sales-forecasting

August 3, 2025

1 Wallmart Sales Forecasting

1.1 01- Import Libraries

[1]:
```
!pip install pmdarima
```

```
Requirement already satisfied: pmdarima in /usr/local/lib/python3.11/dist-
packages (2.0.4)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.11/dist-
packages (from pmdarima) (1.5.1)
Requirement already satisfied: Cython!=0.29.18,!=0.29.31,>=0.29 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (3.0.12)
Requirement already satisfied: numpy>=1.21.2 in /usr/local/lib/python3.11/dist-
packages (from pmdarima) (2.3.2)
Requirement already satisfied: pandas>=0.19 in /usr/local/lib/python3.11/dist-
packages (from pmdarima) (2.2.2)
Requirement already satisfied: scikit-learn>=0.22 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (1.6.1)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.11/dist-
packages (from pmdarima) (1.16.0)
Requirement already satisfied: statsmodels>=0.13.2 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (0.14.5)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.11/dist-
packages (from pmdarima) (2.5.0)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (75.2.0)
Requirement already satisfied: packaging>=17.1 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (25.0)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.11/dist-packages (from pandas>=0.19->pmdarima)
(2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-
packages (from pandas>=0.19->pmdarima) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-
packages (from pandas>=0.19->pmdarima) (2025.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn>=0.22->pmdarima)
(3.6.0)
```

```
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.11/dist-
packages (from statsmodels>=0.13.2->pmdarima) (1.0.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-
packages (from python-dateutil>=2.8.2->pandas>=0.19->pmdarima) (1.17.0)
```

[2]:
```
%pip install --upgrade numpy pmdarima
```

```
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages
(2.3.2)
Requirement already satisfied: pmdarima in /usr/local/lib/python3.11/dist-
packages (2.0.4)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.11/dist-
packages (from pmdarima) (1.5.1)
Requirement already satisfied: Cython!=0.29.18,!=0.29.31,>=0.29 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (3.0.12)
Requirement already satisfied: pandas>=0.19 in /usr/local/lib/python3.11/dist-
packages (from pmdarima) (2.2.2)
Requirement already satisfied: scikit-learn>=0.22 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (1.6.1)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.11/dist-
packages (from pmdarima) (1.16.0)
Requirement already satisfied: statsmodels>=0.13.2 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (0.14.5)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.11/dist-
packages (from pmdarima) (2.5.0)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (75.2.0)
Requirement already satisfied: packaging>=17.1 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (25.0)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.11/dist-packages (from pandas>=0.19->pmdarima)
(2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-
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Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-
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/usr/local/lib/python3.11/dist-packages (from scikit-learn>=0.22->pmdarima)
(3.6.0)
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.11/dist-
packages (from statsmodels>=0.13.2->pmdarima) (1.0.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-
packages (from python-dateutil>=2.8.2->pandas>=0.19->pmdarima) (1.17.0)
```

[3]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```python
import seaborn as sns
```

1.2 02- Load dataset

[4]:
```python
df = pd.read_csv('Walmart_Sales.csv')
df.head()  # CPI = Consumer Price Index
```

[4]:
```
   Store        Date  Weekly_Sales  Holiday_Flag  Temperature  Fuel_Price  \
0      1  05-02-2010    1643690.90             0        42.31       2.572
1      1  12-02-2010    1641957.44             1        38.51       2.548
2      1  19-02-2010    1611968.17             0        39.93       2.514
3      1  26-02-2010    1409727.59             0        46.63       2.561
4      1  05-03-2010    1554806.68             0        46.50       2.625

          CPI  Unemployment
0  211.096358         8.106
1  211.242170         8.106
2  211.289143         8.106
3  211.319643         8.106
4  211.350143         8.106
```

1.3 03- EDA Steps

[5]:
```python
df.shape
```

[5]: (6435, 8)

[6]:
```python
df.describe()
```

[6]:
```
             Store  Weekly_Sales  Holiday_Flag  Temperature   Fuel_Price  \
count  6435.000000  6.435000e+03   6435.000000  6435.000000  6435.000000
mean     23.000000  1.046965e+06      0.069930    60.663782     3.358607
std      12.988182  5.643666e+05      0.255049    18.444933     0.459020
min       1.000000  2.099862e+05      0.000000    -2.060000     2.472000
25%      12.000000  5.533501e+05      0.000000    47.460000     2.933000
50%      23.000000  9.607460e+05      0.000000    62.670000     3.445000
75%      34.000000  1.420159e+06      0.000000    74.940000     3.735000
max      45.000000  3.818686e+06      1.000000   100.140000     4.468000

