```
# Mount Google Drive
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
#Install Required Libraries
!pip install xgboost shap prophet pmdarima tensorflow --quiet
```

```
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.2/2.2 MB 31.0 MB/s eta 0:00:00
```

```
#Import Libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import shap
import warnings
warnings.filterwarnings('ignore')

from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error
import xgboost as xgb

# For time series
from prophet import Prophet
from statsmodels.tsa.statespace.sarimax import SARIMAX

# For LSTM
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from tqdm import tqdm
```

```
# Load and Merge Data

train = pd.read_csv("/content/drive/MyDrive/Capstone Project/train.csv", parse_dates=["Date"])
store = pd.read_csv("/content/drive/MyDrive/Capstone Project/store.csv")

# Merge datasets
df = pd.merge(train, store, on="Store")
df.head()
```

	Store	DayOfWeek	Date	Sales	Customers	Open	Promo	StateHoliday	SchoolHoliday	StoreType	Assortment	CompetitionDistan
0	1	5	2015-07-31	5263	555	1	1	0	1	c	a	127(
1	2	5	2015-07-31	6064	625	1	1	0	1	a	a	57(
2	3	5	2015-07-31	8314	821	1	1	0	1	a	a	1413(
3	4	5	2015-07-31	13995	1498	1	1	0	1	c	c	62(
4	5	5	2015-07-31	4822	559	1	1	0	1	a	a	2991(

```
# Clean & Preprocess Data
# Fill missing values

df['CompetitionDistance'].fillna(df['CompetitionDistance'].median(), inplace=True)
df['StateHoliday'] = df['StateHoliday'].astype(str)
```

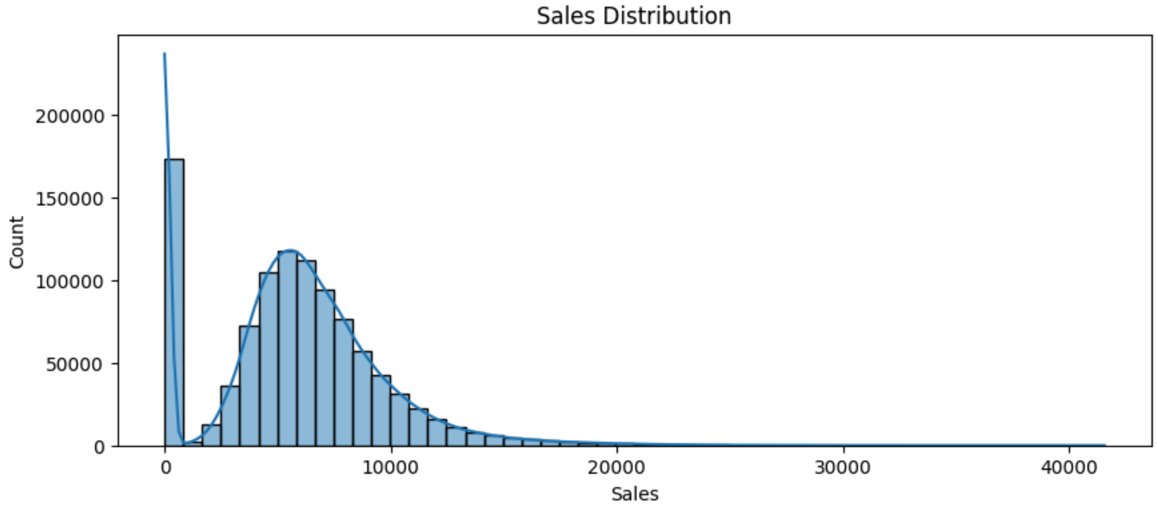
```
#Feature Engineering

# Create date-related features
```

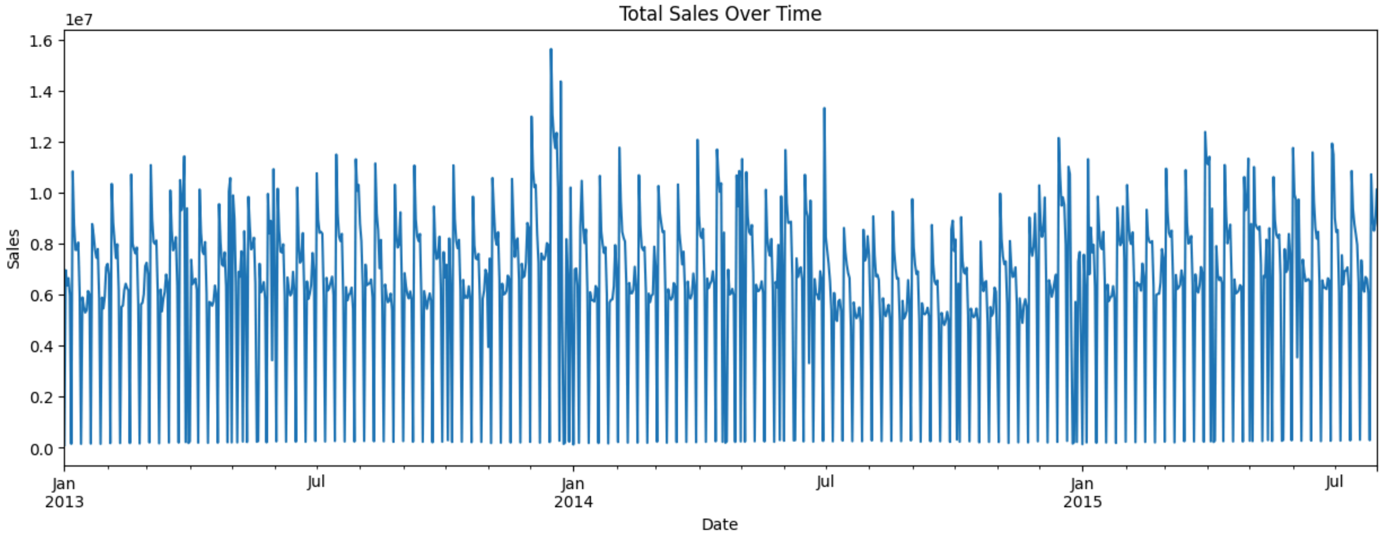
