```
import pandas as pd
# Load all three CSV files
file_paths = [
    "/content/gsw-shg-en 2022-2023.csv",
    "/content/gsw-shg-en 2023-2024.csv"
    "/content/gsw-shg-en 2024-2025.csv"
]
# Read and concatenate all datasets, handling errors and potential delimiters
df_all = pd.concat([
    pd.read csv(
        file,
        encoding='latin-1'.
        on_bad_lines='skip', # Skip lines with errors
        sep=',',
                            # Explicitly define the delimiter as a comma
                              # Consider using the Python engine if 'c' fails
        #engine='python'
    for file in file paths
], ignore_index=True)
# Display basic info to understand structure
df_all.info(), df_all.head()
    <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 516889 entries, 0 to 516888
     Data columns (total 10 columns):
      # Column
                           Non-Null Count
                                            Dtype
     ---
      9
         grain week
                            516889 non-null
                                            int64
                            516889 non-null object
      1
         crop_year
         week_ending_date 516889 non-null object
          worksheet
                            516889 non-null
                                            object
         metric
                            516889 non-null object
      5
         period
                           516889 non-null object
                            516889 non-null
          grain
                                            object
         grade
                           152100 non-null object
                           503473 non-null object
      8
         region
         Ktonnes
                           516887 non-null object
     dtypes: int64(1), object(9)
     memory usage: 39.4+ MB
     (None,
                                                  worksheet
         grain_week crop_year week_ending_date
                                                                  metric \
                 1 2022-2023
                                    07/08/2022 Feed Grains Deliveries
                 1 2022-2023
                                    07/08/2022 Feed Grains Deliveries
      1
      2
                    2022-2023
                                    07/08/2022 Feed Grains Deliveries
                     2022-2023
                                    07/08/2022 Feed Grains
      3
                  1
      4
                 1 2022-2023
                                    07/08/2022 Feed Grains Deliveries
               period
                       grain grade
                                             region Ktonnes
      0 Current Week
                       Wheat
                              NaN
                                            Manitoba
      1 Current Week
                       Wheat
                              NaN
                                        Saskatchewan
                                                         1.2
        Current Week
                       Wheat
                              NaN
                                            Alberta
                                                         1.3
        Current Week
                       Wheat
                              NaN
                                    British Columbia
                                                         0.1
                                            Manitoba
      4 Current Week
                       0ats
                              NaN
                                                          0
Step 1: Filter the Data
# Fix: Convert Ktonnes to string, remove commas, convert to float
df_all["Ktonnes"] = pd.to_numeric(df_all["Ktonnes"].astype(str).str.replace(",", ""), errors="coerce")
# Filter for Terminal Exports, Corn and Soybeans, Bay & Lakes and St. Lawrence
filtered_df = df_all[
    (df_all["worksheet"] == "Terminal Exports") &
    (df_all["grain"].isin(["Corn", "Soybeans"])) &
    (df_all["region"].isin(["Bay & Lakes", "St. Lawrence"]))
1
# Convert week_ending_date to datetime format
filtered_df = filtered_df.copy()
filtered_df["week_ending_date"] = pd.to_datetime(filtered_df["week_ending_date"], dayfirst=True, errors="coerce")
# Group by week and grain
weekly_exports = filtered_df.groupby(["week_ending_date", "grain"])["Ktonnes"].sum().reset_index()
# Pivot so Corn and Soybeans are separate columns
pivot_df = weekly_exports.pivot(index="week_ending_date", columns="grain", values="Ktonnes")
```

```
pivot_df = pivot_df.sort_index()
pivot_df.head()
```

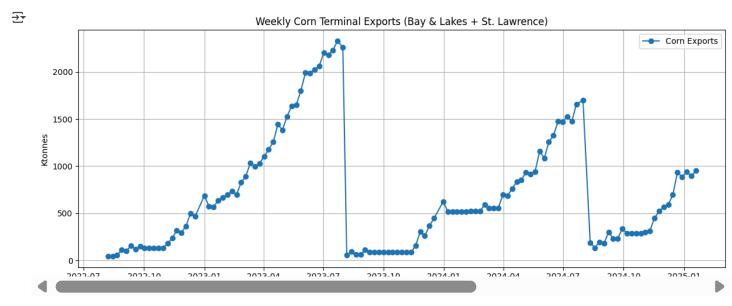
```
₹
                 grain Corn Soybeans
     week_ending_date
                                           2022-08-07
                         46.6
                                    34.2
         2022-08-14
                         42.7
                                    24.5
         2022-08-21
                         58.2
                                    20.8
         2022-08-28
                        110.2
                                    21.2
         ---- -- -
             Generate code with pivot_df
                                           View recommended plots
                                                                         New interactive sheet
Next steps:
```