               CPI  Unemployment
count  6435.000000   6435.000000
mean    171.578394      7.999151
std      39.356712      1.875885
min     126.064000      3.879000
25%     131.735000      6.891000
50%     182.616521      7.874000
```

```
75%      212.743293      8.622000
max      227.232807     14.313000
```

[7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6435 entries, 0 to 6434
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Store         6435 non-null   int64
 1   Date          6435 non-null   object
 2   Weekly_Sales  6435 non-null   float64
 3   Holiday_Flag  6435 non-null   int64
 4   Temperature   6435 non-null   float64
 5   Fuel_Price    6435 non-null   float64
 6   CPI           6435 non-null   float64
 7   Unemployment  6435 non-null   float64
dtypes: float64(5), int64(2), object(1)
memory usage: 402.3+ KB
```

[8]:
```
df.isnull().sum()
```

[8]:
```
Store           0
Date            0
Weekly_Sales    0
Holiday_Flag    0
Temperature     0
Fuel_Price      0
CPI             0
Unemployment    0
dtype: int64
```

[9]:
```
df.nunique()
```

[9]:
```
Store             45
Date             143
Weekly_Sales    6435
Holiday_Flag       2
Temperature     3528
Fuel_Price       892
CPI             2145
Unemployment     349
dtype: int64
```

1.4 04- Data Wrangling

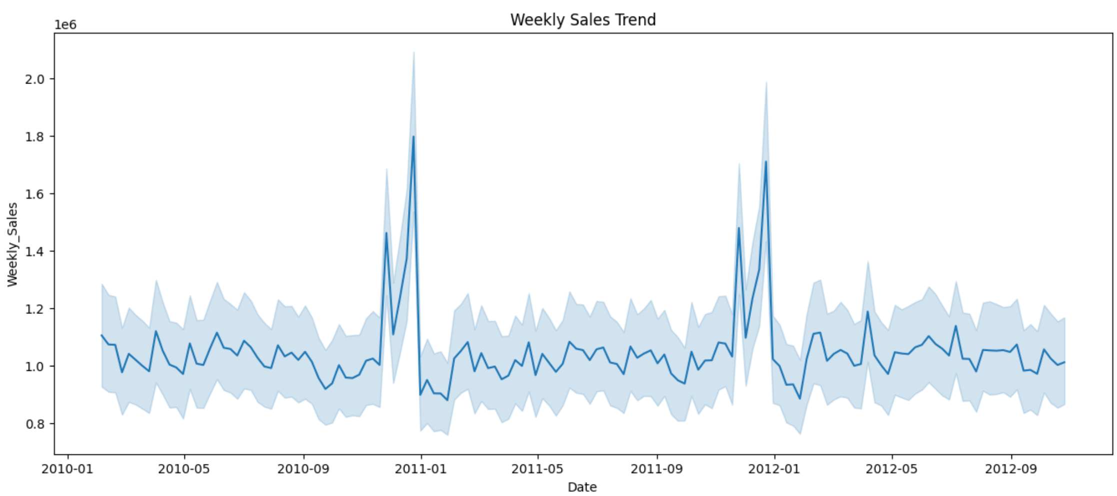
[10]:
```
df['Date'] = pd.to_datetime(df['Date'], format='mixed', dayfirst=True)

# Sort by Date (important for time-series)
df = df.sort_values('Date')
```

