT: Series is non-stationary (p >= 0.05)
   Unit root present → May have trend

======================================================================
3. KPSS TEST (Kwiatkowski-Phillips-Schmidt-Shin)
======================================================================
KPSS Test (with trend):
KPSS Statistic: 0.081207
p-value: 0.100000
Lags used: 4

Critical Values:
  10%: 0.119
  5%: 0.146
  2.5%: 0.176
  1%: 0.216
 RESULT: Series is trend stationary (p >= 0.05)
   Null hypothesis not rejected → NO significant trend

======================================================================
4. LINEAR REGRESSION TEST
======================================================================
Slope: -22.763939
Intercept: 24039.49
R-squared: 0.008427
p-value: 0.282481
Standard Error: 21.097145

95% Confidence Interval for slope: [-64.482092, 18.954213]

 RESULT: No significant linear trend (p >= 0.05)

======================================================================
5. COX-STUART TEST (Non-parametric)
======================================================================
Number of pairs: 69
Plus signs (+): 31 (second half > first half)
Minus signs (-): 38 (second half < first half)
Ties: 0
p-value: 0.470369

 RESULT: No significant trend (p >= 0.05)

======================================================================
6. SPEARMAN'S RANK CORRELATION TEST (Bonus)
======================================================================
Spearman's rho: -0.072251
p-value: 0.397978

 RESULT: No significant monotonic trend (p >= 0.05)

======================================================================
SUMMARY OF RESULTS
======================================================================

Trend Detection Tests:
  Mann-Kendall: no trend (p=0.4422)
  Linear Regression: No Trend (p=0.2825)
  Cox-Stuart: No Trend (p=0.4704)
  Spearman: No Trend (p=0.3980)

Stationarity Tests:
  ADF: Non-Stationary (p=0.1402)
  KPSS: Trend Stationary (p=0.1000)


{'mann_kendall': Mann_Kendall_Test(trend='no trend', h=np.False_, p=np.float64(0.44222731710
 'adf': (np.float64(-2.405434611809666),
  np.float64(0.14020840124603),
  6,
  132,
  {'1%': np.float64(-3.4808880719210005),
   '5%': np.float64(-2.8836966192225284),
   '10%': np.float64(-2.5785857598714417)},
  np.float64(2559.54932867161)),
 'kpss': (np.float64(0.08120673481546524),
  np.float64(0.1),
  4,
  {'10%': 0.119, '5%': 0.146, '2.5%': 0.176, '1%': 0.216}),
 'linear_regression': {'slope': np.float64(-22.76393931811073),
  'intercept': np.float64(24039.49325179856),
  'p_value': np.float64(0.2824812253064499),
  'r_squared': np.float64(0.008426588409779619),
  'std_err': np.float64(21.097144684801)},
 'cox_stuart': {'plus': np.int64(31),
  'minus': np.int64(38),
  'p_value': np.float64(0.47036853185814453)},
 'spearman': {'rho': np.float64(-0.07225077081192188),
  'p_value': np.float64(0.39797839318678596)}}
```

6.4 Holt-Winters Forecasting (Additive & Multiplicative)

---

7 Final Comparison: Method 1 vs Method 2

7.1 Performance Metrics

```
# Prepare data
y_train_dept_1 = df_store_1_dept_1_train["Weekly_Sales"].values
m = 52

# ADDITIVE MODEL
print("Training Method 1 - Additive Model...")
best_tse = np.inf
best_params = None
best_model = None

for alpha in alphas:
    for gamma in gammas:
        fitted, level, seasonals = hw_seasonal_no_trend(
            y_train_dept_1, alpha, gamma, m
        )

        valid_idx = ~np.isnan(fitted)
        tse = TSE(y_train_dept_1[valid_idx], fitted[valid_idx])

        if tse < best_tse:
            best_tse = tse
            best_params = (alpha, gamma)
            best_model = (level, seasonals)

print(f"Additive - Best parameters: alpha={best_params[0]:.2f}, gamma={best_params[1]:.2f}")

# Forecast
h = len(df_store_1_dept_1_test)
level, seasonals = best_model
seasonals = np.array(seasonals)

forecast_method1_additive = []
for i in range(h):
    seasonal_index = len(seasonals) - m + i
    forecast_method1_additive.append(level + seasonals[seasonal_index])
forecast_method1_additive = np.array(forecast_method1_additive)