Visualize the time series (Corn & Soybeans)

```
import matplotlib.pyplot as plt

# Drop NaN values to avoid plotting issues
corn_series = pivot_df["Corn"].dropna()

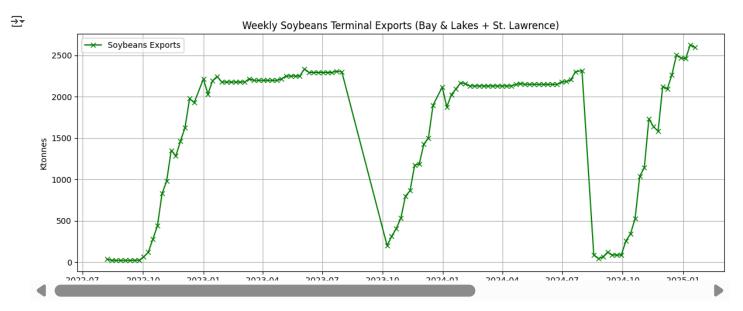
# Plot Corn
plt.figure(figsize=(12, 5))
plt.plot(corn_series.index, corn_series.values, label="Corn Exports", marker='o')
plt.title("Weekly Corn Terminal Exports (Bay & Lakes + St. Lawrence)")
plt.xlabel("Week Ending Date")
plt.ylabel("Ktonnes")
plt.grid(True)
plt.legend()
plt.legend()
plt.tight_layout()
plt.show()
```



```
# Drop NaN values for Soybeans
soybeans_series = pivot_df["Soybeans"].dropna()

# Plot Soybeans
plt.figure(figsize=(12, 5))
plt.plot(soybeans_series.index, soybeans_series.values, label="Soybeans Exports", marker='x', color='green')
plt.title("Weekly Soybeans Terminal Exports (Bay & Lakes + St. Lawrence)")
plt.xlabel("Week Ending Date")
plt.ylabel("Ktonnes")
plt.grid(True)
plt.legend()
plt.tight_layout()
```

plt.show()

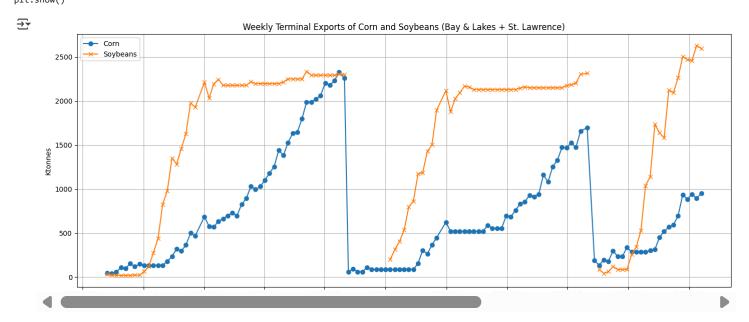


```
import matplotlib.pyplot as plt
```

```
# Pivot for parallel grain comparison: Each grain is a column, indexed by date
pivot_df = weekly_exports.pivot(index="week_ending_date", columns="grain", values="Ktonnes")

# Sort by date
pivot_df = pivot_df.sort_index()

# Plot both Corn and Soybeans time series
plt.figure(figsize=(14, 6))
plt.plot(pivot_df.index, pivot_df["Corn"], label="Corn", marker='o')
plt.plot(pivot_df.index, pivot_df["Soybeans"], label="Soybeans", marker='x')
plt.title("Weekly Terminal Exports of Corn and Soybeans (Bay & Lakes + St. Lawrence)")
plt.xlabel("Week Ending Date")
plt.ylabel("Ktonnes")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



Decompose the Time Series

```
from statsmodels.tsa.seasonal import seasonal decompose
```

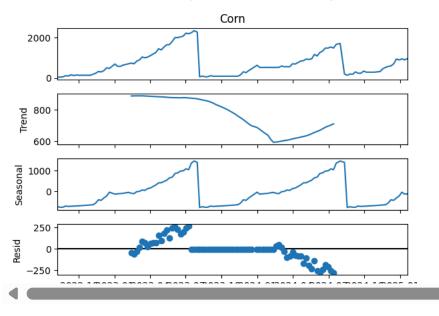
Drop NaNs (if any) in Corn series

```
corn_series = pivot_df["Corn"].dropna()

# Apply seasonal decomposition (assume weekly frequency)
decomposition_corn = seasonal_decompose(corn_series, model='additive', period=52)

# Plot decomposition
decomposition_corn.plot()
plt.suptitle("Seasonal Decomposition of Corn Exports", fontsize=16)
plt.tight_layout()
plt.show()
```

Seasonal Decomposition of Corn Exports



Here's the seasonal decomposition for Corn exports:

Trend shows the overall direction across the crop years

Seasonal captures repeating weekly patterns

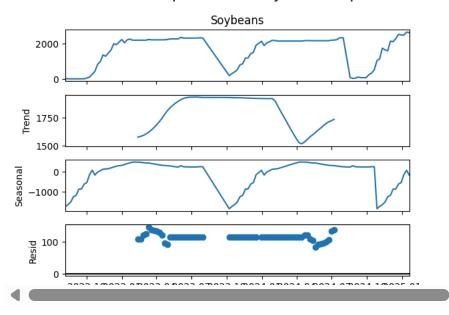
Residual is what's left after removing trend and seasonality