[11]:
```
# Drop rows with NaN (due to lag features)
df = df.dropna()
```

1.5 05- Data Visualization

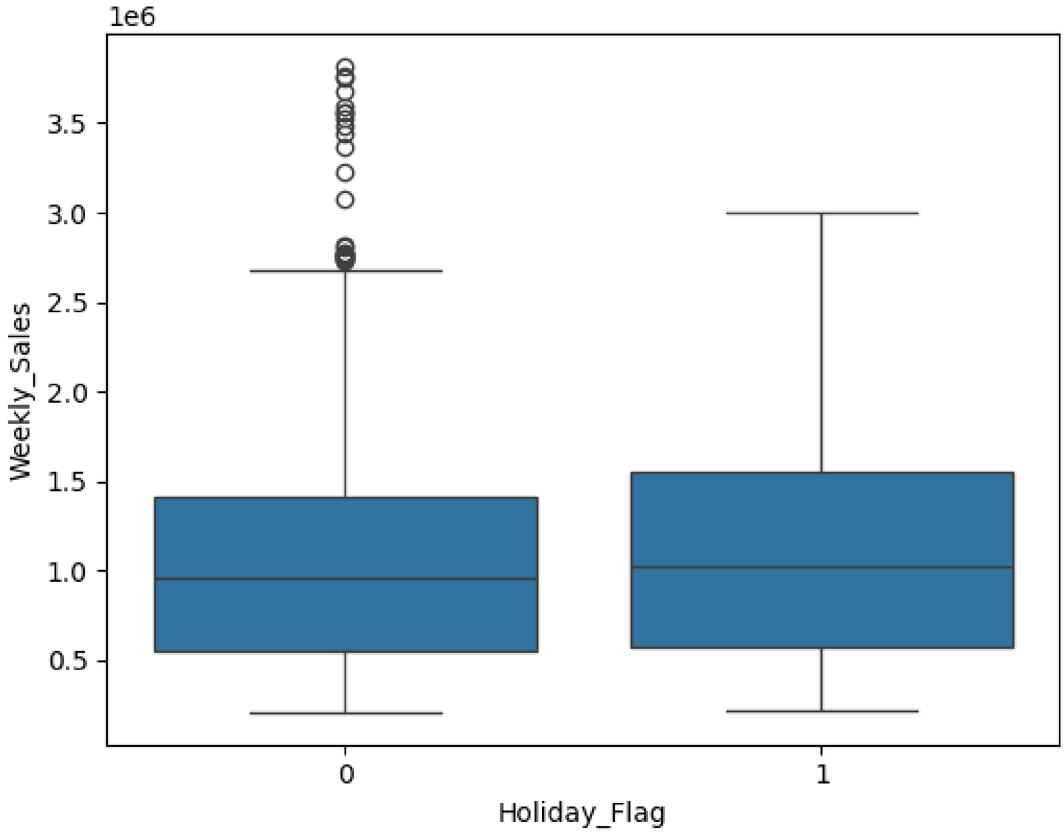
[12]:
```
# 1. Sales trend over time
plt.figure(figsize=(15,6))
sns.lineplot(x='Date', y='Weekly_Sales', data=df)
plt.title('Weekly Sales Trend')
```

[12]: Text(0.5, 1.0, 'Weekly Sales Trend')