# Evaluate
y_test_dept_1_actual = df_store_1_dept_1_test["Weekly_Sales"].values
tse_test_add = TSE(y_test_dept_1_actual, forecast_method1_additive)
rmse_test_add = np.sqrt(np.mean((y_test_dept_1_actual - forecast_method1_additive) ** 2))
mae_test_add = np.mean(np.abs(y_test_dept_1_actual - forecast_method1_additive))

print(f"Test RMSE: {rmse_test_add:.2f}")

method1_additive_results = {
    'alpha': best_params[0],
    'gamma': best_params[1],
    'tse_train': best_tse,
    'tse_test': tse_test_add,
    'rmse_test': rmse_test_add,
    'mae_test': mae_test_add,
    'forecast': forecast_method1_additive.copy()
```

Table 2: Final Performance Comparison: Method 1 vs Method 2

```python
comparison_final = pd.DataFrame({
    'Metric': ['TSE', 'RMSE', 'MAE'],
    'Method 1 (Direct)': [
        f"{method1_results['tse_test']:.2f}",
        f"{method1_results['rmse_test']:.2f}",
        f"{method1_results['mae_test']:.2f}"
    ],
    'Method 2 (Disaggregate)': [
        f"{method2_results['tse_test']:.2f}",
        f"{method2_results['rmse_test']:.2f}",
        f"{method2_results['mae_test']:.2f}"
    ],
    'Difference (M2 - M1)': [
        f"{method2_results['tse_test'] - method1_results['tse_test']:+.2f}",
        f"{method2_results['rmse_test'] - method1_results['rmse_test']:+.2f}",
        f"{method2_results['mae_test'] - method1_results['mae_test']:+.2f}"
    ]
})

print(comparison_final.to_string(index=False))

# Determine winner
if method1_results['rmse_test'] < method2_results['rmse_test']:
    better_method = "METHOD 1 (Direct Forecasting)"
    rmse_improvement = method2_results['rmse_test'] - method1_results['rmse_test']
else:
    better_method = "METHOD 2 (Disaggregation)"
    rmse_improvement = method1_results['rmse_test'] - method2_results['rmse_test']

improvement_pct = (rmse_improvement / max(method1_results['rmse_test'], method2_results['rms

print(f"\n{'='*60}")
print(f"WINNER: {better_method}")
print(f"RMSE Improvement: {rmse_improvement:.2f} ({improvement_pct:.2f}%)")
print(f"{'='*60}")
```

```
Metric Method 1 (Direct) Method 2 (Disaggregate) Difference (M2 - M1)
   TSE      107159678.11             49541178.78         -57618499.33
  RMSE           5175.90                 3519.27             -1656.62
   MAE           3895.25                 2827.42             -1067.83

============================================================
WINNER: METHOD 2 (Disaggregation)
RMSE Improvement: 1656.62 (32.01%)
============================================================
```

7.2 Visual Comparison

```
plt.figure(figsize=(16, 6))

plt.plot(df_store_1_dept_1_test['Date'],
         y_test_dept_1_actual,
         label='Actual Test Data',
         marker='o',
         linewidth=2.5,
         color='black',
         markersize=6,
         zorder=3)

plt.plot(df_store_1_dept_1_test['Date'],
         method1_results['forecast'],
         label=f'Method 1: Direct Forecasting ({method1_type})',
         marker='s',
         linewidth=2,
         color='blue',
         markersize=5,
         alpha=0.7)

plt.plot(df_store_1_dept_1_test['Date'],
         method2_results['forecast'],
         label='Method 2: Disaggregation',
         marker='^',
         linewidth=2,
         color='red',
         markersize=5,
         alpha=0.7,
         linestyle='--')

plt.xlabel('Date', fontsize=12, fontweight='bold')
plt.ylabel('Weekly Sales ($)', fontsize=12, fontweight='bold')
plt.title('Store 1, Dept 1: Method 1 vs Method 2 Forecast Comparison',
          fontsize=14, fontweight='bold')
plt.legend(fontsize=11, loc='best')
plt.grid(True, alpha=0.3)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