```
df['Year'] = df['Date'].dt.year
df['Month'] = df['Date'].dt.month
df['Day'] = df['Date'].dt.day
df['DayOfWeek'] = df['Date'].dt.dayofweek
df['WeekOfYear'] = df['Date'].dt.isocalendar().week
df['IsWeekend'] = df['DayOfWeek'].isin([5, 6])
df['PromoRunning'] = (df['Promo'] == 1) & (df['Open'] == 1)

df.head()
```

	Store	DayOfWeek	Date	Sales	Customers	Open	Promo	StateHoliday	SchoolHoliday	StoreType	...	Promo2	Promo2SinceWeek
0	1	4	2015-07-31	5263	555	1	1	0	1	c	...	0	NaN
1	2	4	2015-07-31	6064	625	1	1	0	1	a	...	1	13.0
2	3	4	2015-07-31	8314	821	1	1	0	1	a	...	1	14.0
3	4	4	2015-07-31	13995	1498	1	1	0	1	c	...	0	NaN
4	5	4	2015-07-31	4822	559	1	1	0	1	a	...	0	NaN

5 rows × 24 columns

```
# EDA — Visualize Sales Trends

plt.figure(figsize=(10,4))
sns.histplot(df['Sales'], bins=50, kde=True)
plt.title('Sales Distribution')
plt.show()

# Sales over time
df.groupby('Date')['Sales'].sum().plot(figsize=(15, 5), title='Total Sales Over Time')
plt.ylabel('Sales')
plt.show()
```





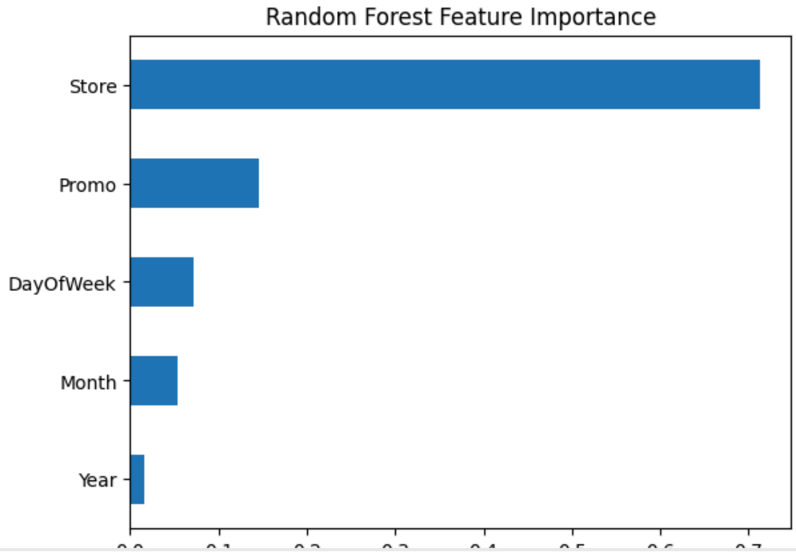

```
# Baseline Model – Linear Regression

model_df = df[(df['Open'] == 1) & (df['Sales'] > 0)].copy()

features = ['Store', 'Promo', 'DayOfWeek', 'Month', 'Year']
X = model_df[features]
y = model_df['Sales']

X_train, X_test, y_train, y_test = train_test_split(X, y, shuffle=False, test_size=0.2)

lr = LinearRegression()
lr.fit(X_train, y_train)
y_pred = lr.predict(X_test)

print("Linear Regression RMSE:", np.sqrt(mean_squared_error(y_test, y_pred)))
print("Linear Regression MAE:", mean_absolute_error(y_test, y_pred))
```

```
Linear Regression RMSE: 2818.890915809172