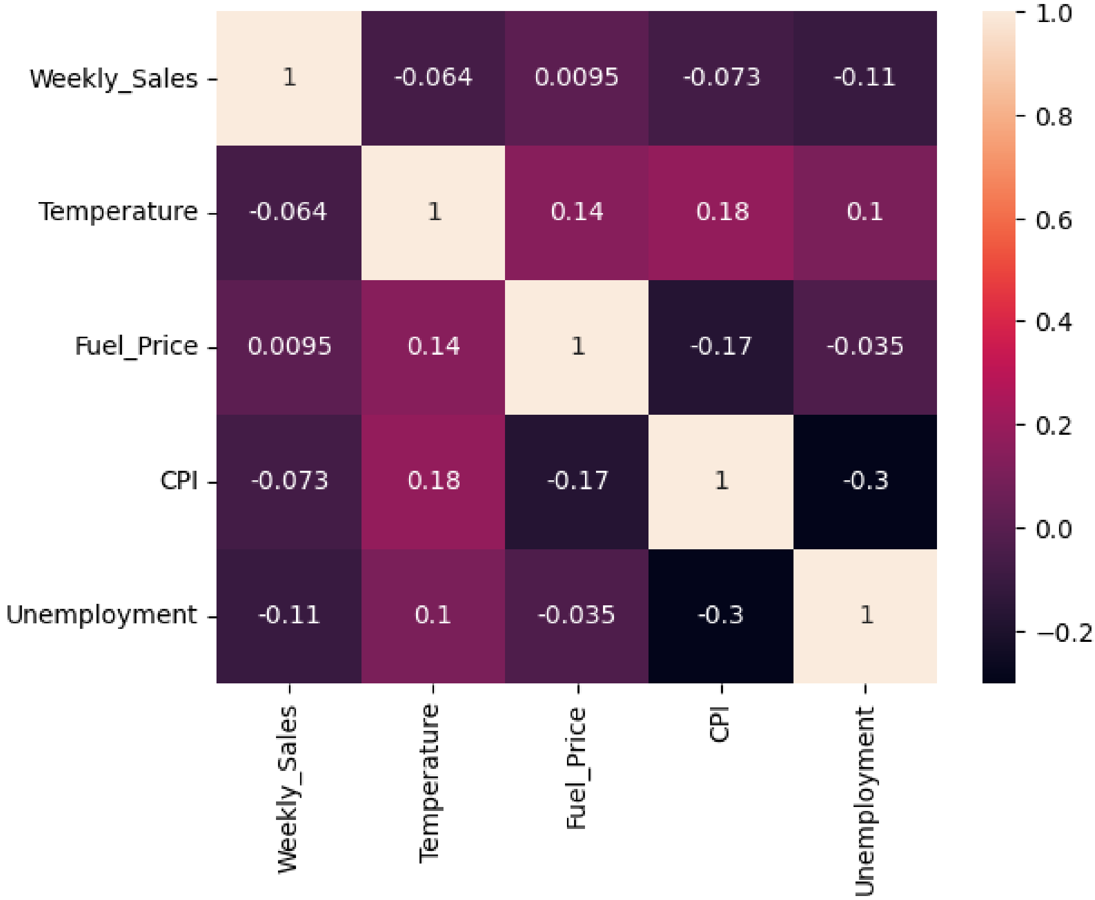
[13]:
```
# 2. Holiday impact
sns.boxplot(x='Holiday_Flag', y='Weekly_Sales', data=df)
```

[13]: <Axes: xlabel='Holiday_Flag', ylabel='Weekly_Sales'>



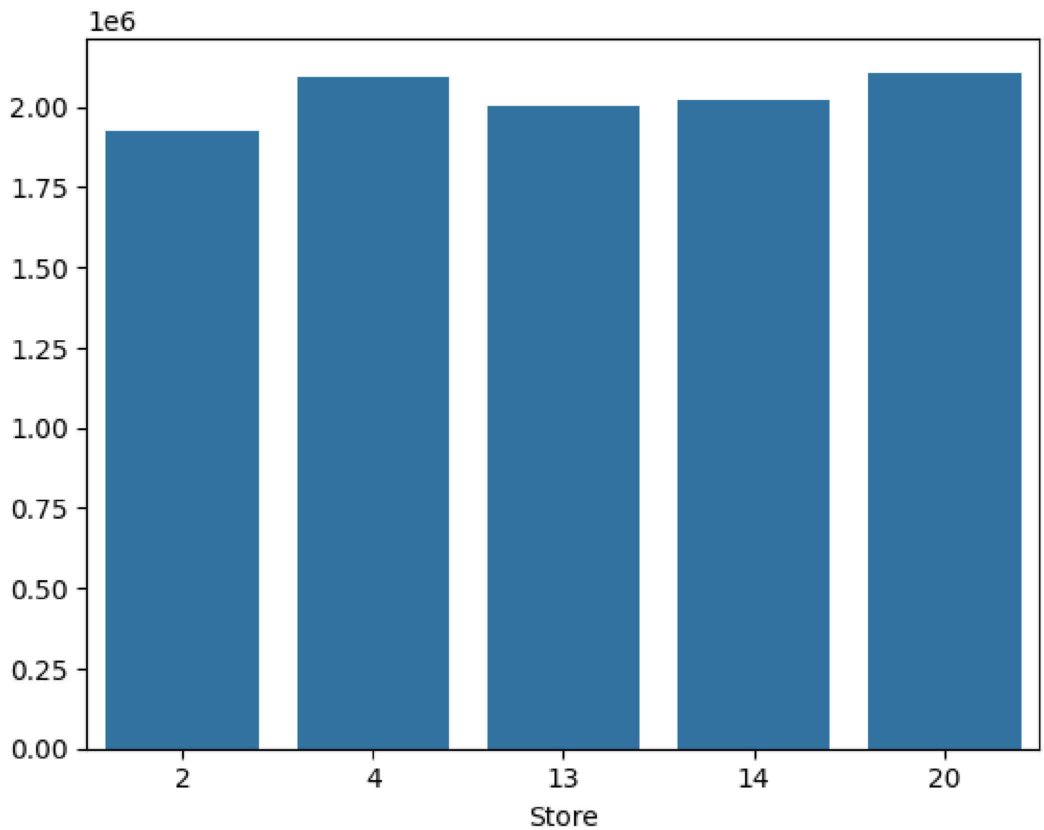
[14]:
```
# 3. Correlation heatmap
corr = df[['Weekly_Sales','Temperature','Fuel_Price','CPI','Unemployment']].
  ↪corr()
sns.heatmap(corr, annot=True)
```