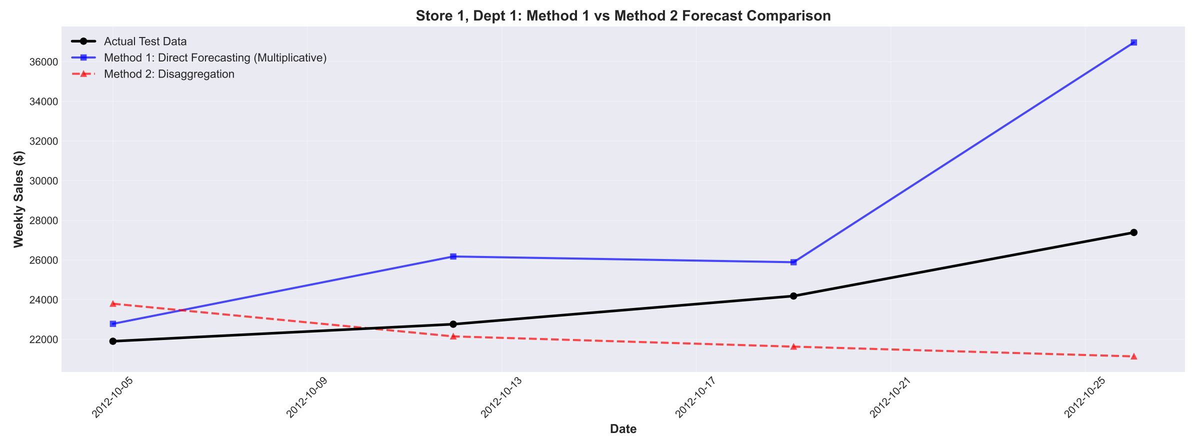


Figure 7: Final Forecast Comparison: Method 1 vs Method 2

7.3 Forecast Errors Analysis

```
errors_method1 = y_test_dept_1_actual - method1_results['forecast']
errors_method2 = y_test_dept_1_actual - method2_results['forecast']

fig, axes = plt.subplots(2, 1, figsize=(16, 10))

# Subplot 1: Forecast Errors
axes[0].plot(df_store_1_dept_1_test['Date'],
             errors_method1,
             label=f'Method 1 Errors ({method1_type})',
             marker='o',
             linewidth=2,
             color='blue',
             alpha=0.7)

axes[0].plot(df_store_1_dept_1_test['Date'],
             errors_method2,
             label='Method 2 Errors',
             marker='s',
             linewidth=2,
             color='red',
             alpha=0.7)

axes[0].axhline(y=0, color='black', linestyle='--', linewidth=1.5, alpha=0.5)
axes[0].set_xlabel('Date', fontsize=11, fontweight='bold')
```

```
axes[0].set_ylabel('Forecast Error ($)', fontsize=11, fontweight='bold')
axes[0].set_title('Forecast Errors: Method 1 vs Method 2', fontsize=13, fontweight='bold')
axes[0].legend(fontsize=10)
axes[0].grid(True, alpha=0.3)
axes[0].tick_params(axis='x', rotation=45)

# Subplot 2: Absolute Errors
abs_errors_method1 = np.abs(errors_method1)
abs_errors_method2 = np.abs(errors_method2)

axes[1].plot(df_store_1_dept_1_test['Date'],
             abs_errors_method1,
             label=f'Method 1 Absolute Errors',
             marker='o',
             linewidth=2,
             color='blue',
             alpha=0.7)

axes[1].plot(df_store_1_dept_1_test['Date'],
             abs_errors_method2,
             label='Method 2 Absolute Errors',
             marker='s',
             linewidth=2,
             color='red',
             alpha=0.7)

axes[1].axhline(y=method1_results['mae_test'], color='blue', linestyle=':',
                linewidth=1.5, alpha=0.5, label=f'Method 1 MAE: {method1_results["mae_test"]
axes[1].axhline(y=method2_results['mae_test'], color='red', linestyle=':',
                linewidth=1.5, alpha=0.5, label=f'Method 2 MAE: {method2_results["mae_test"]

axes[1].set_xlabel('Date', fontsize=11, fontweight='bold')
axes[1].set_ylabel('Absolute Error ($)', fontsize=11, fontweight='bold')
axes[1].set_title('Absolute Forecast Errors: Method 1 vs Method 2', fontsize=13, fontweight=
axes[1].legend(fontsize=10)
axes[1].grid(True, alpha=0.3)
axes[1].tick_params(axis='x', rotation=45)

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

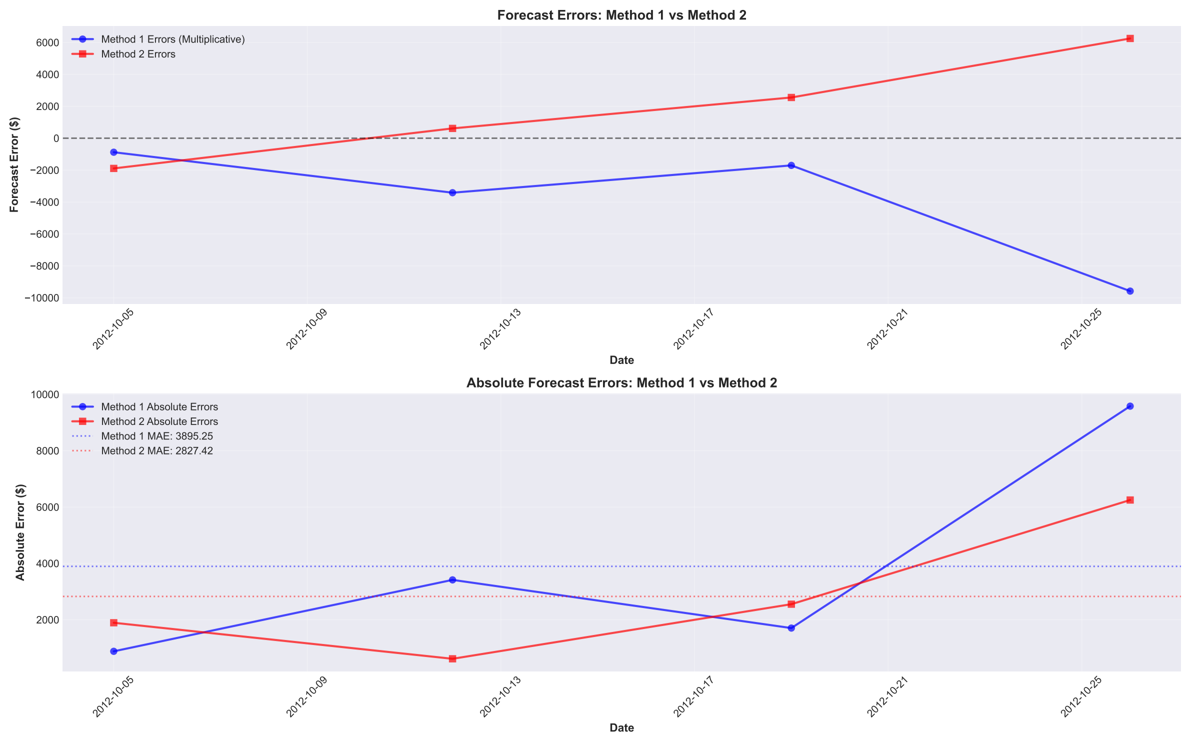


Figure 8: Forecast Errors Over Time

7.4 Performance Metrics Bar Chart