Linear Regression MAE: 2005.879302679858
```

```
# Random Forest Model with Feature Importance

rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)
y_pred_rf = rf.predict(X_test)

print("Random Forest RMSE:", np.sqrt(mean_squared_error(y_test, y_pred_rf)))
print("Random Forest MAE:", mean_absolute_error(y_test, y_pred_rf))
```

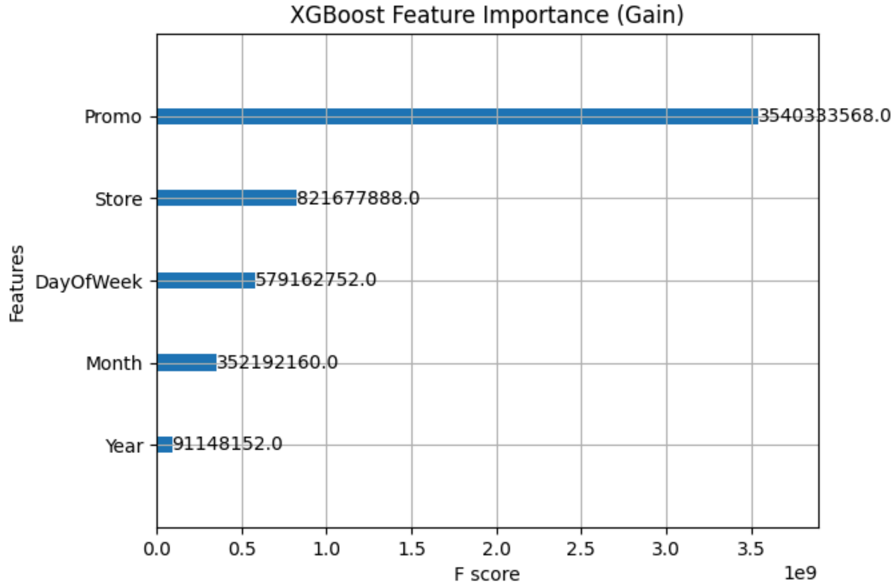
```
importances = pd.Series(rf.feature_importances_, index=features)
importances.sort_values().plot(kind='barh')
plt.title("Random Forest Feature Importance")
plt.show()
```

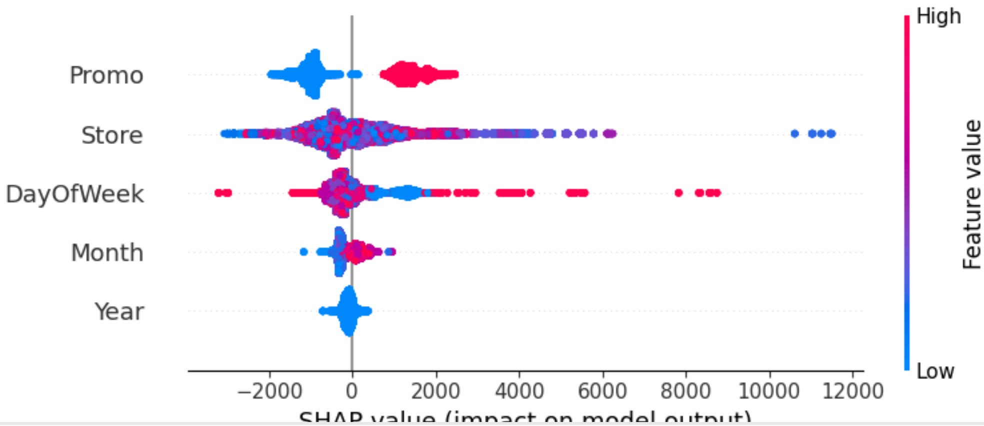
```
Random Forest RMSE: 1242.7580912859767
Random Forest MAE: 854.9868925638202
```



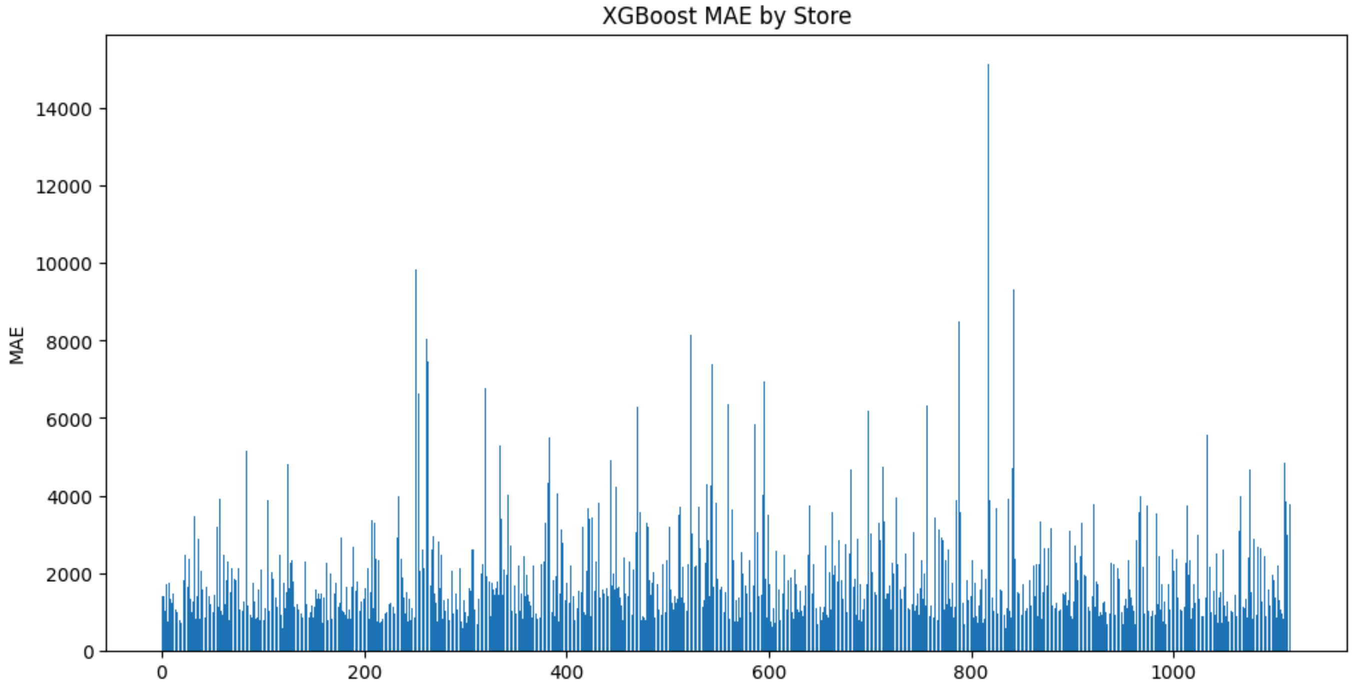

```
# XGBoost Model

xgb_model = xgb.XGBRegressor(objective="reg:squarederror", n_estimators=100)
xgb_model.fit(X_train, y_train)

y_pred_xgb = xgb_model.predict(X_test)

print("XGBoost RMSE:", np.sqrt(mean_squared_error(y_test, y_pred_xgb)))
print("XGBoost MAE:", mean_absolute_error(y_test, y_pred_xgb))

# Feature Importance
xgb.plot_importance(xgb_model, importance_type='gain')
plt.title("XGBoost Feature Importance (Gain)")
plt.show()

explainer = shap.Explainer(xgb_model)
shap_values = explainer(X_test)
shap.summary_plot(shap_values, X_test)
```

```
XGBoost RMSE: 2524.008716308246
XGBoost MAE: 1862.8778076171875
```



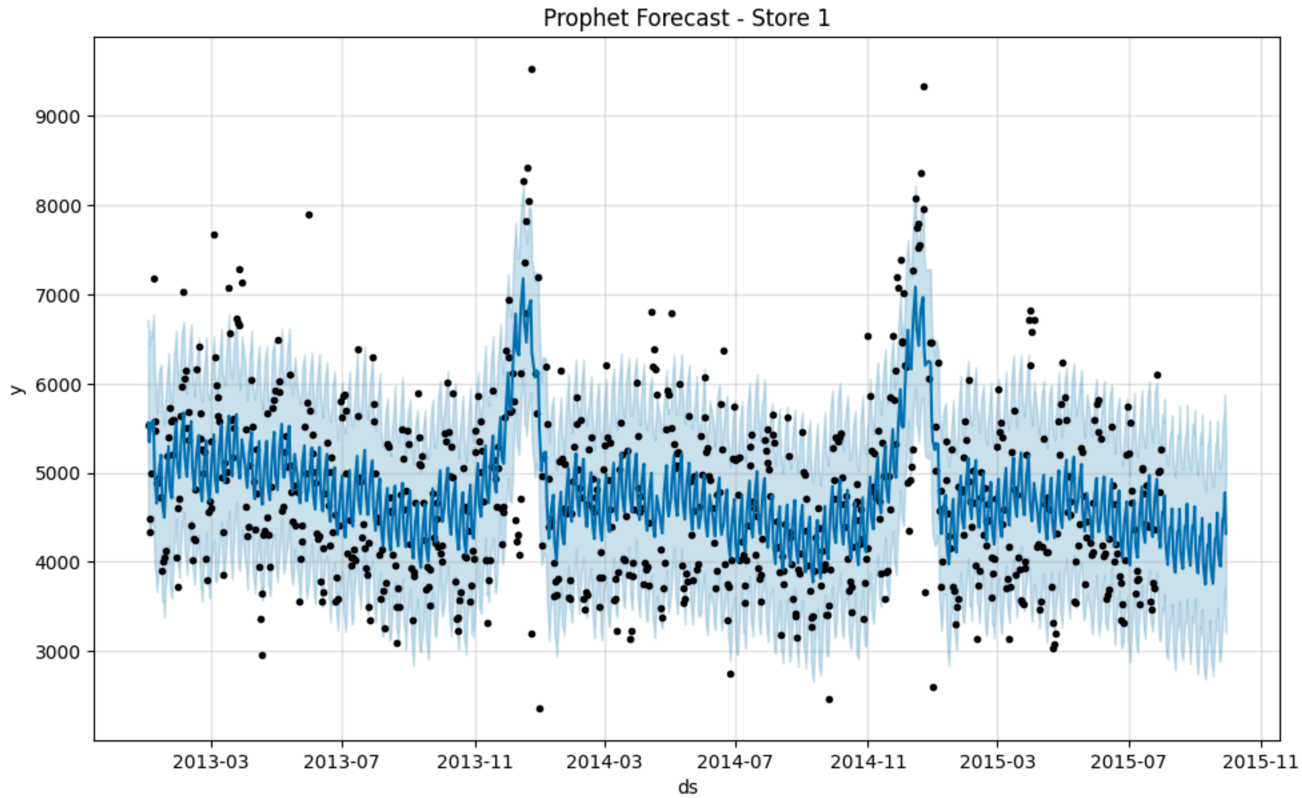


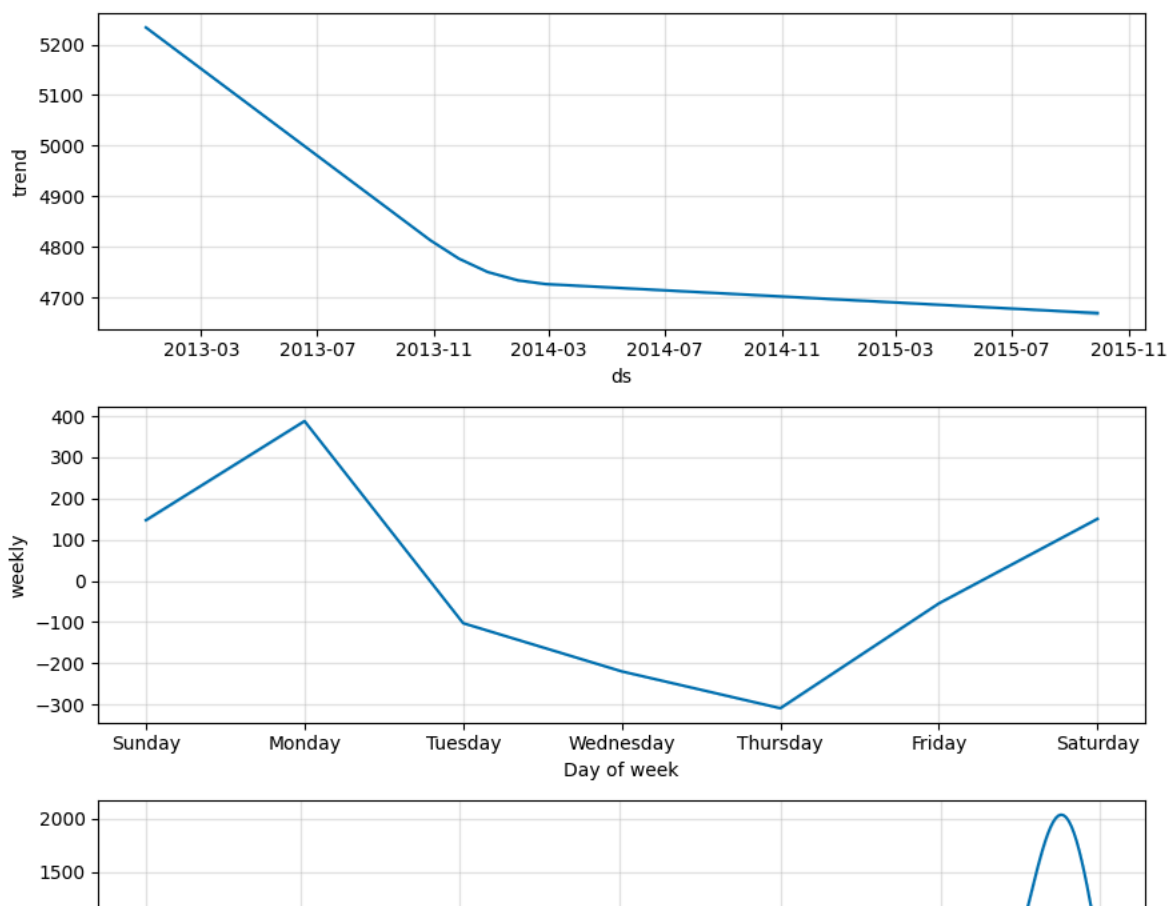

```
# Store-Level Performance Analysis (XGBoost)

X_test_with_store = X_test.copy()
X_test_with_store['Store'] = model_df.loc[X_test.index, 'Store']
X_test_with_store['Actual'] = y_test