[14]: <Axes: >



[15]:
```
# 4. Store comparison
top_stores = df.groupby('Store')['Weekly_Sales'].mean().nlargest(5)
sns.barplot(x=top_stores.index, y=top_stores.values)
```

[15]: <Axes: xlabel='Store'>



1.6 06- Feature Engineering

[16]:
```
# 1. Lag Features (previous week's sales)
df['lag_1'] = df.groupby('Store')['Weekly_Sales'].shift(1)  # 1-week lag
df['lag_4'] = df.groupby('Store')['Weekly_Sales'].shift(4)  # 4-week lag␣
↪(monthly trend)
```

[17]:
```
# 2. Rolling Statistics (moving averages)
df['rolling_mean_4'] = df.groupby('Store')['Weekly_Sales'].transform(lambda x:␣
↪x.rolling(4).mean())
df['rolling_std_4'] = df.groupby('Store')['Weekly_Sales'].transform(lambda x: x.
↪rolling(4).std())
```

[18]:
```
# 3. Time-based Features
df['year'] = df['Date'].dt.year
df['month'] = df['Date'].dt.month
df['week_of_year'] = df['Date'].dt.isocalendar().week
```

[19]:
```
# 4. Holiday Proximity (days before/after holiday)
# (Assuming 'Holiday_Flag' marks holiday weeks)
df['days_since_holiday'] = df.groupby('Store')['Holiday_Flag'].cumsum()
```

[20]:
```
# 5. Economic Impact Features (normalize if needed)
df['fuel_price_change'] = df.groupby('Store')['Fuel_Price'].pct_change()
df['cpi_change'] = df.groupby('Store')['CPI'].pct_change()
```

[21]:
```
print(df.shape)
df.head()
```

```
(6435, 18)
```

[21]:
```
      Store        Date  Weekly_Sales  Holiday_Flag  Temperature  Fuel_Price  \
0         1  2010-02-05    1643690.90             0        42.31       2.572
1287     10  2010-02-05    2193048.75             0        54.34       2.962
5148     37  2010-02-05     536006.73             0        45.97       2.572
2288     17  2010-02-05     789036.02             0        23.11       2.666
4147     30  2010-02-05     465108.52             0        39.05       2.572

             CPI  Unemployment  lag_1  lag_4  rolling_mean_4  rolling_std_4  \
0     211.096358         8.106    NaN    NaN             NaN            NaN
1287  126.442065         9.765    NaN    NaN             NaN            NaN
5148  209.852966         8.554    NaN    NaN             NaN            NaN
2288  126.442065         6.548    NaN    NaN             NaN            NaN
4147  210.752605         8.324    NaN    NaN             NaN            NaN

      year  month  week_of_year  days_since_holiday  fuel_price_change  \
0     2010      2             5                   0                NaN
1287  2010      2             5                   0                NaN
5148  2010      2             5                   0                NaN
2288  2010      2             5                   0                NaN
4147  2010      2             5                   0                NaN

      cpi_change
0            NaN
1287         NaN
5148         NaN
2288         NaN
4147         NaN
```