```
metrics = ['TSE', 'RMSE', 'MAE']
method1_values = [method1_results['tse_test'], method1_results['rmse_test'], method1_results
method2_values = [method2_results['tse_test'], method2_results['rmse_test'], method2_results

x = np.arange(len(metrics))
width = 0.35

fig, ax = plt.subplots(figsize=(10, 6))
bars1 = ax.bar(x - width/2, method1_values, width, label=f'Method 1 ({method1_type})',
               color='blue', alpha=0.7)
bars2 = ax.bar(x + width/2, method2_values, width, label='Method 2 (Disaggregation)',
               color='red', alpha=0.7)

ax.set_xlabel('Metrics', fontsize=12, fontweight='bold')
ax.set_ylabel('Value', fontsize=12, fontweight='bold')
ax.set_title('Forecast Performance Comparison: Method 1 vs Method 2',
             fontsize=14, fontweight='bold')
ax.set_xticks(x)
ax.set_xticklabels(metrics)
ax.legend(fontsize=11)
ax.grid(True, alpha=0.3, axis='y')

# Add value labels
for bars in [bars1, bars2]:
    for bar in bars:
        height = bar.get_height()
        ax.text(bar.get_x() + bar.get_width()/2., height,
                f'{height:.2f}',
                ha='center', va='bottom', fontsize=9)