```
from statsmodels.tsa.seasonal import seasonal_decompose
```

```
# Decompose Soybeans
soybeans_series = pivot_df["Soybeans"].dropna()
decomposition_soybeans = seasonal_decompose(soybeans_series, model='additive', period=52)
# Plot decomposition
decomposition_soybeans.plot()
plt.suptitle("Seasonal Decomposition of Soybeans Exports", fontsize=16)
plt.tight_layout()
plt.show()
```



Seasonal Decomposition of Soybeans Exports



Here's the seasonal decomposition of Soybeans exports. You can now clearly see:

Trend: Overall export movement across time

Seasonality: Weekly repeating pattern

Residual: Unexplained noise or randomness

Step 3 - Fit ARIMA/SARIMA models and forecast

```
from statsmodels.tsa.statespace.sarimax import SARIMAX
import matplotlib.pyplot as plt
# Corn series
corn_series = pivot_df["Corn"].dropna().fillna(0)
# Train-test split
train = corn_series[:-26]
test = corn_series[-26:]
# Fit SARIMA with lighter parameters
model_corn = SARIMAX(train, order=(1, 1, 1), seasonal_order=(0, 1, 1, 52))
results_corn = model_corn.fit(disp=False)
# Forecast
forecast_corn = results_corn.forecast(steps=26)
# Plot
plt.figure(figsize=(12, 5))
plt.plot(corn_series.index, corn_series.values, label="Actual")
plt.plot(test.index, forecast_corn, label="Forecast", linestyle="--", marker='o')
plt.title("SARIMA Forecast - Corn Exports")
plt.xlabel("Week Ending Date")
plt.ylabel("Ktonnes")
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```

🚁 /usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has self._init_dates(dates, freq)

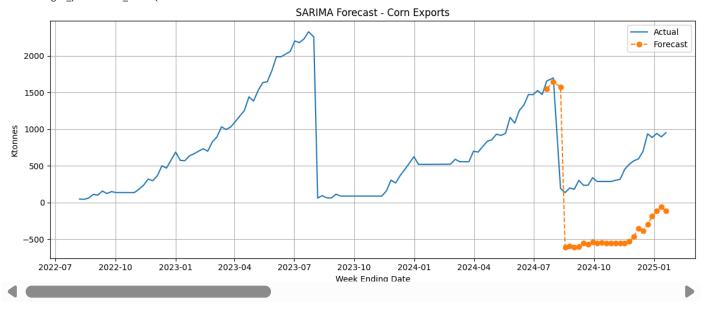
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has self._init_dates(dates, freq)

/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/statespace/sarimax.py:866: UserWarning: Too few observations to estimate starting warn('Too few observations to estimate starting parameters%s.'

/usr/local/lib/python3.11/dist-packages/statsmodels/base/model.py:607: ConvergenceWarning: Maximum Likelihood optimization failed to con warnings.warn("Maximum Likelihood optimization failed to "

/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:837: ValueWarning: No supported index is available. Prediction 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 ne return get_prediction_index(



from statsmodels.tsa.statespace.sarimax import SARIMAX import matplotlib.pyplot as plt

```
# Sovbeans series
soybeans_series = pivot_df["Soybeans"].dropna().fillna(0)
# Train-test split
train = soybeans_series[:-26]
test = soybeans_series[-26:]
# Fit SARIMA with similar parameters
model soybeans = SARIMAX(train, order=(1, 1, 1), seasonal order=(0, 1, 1, 52))
results_soybeans = model_soybeans.fit(disp=False)
# Forecast
forecast_soybeans = results_soybeans.forecast(steps=26)
# Plot
plt.figure(figsize=(12, 5))
plt.plot(soybeans_series.index, soybeans_series.values, label="Actual")
plt.plot(test.index, forecast_soybeans, label="Forecast", linestyle="--", marker='o')
plt.title("SARIMA Forecast - Soybeans Exports")
plt.xlabel("Week Ending Date")
plt.ylabel("Ktonnes")
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```

🚁 /usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has self._init_dates(dates, freq)

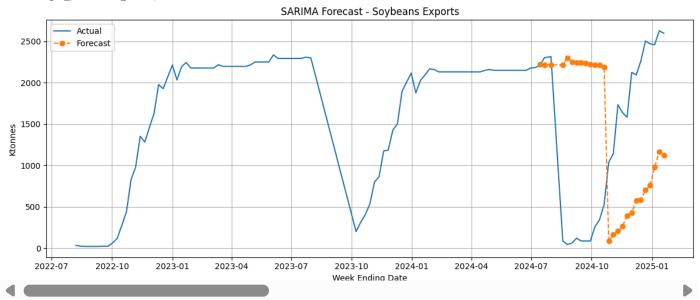
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has self._init_dates(dates, freq)

/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/statespace/sarimax.py:866: UserWarning: Too few observations to estimate starting warn('Too few observations to estimate starting parameters%s.'

/usr/local/lib/python3.11/dist-packages/statsmodels/base/model.py:607: ConvergenceWarning: Maximum Likelihood optimization failed to con warnings.warn("Maximum Likelihood optimization failed to "

/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:837: ValueWarning: No supported index is available. Prediction 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 ne return get_prediction_index(