X_test_with_store['Predicted_XGB'] = y_pred_xgb

store_mae = X_test_with_store.groupby('Store').apply(lambda x: mean_absolute_error(x['Actual'], x['Predicted_XGB'])).reset_index
store_mae.columns = ['Store', 'MAE_XGB']

plt.figure(figsize=(12,6))
plt.bar(store_mae['Store'], store_mae['MAE_XGB'])
plt.xlabel("Store")
plt.ylabel("MAE")
plt.title("XGBoost MAE by Store")
plt.show()
```

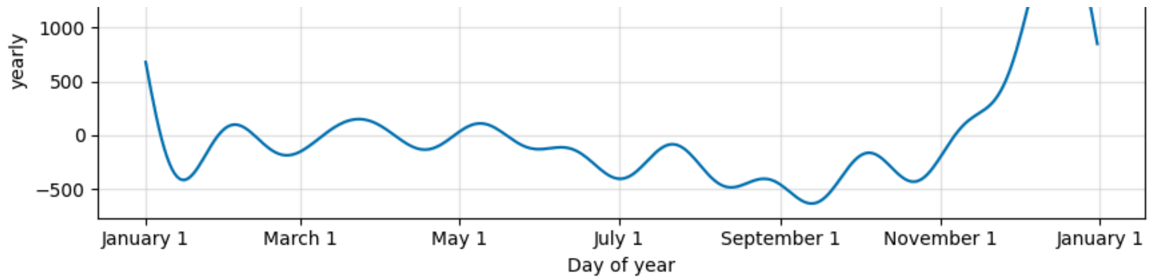



```
# Prophet: Time Series Forecasting for Store 1

store1_df = df[(df['Store'] == 1) & (df['Open'] == 1) & (df['Sales'] > 0)]
store1_ts = store1_df.groupby('Date')['Sales'].sum().reset_index()
prophet_df = store1_ts.rename(columns={'Date':'ds','Sales':'y'})

model_p = Prophet()
model_p.fit(prophet_df)

future = model_p.make_future_dataframe(periods=60)
forecast = model_p.predict(future)

model_p.plot(forecast)
plt.title("Prophet Forecast - Store 1")
plt.show()

model_p.plot_components(forecast)
plt.show()
```

```
INFO:prophet:Disabling daily seasonality. Run prophet with daily_seasonality=True to override this.
DEBUG:cmdstanpy:input tempfile: /tmp/tmpaebej2rt/8_84xxgn.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpaebej2rt/tkgm2zqf.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',
16:25:02 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
16:25:02 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
```

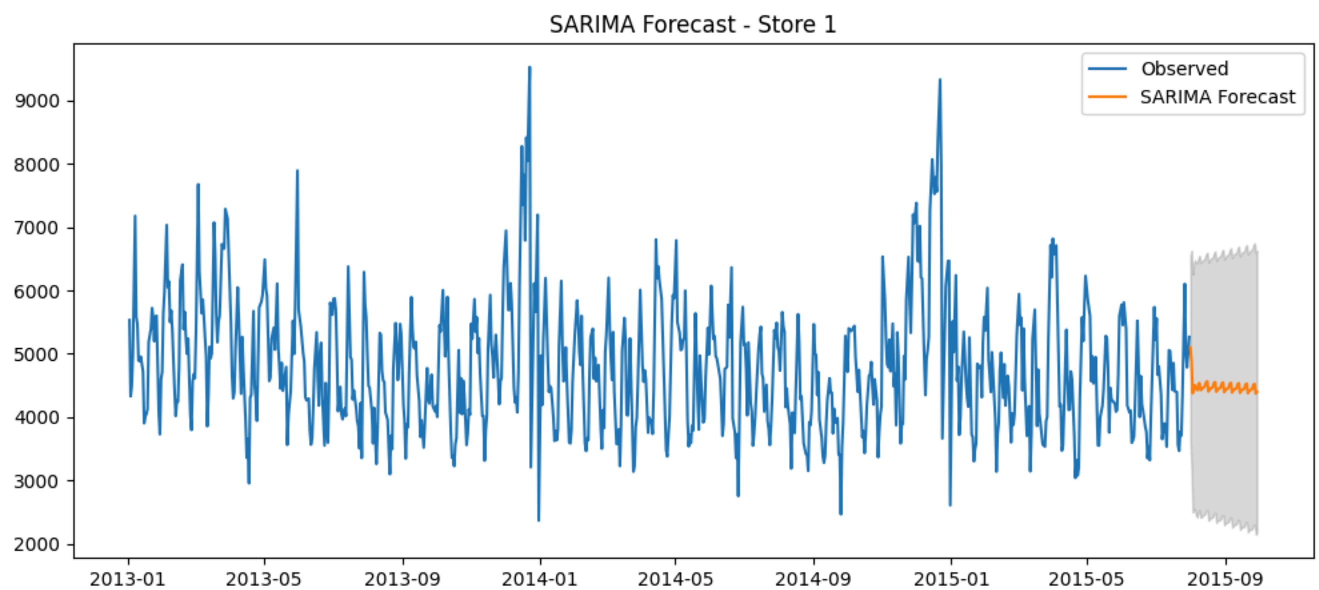







```
# SARIMA: Time Series Forecasting for Store 1

store_ts_arima = store1_ts.set_index('Date')['Sales']

model_sarima = SARIMAX(store_ts_arima,
                       order=(1,1,1),