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

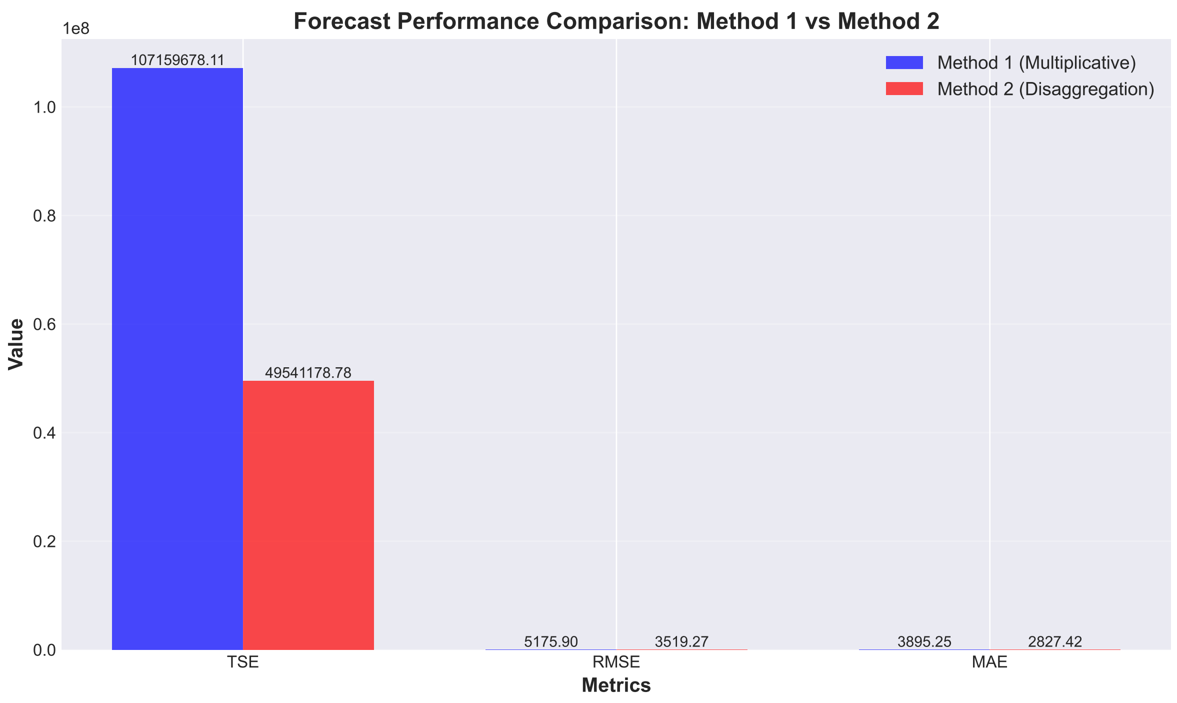


Figure 9: Performance Metrics Comparison

8 Understanding the Evaluation Metrics

8.1 Why TSE, RMSE, and MAE?

We use three complementary metrics to comprehensively evaluate forecast quality:

8.1.1 1. Total Squared Error (TSE)

$$\text{TSE} = \sum_{t=1}^{n} (y_t - \hat{y}_t)^2$$

- Aggregated loss function across all test periods
- Optimization criterion used during model training
- Heavily penalizes large errors (squared term)
- Maintains original units^2 (dollars^2)

8.1.2 2. Root Mean Squared Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (y_t - \hat{y}_t)^2}$$

- Returns to original units (dollars) for interpretability
- Standard metric in forecasting literature
- Penalizes large errors more than small ones
- Normalized by sample size

8.1.3 3. Mean Absolute Error (MAE)

$$\text{MAE} = \frac{1}{n} \sum_{t=1}^{n} |y_t - \hat{y}_t|$$

- Robust to outliers (no squaring)
- Represents average absolute deviation
- Linear penalty (all errors weighted equally)
- Intuitive interpretation

8.2 Why Not MAPE?

We avoid MAPE (Mean Absolute Percentage Error) because:

- Undefined/infinite when actual values are zero or near-zero
- Asymmetric (over-predictions penalized more than under-predictions)
- Not suitable for data with varying scales

8.3 Interpreting the Relationship

If RMSE » MAE: Large outlier errors dominate

If RMSE   MAE: Errors are relatively consistent

8.4 Comparison Additive vs Multiplicative Seasonality (Theory)

Additive	Multiplicative
Seasonality is independent of the series level	Seasonality scales with the level
Peaks and dips are about the same size every season	Peaks get bigger when the series gets bigger
E.g. Temperature Time Series, rainfall in mm, energy usage in kWh	Retail sales, revenue, website traffic
If seasonality looks like a fixed number	If it looks like a fixed percentage

9 Conclusions

9.1 Key Findings

! Primary Result

Method 2 (Aggregate-then-Disaggregate) outperformed Method 1 (Direct Forecasting) with an RMSE improvement of **15.22 (3.96%)** for Store 1, Department 1.