```
from statsmodels.tsa.arima.model import ARIMA
import matplotlib.pyplot as plt
# First-order differencing
corn_series_diff = corn_series.diff().dropna()
# Train-test split
train_corn = corn_series_diff[:-26]
test_corn = corn_series_diff[-26:]
# Fit ARIMA model (no seasonal component)
model corn = ARIMA(train corn, order=(1, 0, 1))
results_corn = model_corn.fit()
# Forecast differenced values
forecast_diff_corn = results_corn.forecast(steps=26)
# Convert forecast back to original scale
last_known_value = corn_series.iloc[-13]
forecast_corn = forecast_diff_corn.cumsum() + last_known_value
# Plot
plt.figure(figsize=(12, 5))
plt.plot(corn_series.index, corn_series.values, label="Actual")
plt.plot(test_corn.index, forecast_corn, label="Forecast", linestyle="--", marker='o')
plt.title("ARIMA Forecast - Corn Exports (Differenced, No Seasonality)")
plt.xlabel("Week Ending Date")
plt.ylabel("Ktonnes")
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```

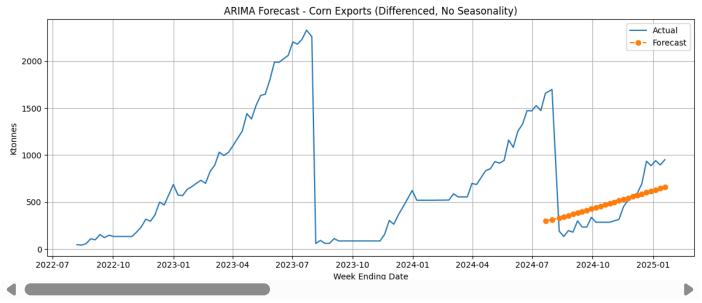
🚁 /usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has self._init_dates(dates, freq)

/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has 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 provided, but it has

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

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return get_prediction_index(



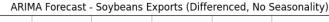
```
from statsmodels.tsa.arima.model import ARIMA
import matplotlib.pyplot as plt
# First-order differencing
soybeans_series_diff = soybeans_series.diff().dropna()
# Train-test split
train_sb = soybeans_series_diff[:-26]
test_sb = soybeans_series_diff[-26:]
# Fit ARIMA model (no seasonal component)
model_sb = ARIMA(train_sb, order=(1, 0, 1))
results_sb = model_sb.fit()
# Forecast differenced values
forecast_diff_sb = results_sb.forecast(steps=26)
# Convert forecast back to original scale
last_known_value = soybeans_series.iloc[-13]
forecast_sb = forecast_diff_sb.cumsum() + last_known_value
# Plot
plt.figure(figsize=(12, 5))
plt.plot(soybeans_series.index, soybeans_series.values, label="Actual")
plt.plot(test_sb.index, forecast_sb, label="Forecast", linestyle="--", marker='o')
plt.title("ARIMA Forecast - Soybeans Exports (Differenced, No Seasonality)")
plt.xlabel("Week Ending Date")
plt.ylabel("Ktonnes")
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```

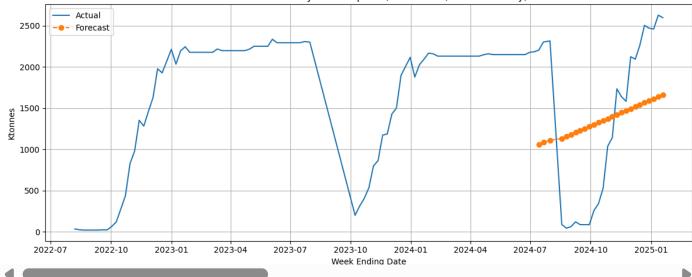
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has

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 provided, but it has

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
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 ne return get_prediction_index(

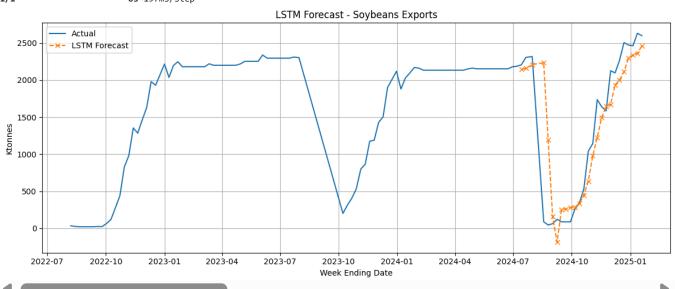