                       seasonal_order=(1,1,1,7),
                       enforce_stationarity=False,
                       enforce_invertibility=False)

results = model_sarima.fit()
print(results.summary())

forecast = results.get_forecast(steps=60)
forecast_ci = forecast.conf_int()
forecast_index = pd.date_range(start=store_ts_arima.index[-1] + pd.Timedelta(days=1), periods=60)
forecast_values = forecast.predicted_mean

plt.figure(figsize=(12,5))
plt.plot(store_ts_arima, label="Observed")
plt.plot(forecast_index, forecast_values, label="SARIMA Forecast")
plt.fill_between(forecast_index, forecast_ci.iloc[:,0], forecast_ci.iloc[:,1], color='gray', alpha=0.3)
plt.title("SARIMA Forecast - Store 1")
plt.legend()
plt.show()
```

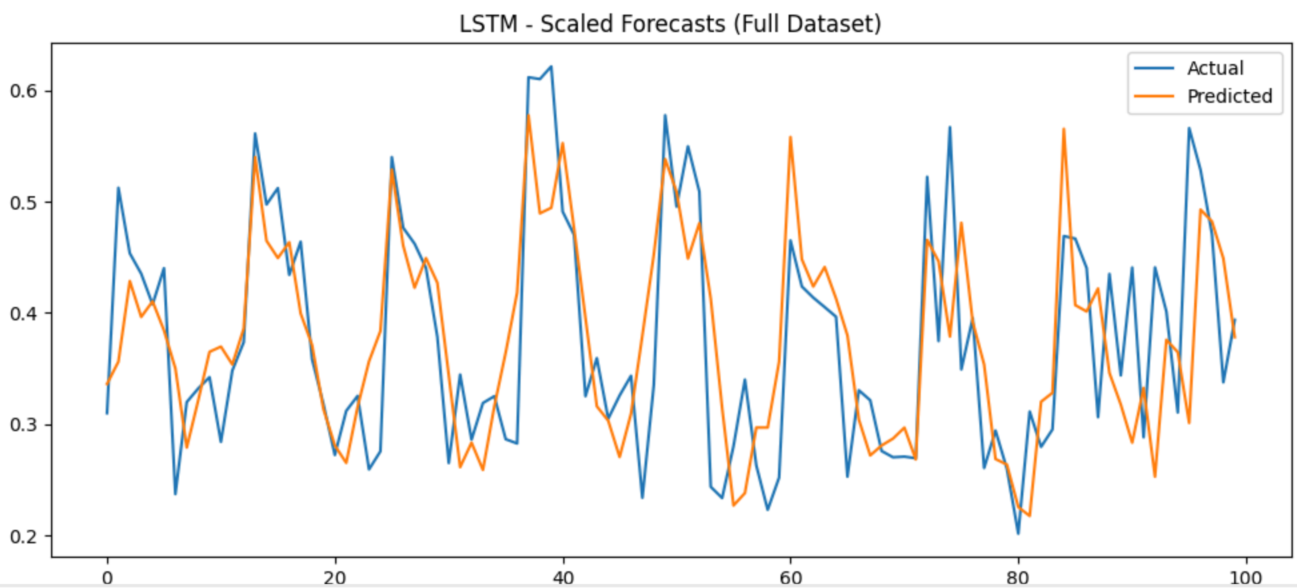
```
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provi
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provi
  self._init_dates(dates, freq)
                                     SARIMAX Results
=========================================================================================
Dep. Variable:                            Sales   No. Observations:                  781
Model:             SARIMAX(1, 1, 1)x(1, 1, 1, 7)   Log Likelihood               -6143.460
Date:                          Sun, 13 Jul 2025   AIC                          12296.921
Time:                                  16:25:33   BIC                          12320.113
Sample:                                       0   HQIC                         12305.850
                                          - 781