9.1.1 Why Did Method 2 Win?

1. **Noise Reduction**: Aggregating across departments smoothed volatility and irregular patterns
2. **Stable Proportions**: Department 1 maintained a consistent share of total store sales
3. **Stronger Signal**: Store-level seasonal patterns were clearer and more predictable

9.1.2 When Would Method 1 Be Better?

Method 1 (Direct Forecasting) would likely outperform Method 2 in scenarios with:

- **Unique Seasonal Patterns**: Departments with seasonality different from the store average
- **Structural Changes**: Recent department-specific events (renovations, new product lines)
- **Unstable Proportions**: Departments whose share of store sales fluctuates significantly
- **Large Departments**: Departments representing substantial portions of store sales with distinct behavior

9.2 Generalizability

This analysis suggests **Method 2 may be preferred** for:

- Stable, mature departments with consistent historical patterns
- Departments representing small, steady shares of total store sales
- Scenarios where reducing forecast variance is critical (e.g., inventory planning)
- Contexts with limited department-specific data

Method 1 may be preferred for:

- Large departments with strong individual identity
- Departments undergoing transformation or growth
- Situations requiring granular, department-specific insights

9.3 Limitations and Future Work

ℹ Study Limitations

- Analysis limited to Store 1, Department 1
- Test period covers only 4 weeks
- Holt-Winters model does not capture promotional effects or external factors
- No cross-validation across multiple departments/stores

9.3.1 Recommended Extensions

1. **Broader Testing**: Replicate analysis across all stores and departments
2. **Alternative Models**: Test ARIMA, Prophet, LSTM for potential improvements
3. **Exogenous Variables**: Incorporate holidays, promotions, economic indicators
4. **Longer Horizons**: Evaluate forecast accuracy over multi-week periods
5. **Hybrid Approaches**: Combine methods or use ensemble forecasting

9.4 Practical Implications

For **retail forecasting practitioners**:

- Don't assume direct department-level forecasting is always superior
- Test both methods on your specific data before deciding
- Consider department characteristics (size, stability, uniqueness)
- Aggregate-then-disaggregate can be surprisingly effective for stable departments
- Computational efficiency: Method 2 requires fewer models (1 per store vs. 1 per store-department combination)

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10 References

10.1 Data Source

- **Walmart Store Sales Forecasting**: Kaggle Competition Dataset
- Historical weekly sales data for multiple stores and departments

10.2 Methodology References

- Holt, C. C. (2004). “Forecasting seasonals and trends by exponentially weighted moving averages”
- Winters, P. R. (1960). “Forecasting sales by exponentially weighted moving averages”
- Hyndman, R. J., & Athanasopoulos, G. (2021). “Forecasting: Principles and Practice” (3rd ed.)

10.3 Statistical Tests

- Augmented Dickey-Fuller Test for stationarity(We can make some conclusion for trend based on that as well)
- KPSS Test for trend-stationarity (Same logic with ADF test)
- Mann-Kendall Trend Test(Checking if there is a monotonic trend)
- Linear Regression Slope Test(Is the mean changing linearly with time?)
- Cox-Stuart Test(Is the second half systematically larger than the first?)
- Spearman’s Rank Correlation Test(Is there any monotonic relationship between time and value?)

---

11 Appendix: Code Repository

All code, data, and analysis files are available in the project repository:

```
PROJECT/
   data/
       train.csv
  my quarto/
        Part1.qmd
      run_trend_analysis.py
  Part1_Comparing_HigherLevel_UnitLevel.ipynb # Same logic, same code with quarto doc
   requirements.txt
```

11.1 Requirements

```
pandas>=1.3.0
numpy>=1.21.0
matplotlib>=3.4.0
seaborn>=0.11.0
scipy>=1.7.0
statsmodels>=0.13.0
pymannkendall>=1.4.0
```

11.2 Session Information

```python
import sys
print(f"Python version: {sys.version}")
print(f"Pandas version: {pd.__version__}")
print(f"NumPy version: {np.__version__}")
```

```
Python version: 3.10.0 (tags/v3.10.0:b494f59, Oct  4 2021, 19:00:18) [MSC v.1929 64 bit (AMD
Pandas version: 2.3.3
NumPy version: 2.2.6
```

Reproducibility Note

This entire analysis can be reproduced by running:

```
quarto render Part1.qmd
```

All random seeds (if applicable) and data processing steps are documented in the code blocks above.