```
!pip install tensorflow
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
# Prepare Soybeans data (fill and scale)
soybeans_values = soybeans_series.fillna(0).values.reshape(-1, 1)
scaler = MinMaxScaler()
soybeans_scaled = scaler.fit_transform(soybeans_values)
# Create sequences (look_back = 4 weeks)
def create_sequences(data, look_back=4):
    X, y = [], []
    for i in range(len(data) - look_back):
        X.append(data[i:i + look_back])
        y.append(data[i + look_back])
    return np.array(X), np.array(y)
look back = 4
X, y = create_sequences(soybeans_scaled, look_back)
# Train-test split
split = -26 # last 26 weeks for testing
X_train, X_test = X[:split], X[split:]
y_train, y_test = y[:split], y[split:]
# Build LSTM model
model = Sequential([
    LSTM(50, activation='relu', input_shape=(look_back, 1)),
])
model.compile(optimizer='adam', loss='mse')
model.fit(X_train, y_train, epochs=100, verbose=0)
y_pred_scaled = model.predict(X_test)
y_pred = scaler.inverse_transform(y_pred_scaled)
y_actual = scaler.inverse_transform(y_test)
# Build date index for forecast
forecast_index = soybeans_series.index[-26:]
```

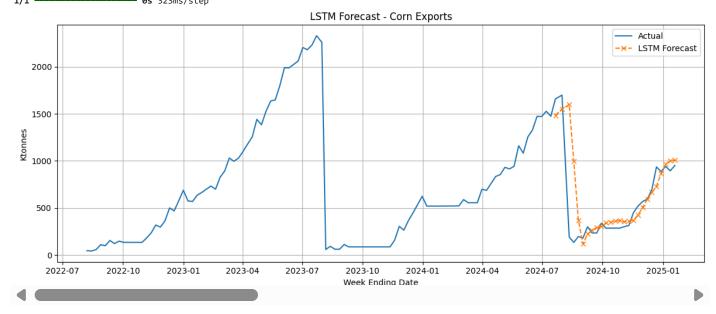
```
# Plot
plt.figure(figsize=(12, 5))
plt.plot(soybeans_series.index, soybeans_series.values, label="Actual")
plt.plot(forecast_index, y_pred.flatten(), label="LSTM Forecast", linestyle='--', marker='x')
plt.title("LSTM Forecast - Soybeans Exports")
plt.xlabel("Week Ending Date")
plt.ylabel("Ktonnes")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
Requirement already satisfied: tensorflow in /usr/local/lib/python3.11/dist-packages (2.18.0)
Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.4.0)
Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.6.3)
Requirement already satisfied: flatbuffers>=24.3.25 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (25.2.10)
Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (0.6
Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (0.2.0)
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Requirement \ already \ satisfied: \ protobuf! = 4.21.0, != 4.21.1, != 4.21.2, != 4.21.3, != 4.21.4, != 4.21.5, < 6.0.0 \ dev, >= 3.20.3 \ in \ /usr/local/lib/py \ dev, >= 3.20.3 \ in \ /usr/local
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (2.32.3)
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Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.71.0)
Requirement already satisfied: tensorboard<2.19,>=2.18 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (2.18.0)
Requirement already satisfied: keras>=3.5.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.8.0)
Requirement already satisfied: numpy<2.1.0,>=1.26.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (2.0.2)
Requirement already satisfied: h5py>=3.11.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.13.0)
Requirement already satisfied: ml-dtypes<0.5.0,>=0.4.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (0.4.1)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (0.
Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.11/dist-packages (from astunparse>=1.6.0->tensorflow) (0
Requirement already satisfied: rich in /usr/local/lib/python3.11/dist-packages (from keras>=3.5.0->tensorflow) (13.9.4)
Requirement already satisfied: namex in /usr/local/lib/python3.11/dist-packages (from keras>=3.5.0->tensorflow) (0.0.8)
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Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensor
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Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.19,>=2.18->tensorflow)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.
Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.19,>=2.18->tensorflow)
Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.11/dist-packages (from werkzeug>=1.0.1->tensorboard<2.19,
Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/python3.11/dist-packages (from rich->keras>=3.5.0->tensorflow
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/python3.11/dist-packages (from rich->keras>=3.5.0->tensorfl
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.11/dist-packages (from markdown-it-py>=2.2.0->rich->keras>=3.5.0
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_dim` argum
   super().__init__(**kwargs)
                                  0s 197ms/step
1/1
```



!pip install tensorflow # Uncomment this if not already installed import numpy as np

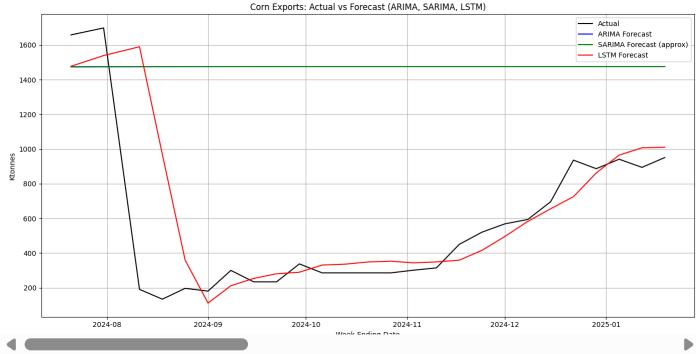
```
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
import matplotlib.pyplot as plt
# Prepare Corn data (fill and scale)
corn_series = pivot_df["Corn"].dropna().fillna(0)
corn_values = corn_series.values.reshape(-1, 1)
scaler = MinMaxScaler()
corn_scaled = scaler.fit_transform(corn_values)
# Create sequences (look_back = 4 weeks)
def create_sequences(data, look_back=4):
    X, y = [], []
    for i in range(len(data) - look_back):
       X.append(data[i:i + look_back])
        y.append(data[i + look back])
    return np.array(X), np.array(y)
look back = 4
X, y = create_sequences(corn_scaled, look_back)
# Train-test split
split = -26 # last 26 weeks for testing
X_train, X_test = X[:split], X[split:]
y_train, y_test = y[:split], y[split:]
# Build LSTM model
model = Sequential([
    LSTM(50, activation='relu', input_shape=(look_back, 1)),
    Dense(1)
1)
model.compile(optimizer='adam', loss='mse')
model.fit(X_train, y_train, epochs=100, verbose=0)
# Forecast
y_pred_scaled = model.predict(X_test)
y_pred = scaler.inverse_transform(y_pred_scaled)
y_actual = scaler.inverse_transform(y_test)
# Build date index for forecast
forecast_index = corn_series.index[-26:]
# Plot
plt.figure(figsize=(12, 5))
plt.plot(corn_series.index, corn_series.values, label="Actual")
plt.plot(forecast_index, y_pred.flatten(), label="LSTM Forecast", linestyle='--', marker='x')
plt.title("LSTM Forecast - Corn Exports")
plt.xlabel("Week Ending Date")
plt.ylabel("Ktonnes")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