Covariance Type:                            opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.6434      0.026     24.791      0.000       0.592       0.694
ma.L1         -0.9666      0.008   -121.186      0.000      -0.982      -0.951
ar.S.L7       -0.1302      0.035     -3.767      0.000      -0.198      -0.062
ma.S.L7       -0.9853      0.019    -53.230      0.000      -1.022      -0.949
sigma2      5.482e+05      2e+04     27.395      0.000    5.09e+05    5.87e+05
===================================================================================
Ljung-Box (L1) (Q):                   0.16   Jarque-Bera (JB):               641.24
Prob(Q):                              0.69   Prob(JB):                         0.00
Heteroskedasticity (H):               1.37   Skew:                            -0.16
Prob(H) (two-sided):                  0.01   Kurtosis:                         7.48
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:837: ValueWarning: No supported index is avail
  return get_prediction_index(
```




```
# LSTM Model Development


sequence_length = 30
X_all, y_all = [], []

store_ids = df['Store'].unique()

for store in tqdm(store_ids):
    store_data = df[(df['Store'] == store) & (df['Open'] == 1) & (df['Sales'] > 0)].copy()
    store_data = store_data.sort_values('Date')

    scaler = MinMaxScaler()
    scaled_sales = scaler.fit_transform(store_data[['Sales']])

    for i in range(len(scaled_sales) - sequence_length):
        X_all.append(scaled_sales[i:i+sequence_length])
        y_all.append(scaled_sales[i+sequence_length])

X_all = np.array(X_all)
```

```
y_all = np.array(y_all)

split = int(len(X_all) * 0.8)