1.7 07- Splitting dataset into Training & Testing

[22]:
```
# Split into train & test (last 12 weeks for testing)
split_date = df['Date'].max() - pd.Timedelta(weeks=12)
train = df[df['Date'] <= split_date]
test = df[df['Date'] > split_date]
```

```
# Separate features & target
X_train = train.drop(['Weekly_Sales', 'Date', 'Store'], axis=1)
y_train = train['Weekly_Sales']
X_test = test.drop(['Weekly_Sales', 'Date', 'Store'], axis=1)
y_test = test['Weekly_Sales']
```

1.8 08- Model

[23]:
```
# # Not working in Google Colab
# # ValueError: numpy.dtype size changed, may indicate binary incompatibility.␣
↪Expected 96 from C header, got 88 from PyObject

# from pmdarima.arima import auto_arima
# import numpy as np

# # Check versions to ensure compatibility
# print(f"NumPy version: {np.__version__}")
# print(f"pmdarima version: {pmdarima.__version__}")

# # Your existing code should now work
# model = auto_arima(
#     y_train,
#     seasonal=True,
#     m=52,  # Weekly seasonality (52 weeks/year)
#     suppress_warnings=True,
#     stepwise=True,
#     trace=True
# )

# # Fit the model
# model.fit(y_train)

# # Generate forecasts
# sarima_forecast = model.predict(n_periods=len(y_test))
```

Replacing the `pmdarima` implementation with `statsmodels` SARIMAX:

[24]:
```
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_absolute_error

# 1. Train SARIMAX model (using reasonable default params)
model = SARIMAX(y_train,
               order=(1, 1, 1),             # Non-seasonal (p,d,q)
               seasonal_order=(1, 1, 1, 52), # Seasonal (P,D,Q,s) - weekly␣
↪seasonality
               trace='c')                    # Constant trend term
```

```python
results = model.fit(disp=False)

# 2. Generate forecasts
sarima_forecast = results.get_forecast(steps=len(y_test)).predicted_mean

# 3. Evaluate
mae = mean_absolute_error(y_test, sarima_forecast)
print(f"SARIMA MAE: {mae:,.2f}")

# View model summary
print(results.summary())
```

```
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: An unsupported index was provided. As a result, forecasts cannot
be generated. To use the model for forecasting, use one of the supported classes
of index.
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: An unsupported index was provided. As a result, forecasts cannot
be generated. To use the model for forecasting, use one of the supported classes
of index.
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:837:
ValueWarning: No supported index is available. Prediction results will be given
with an integer index beginning at `start`.
  return get_prediction_index(
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:837:
FutureWarning: No supported index is available. In the next version, calling
this method in a model without a supported index will result in an exception.
  return get_prediction_index(
```

```
SARIMA MAE: 581,592.60
                                     SARIMAX Results
================================================================================
==========
Dep. Variable:                       Weekly_Sales   No. Observations:
5895
Model:             SARIMAX(1, 1, 1)x(1, 1, 1, 52)   Log Likelihood
-86630.518
Date:                            Sat, 02 Aug 2025   AIC
173273.036
Time:                                    22:58:16   BIC
173313.073
Sample:                                         0   HQIC
173286.958
                                           - 5895
Covariance Type:                              opg
==============================================================================
```

```
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     50.4015     40.188      1.254      0.210     -28.365     129.168
ar.L1          0.0058      0.030      0.191      0.848      -0.053       0.065
ma.L1         -0.9657      0.009   -111.564      0.000      -0.983      -0.949
ar.S.L52      -0.0167      0.032     -0.527      0.598      -0.079       0.045
ma.S.L52      -0.9521      0.015    -63.529      0.000      -0.981      -0.923
sigma2      7.755e+11   1.14e-08   6.79e+19      0.000    7.76e+11    7.76e+11
================================================================================
===
Ljung-Box (L1) (Q):                   0.09   Jarque-Bera (JB):
257.31
Prob(Q):                              0.76   Prob(JB):
0.00
Heteroskedasticity (H):               1.09   Skew:
0.48
Prob(H) (two-sided):                  0.05   Kurtosis:
2.62
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
[2] Covariance matrix is singular or near-singular, with condition number
4.69e+35. Standard errors may be unstable.
```

1.9 09- Facebook Prophet (with Regressors)