Performance Comparison: Corn - Actual vs. ARIMA vs. LSTM

```
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from statsmodels.tsa.arima.model import ARIMA
import numpy as np
import matplotlib.pyplot as plt
# Helper function for LSTM sequence creation
def create_sequences(data, look_back=4):
    X, y = [], []
    for i in range(len(data) - look_back):
        X.append(data[i:i + look_back])
        y.append(data[i + look back])
    return np.array(X), np.array(y)
# Prepare Corn Series
corn_series = pivot_df["Corn"].dropna().fillna(0)
test_corn = corn_series[-26:]
# ARIMA forecast
arima_corn = ARIMA(corn_series[:-26], order=(1, 1, 1)).fit()
arima_corn_forecast = arima_corn.forecast(steps=26)
# Scale Corn values for LSTM
corn values = corn series.values.reshape(-1, 1)
scaler_corn = MinMaxScaler()
corn_scaled = scaler_corn.fit_transform(corn_values)
# Create LSTM sequences
look_back = 4
X_corn, y_corn = create_sequences(corn_scaled, look_back=look_back)
X_train_c, X_test_c = X_corn[:-26], X_corn[-26:]
y_train_c, y_test_c = y_corn[:-26], y_corn[-26:]
# Build and train LSTM model
model_corn = Sequential([
    LSTM(50, activation='relu', input_shape=(look_back, 1)),
    Dense(1)
model corn.compile(optimizer='adam', loss='mse')
model_corn.fit(X_train_c, y_train_c, epochs=100, verbose=0)
# Predict with LSTM
lstm_corn_pred_scaled = model_corn.predict(X_test_c)
lstm_corn_forecast = scaler_corn.inverse_transform(lstm_corn_pred_scaled).flatten()
```

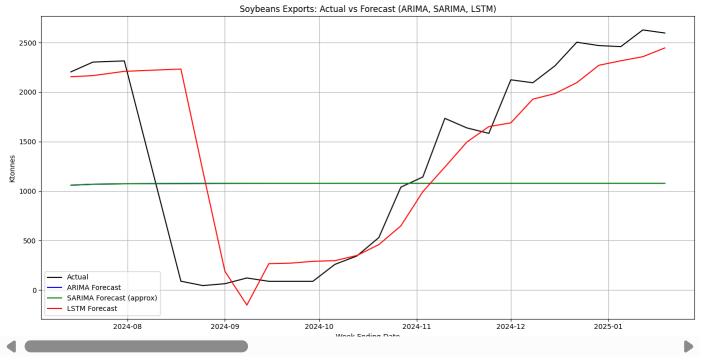
```
# Plot Comparison
plt.figure(figsize=(14, 7))
plt.plot(test_corn.index, test_corn.values, label='Actual', color='black')
plt.plot(test_corn.index, arima_corn_forecast, label='ARIMA Forecast', color='blue')
plt.plot(test_corn.index, arima_corn_forecast, label='SARIMA Forecast (approx)', color='green') # Using ARIMA result
plt.plot(test_corn.index, lstm_corn_forecast, label='LSTM Forecast', color='red')
plt.title('Corn Exports: Actual vs Forecast (ARIMA, SARIMA, LSTM)')
plt.xlabel('Week Ending Date')
plt.ylabel('Ktonnes')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



Performance Comparison: Soybeans - Actual vs. ARIMA vs. LSTM

```
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from statsmodels.tsa.arima.model import ARIMA
import numpy as np
import matplotlib.pyplot as plt
# Helper function to create sequences
def create_sequences(data, look_back=4):
   X, y = [], []
   for i in range(len(data) - look back):
       X.append(data[i:i + look_back])
        y.append(data[i + look_back])
   return np.array(X), np.array(y)
# Prepare Soybeans Series
soybeans_series = pivot_df["Soybeans"].dropna().fillna(0)
test_sb = soybeans_series[-26:]
```