X_train, X_test = X_all[:split], X_all[split:]
y_train, y_test = y_all[:split], y_all[split:]

model = Sequential([
    LSTM(50, activation='relu', input_shape=(sequence_length,1)),
    Dense(1)
])
model.compile(optimizer='adam', loss='mse')
model.fit(X_train, y_train, epochs=5, batch_size=128)

y_pred = model.predict(X_test)

rmse = np.sqrt(mean_squared_error(y_test, y_pred))
mae = mean_absolute_error(y_test, y_pred)

print(f"LSTM (Full Dataset) RMSE (scaled): {rmse:.4f}")
print(f"LSTM (Full Dataset) MAE (scaled): {mae:.4f}")

# Plot sample predictions
plt.figure(figsize=(12, 5))
plt.plot(y_test[:100], label='Actual')
plt.plot(y_pred[:100], label='Predicted')
plt.title("LSTM - Scaled Forecasts (Full Dataset)")
plt.legend()
plt.show()
```

```
100%|██████████| 1115/1115 [00:19<00:00, 58.66it/s]
Epoch 1/5
5069/5069 ━━━━━━━━━━━━━━━━━━━━ 150s 29ms/step - loss: 0.0204
Epoch 2/5
5069/5069 ━━━━━━━━━━━━━━━━━━━━ 152s 30ms/step - loss: 0.0135
Epoch 3/5
5069/5069 ━━━━━━━━━━━━━━━━━━━━ 147s 29ms/step - loss: 0.0117
Epoch 4/5
5069/5069 ━━━━━━━━━━━━━━━━━━━━ 146s 29ms/step - loss: 0.0105
Epoch 5/5
5069/5069 ━━━━━━━━━━━━━━━━━━━━ 202s 29ms/step - loss: 0.0096
5069/5069 ━━━━━━━━━━━━━━━━━━━━ 30s 6ms/step
LSTM (Full Dataset) RMSE (scaled): 0.0973
LSTM (Full Dataset) MAE (scaled): 0.0692
```




```
# LSTM Model Development for Store 1

# Define sequence length
SEQ_LENGTH = 30

# 2. Prepare dataset for Store 1
# Filter only open stores with valid sales for Store 1
store_data = df[(df['Store'] == 1) & (df['Open'] == 1) & (df['Sales'] > 0)].copy()
store_data = store_data.sort_values('Date')
```

```