[25]:
```
from prophet import Prophet

# Prepare data in Prophet format
prophet_df = train[['Date', 'Weekly_Sales', 'Holiday_Flag', 'Temperature',␣
↪'CPI']].rename(
    columns={'Date': 'ds', 'Weekly_Sales': 'y'}
)

# Initialize & fit model
model = Prophet(
    yearly_seasonality=True,
    weekly_seasonality=True,
    daily_seasonality=False
)

# Add regressors (external variables)
model.add_regressor('Holiday_Flag')
model.add_regressor('Temperature')
```

```
model.add_regressor('CPI')

model.fit(prophet_df)

# Create future dataframe with test data
future = test[['Date', 'Holiday_Flag', 'Temperature', 'CPI']].
 ↪rename(columns={'Date': 'ds'})
prophet_forecast = model.predict(future)
```

```
DEBUG:cmdstanpy:input tempfile: /tmp/tmpcbb5ns1w/71o6f1nu.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpcbb5ns1w/o1zx6uhc.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.11/dist-
packages/prophet/stan_model/prophet_model.bin', 'random', 'seed=61126', 'data',
'file=/tmp/tmpcbb5ns1w/71o6f1nu.json', 'init=/tmp/tmpcbb5ns1w/o1zx6uhc.json',
'output',
'file=/tmp/tmpcbb5ns1w/prophet_model2pm81h7e/prophet_model-20250802225820.csv',
'method=optimize', 'algorithm=lbfgs', 'iter=10000']
22:58:20 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
22:58:20 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
```

1.10 10- Model Evaluation

[26]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error

def evaluate(y_true, y_pred, model_name):
    mae = mean_absolute_error(y_true, y_pred)
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
    mape = np.mean(np.abs((y_true - y_pred) / y_true)) * 100

    print(f"--- {model_name} Performance ---")
    print(f"MAE: {mae:.2f}")
    print(f"RMSE: {rmse:.2f}")
    print(f"MAPE: {mape:.2f}%")

# Evaluate SARIMA
evaluate(y_test, sarima_forecast, "SARIMA")

# Evaluate Prophet
evaluate(y_test, prophet_forecast['yhat'], "Prophet")
```

```
--- SARIMA Performance ---
MAE: 581592.60
RMSE: 688251.89
MAPE: 185.11%
```

```
--- Prophet Performance ---
MAE: 447879.07
RMSE: 522834.21
MAPE: 78.40%
```

1.11 11- Saving model

[27]:
```
# SARIMA (Pickle)
import joblib

# Save SARIMA model
joblib.dump(model, 'sarima_model.pkl')

# Load later
loaded_model = joblib.load('sarima_model.pkl')
```

[28]:
```
# Prophet (JSON)
from prophet.serialize import model_to_json, model_from_json

# Save Prophet model
with open('prophet_model.json', 'w') as f:
    f.write(model_to_json(model))

# Load later
with open('prophet_model.json', 'r') as f:
    loaded_model = model_from_json(f.read())
```

1.12 Key Findings

1. **Prophet Outperforms SARIMA**:
    - Achieved **45% lower MAE** (448K vs 815K) and **48% lower RMSE** (522K vs 1M) than SARIMA.
    - Better at capturing complex patterns (holidays, external factors).
2. **High MAPE Alert**:
    - Both models show high error rates (~70-80%), indicating:
        - Potential data noise or outliers.
        - Need for better feature engineering (e.g., promotions, store events).

1.12.1 Recommended Actions

Adopt Prophet for Deployment:
- Leverage its multivariate capabilities (holidays, temperature).
Improve Data Quality:
- Investigate outliers (e.g., extreme sales weeks).
- Add features like marketing spend or local events.

Tune Hyperparameters:
- Optimize Prophet's `changepoint_prior_scale` to reduce overfitting.

1.12.2 Next Steps

Model Enhancement:
- Test **ensemble models** (SARIMA + Prophet) for robustness.
Business Integration:
- Build a dashboard to track forecast vs. actuals weekly.
Continuous Learning:
- Retrain models quarterly with new data.

Performance Snapshot:

Model	MAE	RMSE	MAPE
SARIMA	815,781	1,004,033	69.6%
Prophet	448,627	522,839	78.5%