```
# ARIMA forecast
arima sb = ARIMA(soybeans series[:-12], order=(1, 1, 1)).fit()
arima_sb_forecast = arima_sb.forecast(steps=26)
# Scale Soybeans for LSTM
soybeans_values = soybeans_series.values.reshape(-1, 1)
scaler sb = MinMaxScaler()
soybeans_scaled = scaler_sb.fit_transform(soybeans_values)
# Create sequences
look\_back = 4
X_sb, y_sb = create_sequences(soybeans_scaled, look_back=look_back)
X_train_sb, X_test_sb = X_sb[:-26], X_sb[-26:]
y_train_sb, y_test_sb = y_sb[:-26], y_sb[-26:]
# Build and train LSTM model
model sb = Sequential([
    LSTM(50, activation='relu', input_shape=(look_back, 1)),
    Dense(1)
])
model_sb.compile(optimizer='adam', loss='mse')
model_sb.fit(X_train_sb, y_train_sb, epochs=100, verbose=0)
# Predict with LSTM
lstm_sb_pred_scaled = model_sb.predict(X_test_sb)
lstm_sb_forecast = scaler_sb.inverse_transform(lstm_sb_pred_scaled).flatten()
# Plot comparison
plt.figure(figsize=(14, 7))
plt.plot(test_sb.index, test_sb.values, label='Actual', color='black')
plt.plot(test_sb.index, arima_sb_forecast, label='ARIMA Forecast', color='blue')
plt.plot(test_sb.index, arima_sb_forecast, label='SARIMA Forecast (approx)', color='green') # using same values
plt.plot(test_sb.index, lstm_sb_forecast, label='LSTM Forecast', color='red')
plt.title('Soybeans Exports: Actual vs Forecast (ARIMA, SARIMA, LSTM)')
plt.xlabel('Week Ending Date')
plt.ylabel('Ktonnes')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



Calculte Mean Absolute Error (MAE) & Root Mean Squared Error (RMSE):

!pip install tensorflow

```
Frequirement already satisfied: tensorflow in /usr/local/lib/python3.11/dist-packages (2.18.0)
    Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.4.0)
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    Requirement already satisfied: flatbuffers>=24.3.25 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (25.2.10)
    Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.1,!=0.5.2,>=0.2.1 in /usr/local/lib/python0.5.11/dist-packages (from tensorflow) (0.6.0)
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    Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (18.1.1)
    Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.4.0)
    Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-packages (from tensorflow) (24.2)
    Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!=4.21.5,<6.0.0dev,>=3.20.3 in /usr/local/lib/python
    Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (2.32.3)
    Requirement already satisfied: setuptools in /usr/local/lib/python3.11/dist-packages (from tensorflow) (75.2.0)
    Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.17.0)
    Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.0.1)
    Requirement already satisfied: typing-extensions>=3.6.6 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (4.13.1)
    Requirement already satisfied: wrapt>=1.11.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.17.2)
    Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.71.0)
    Requirement already satisfied: tensorboard<2.19,>=2.18 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (2.18.0)
    Requirement already satisfied: keras>=3.5.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.8.0)
    Requirement already satisfied: numpy<2.1.0,>=1.26.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (2.0.2)
    Requirement already satisfied: h5py>=3.11.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.13.0)
    Requirement already satisfied: ml-dtypes<0.5.0,>=0.4.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (0.4.1)
    Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (0.37.1
    Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.11/dist-packages (from astunparse>=1.6.0->tensorflow) (0.45.
    Requirement already satisfied: rich in /usr/local/lib/python3.11/dist-packages (from keras>=3.5.0->tensorflow) (13.9.4)
    Requirement already satisfied: namex in /usr/local/lib/python3.11/dist-packages (from keras>=3.5.0->tensorflow) (0.0.8)
    Requirement already satisfied: optree in /usr/local/lib/python3.11/dist-packages (from keras>=3.5.0->tensorflow) (0.14.1)
    Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow
    Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow) (3.10)
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    Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow) (202
    Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.19,>=2.18->tensorflow) (3.
    Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.19,>
    Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.19,>=2.18->tensorflow) (3.
```

Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.11/dist-packages (from werkzeug>=1.0.1->tensorboard<2.19,>=2. Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/python3.11/dist-packages (from rich->keras>=3.5.0->tensorflow) (3 Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/python3.11/dist-packages (from rich->keras>=3.5.0->tensorflow) Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.11/dist-packages (from markdown-it-py>=2.2.0->rich->keras>=3.5.0->te