# 3. Normalize and generate sequences for Store 1
scaler = MinMaxScaler()
scaled_sales = scaler.fit_transform(store_data[['Sales']])

X, y = [], []

# Create sequences
for i in range(len(scaled_sales) - SEQ_LENGTH):
    X.append(scaled_sales[i:i + SEQ_LENGTH])
    y.append(scaled_sales[i + SEQ_LENGTH])

X = np.array(X)
y = np.array(y)

# 4. Train-test split (for Store 1 data)
split = int(len(X) * 0.8)
X_train, X_test = X[:split], X[split:]
y_train, y_test = y[:split], y[split:]


# 5. Build LSTM model
model = Sequential()
model.add(LSTM(50, activation='relu', input_shape=(SEQ_LENGTH, 1)))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')

# 6. Train model
history = model.fit(X_train, y_train, epochs=20, batch_size=32, validation_split=0.1)

# 7. Plot training & validation loss
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='validation')
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend()
plt.show()

# 8. Predict on test set
y_pred = model.predict(X_test)

# Inverse transform to original scale
y_test_inv = scaler.inverse_transform(y_test)
y_pred_inv = scaler.inverse_transform(y_pred)

# 9. Evaluate model
from sklearn.metrics import mean_squared_error, mean_absolute_error

rmse = np.sqrt(mean_squared_error(y_test_inv, y_pred_inv))
mae = mean_absolute_error(y_test_inv, y_pred_inv)

print("LSTM RMSE:", rmse)
print("LSTM MAE:", mae)

# 10. Plot actual vs predicted
plt.figure(figsize=(12,5))
plt.plot(y_test_inv, label='Actual')
plt.plot(y_pred_inv, label='Predicted')
plt.title('LSTM Forecast vs Actual - Store 1')
plt.xlabel('Time Step')
plt.ylabel('Sales')
plt.legend()
plt.show()
```