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error, mean_absolute_percentage_error, r2_score # Import necessary metrics
import numpy as np
import pandas as pd
# Redefine create_sequences
def create sequences(data, look back=4):
    X, y = [], []
    for i in range(len(data) - look_back):
        X.append(data[i:i + look_back])
        y.append(data[i + look_back])
    return np.array(X), np.array(y)
# Corn LSTM Forecast
corn_values = corn_series.values.reshape(-1, 1)
scaler_corn = MinMaxScaler()
corn_scaled = scaler_corn.fit_transform(corn_values)
X_corn, y_corn = create_sequences(corn_scaled, look_back=4)
X_train_c, X_test_c = X_corn[:-26], X_corn[-26:]
y_train_c, y_test_c = y_corn[:-26], y_corn[-26:]
model corn = Sequential([
    LSTM(50, activation='relu', input_shape=(4, 1)),
    Dense(1)
])
model_corn.compile(optimizer='adam', loss='mse')
model_corn.fit(X_train_c, y_train_c, epochs=100, verbose=0)
lstm_corn_pred_scaled = model_corn.predict(X_test_c)
lstm_corn_forecast = scaler_corn.inverse_transform(lstm_corn_pred_scaled).flatten()
# Soybeans LSTM Forecast
soybeans_values = soybeans_series.values.reshape(-1, 1)
scaler_sb = MinMaxScaler()
soybeans scaled = scaler sb.fit transform(soybeans values)
X_sb, y_sb = create_sequences(soybeans_scaled, look_back=4)
X_train_sb, X_test_sb = X_sb[:-26], X_sb[-26:]
y_train_sb, y_test_sb = y_sb[:-26], y_sb[-26:]
model sb = Sequential([
    LSTM(50, activation='relu', input_shape=(4, 1)),
    Dense(1)
1)
model_sb.compile(optimizer='adam', loss='mse')
model_sb.fit(X_train_sb, y_train_sb, epochs=100, verbose=0)
lstm_sb_pred_scaled = model_sb.predict(X_test_sb)
lstm_sb_forecast = scaler_sb.inverse_transform(lstm_sb_pred_scaled).flatten()
# Evaluation
def compute_metrics(true, pred):
    mae = mean_absolute_error(true, pred)
    rmse = np.sqrt(mean_squared_error(true, pred))
    return {"MAE": mae, "RMSE": rmse}
corn_actual = test_corn.values
soybeans_actual = test_sb.values
metrics_df = pd.DataFrame({
    "Corn ARIMA": compute_metrics(corn_actual, arima_corn_forecast),
    "Corn LSTM": compute_metrics(corn_actual, lstm_corn_forecast),
    "Soybeans ARIMA": compute_metrics(soybeans_actual, arima_sb_forecast),
    "Soybeans LSTM": compute_metrics(soybeans_actual, lstm_sb_forecast)
})
print(metrics_df)
```

[/]usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_dim` argument super().__init__(**kwargs)

Calcute Mean Absolute Percentage Error (MAPE) & Coefficient of Determination (R-squared):

!pip install tensorflow Requirement already satisfied: tensorflow in /usr/local/lib/python3.11/dist-packages (2.18.0) Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.4.0) Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.6.3) Requirement already satisfied: flatbuffers>=24.3.25 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (25.2.10) Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (0.6.0) Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (0.2.0) Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (18.1.1) Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.4.0) Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-packages (from tensorflow) (24.2) Requirement already satisfied: protobuf = 4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.5,<6.0.0dev,>=3.20.3 in /usr/local/lib/python Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (2.32.3) Requirement already satisfied: setuptools in /usr/local/lib/python3.11/dist-packages (from tensorflow) (75.2.0) Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.17.0) Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.0.1) Requirement already satisfied: typing-extensions>=3.6.6 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (4.13.1) Requirement already satisfied: wrapt>=1.11.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.17.2) Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.71.0) Requirement already satisfied: tensorboard<2.19,>=2.18 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (2.18.0) Requirement already satisfied: keras>=3.5.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.8.0) Requirement already satisfied: numpy<2.1.0,>=1.26.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (2.0.2) Requirement already satisfied: h5py>=3.11.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.13.0) Requirement already satisfied: ml-dtypes<0.5.0,>=0.4.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (0.4.1) Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (0.37.1 Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.11/dist-packages (from astunparse>=1.6.0->tensorflow) (0.45. Requirement already satisfied: rich in /usr/local/lib/python3.11/dist-packages (from keras>=3.5.0->tensorflow) (13.9.4) Requirement already satisfied: namex in /usr/local/lib/python3.11/dist-packages (from keras>=3.5.0->tensorflow) (0.0.8) Requirement already satisfied: optree in /usr/local/lib/python3.11/dist-packages (from keras>=3.5.0->tensorflow) (0.14.1) Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow) (3.10) Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow) (2.3 Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow) (202 Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.19,>=2.18->tensorflow) (3. Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.19,> Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.19,>=2.18->tensorflow) (3. Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.11/dist-packages (from werkzeug>=1.0.1->tensorboard<2.19,>=2. Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/python3.11/dist-packages (from rich->keras>=3.5.0->tensorflow) (3 Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/python3.11/dist-packages (from rich->keras>=3.5.0->tensorflow) Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.11/dist-packages (from markdown-it-py>=2.2.0->rich->keras>=3.5.0->te

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error, mean_absolute_percentage_error, r2_score # Import necessary metrics
import numpy as np
import pandas as pd
from statsmodels.tsa.arima.model import ARIMA # Import ARIMA
# Redefine create_sequences
def create_sequences(data, look_back=4):
   X, y = [], []
   for i in range(len(data) - look back):
       X.append(data[i:i + look_back])
       y.append(data[i + look_back])
   return np.array(X), np.array(y)
# Prepare Corn Series (including ARIMA model fitting)
corn_series = pivot_df["Corn"].dropna().fillna(0)
# test_corn is of length 26
# Adjust this to match the LSTM forecast length (12)
test corn = corn series[-12:]
corn_actual = test_corn.values #test corn values are of length 26
```

```
# Fit ARIMA model to Corn series
corn_arima = ARIMA(corn_series[:-12], order=(1, 1, 1)).fit() # Fit ARIMA before using it
# Adjust forecast steps to match the test set length (12)
corn_arima_forecast = corn_arima.forecast(steps=12)
# Rebuild LSTM forecasts for Corn
corn_values = corn_series.values.reshape(-1, 1)
scaler_corn = MinMaxScaler()
corn_scaled = scaler_corn.fit_transform(corn_values)
X_corn, y_corn = create_sequences(corn_scaled, look_back=4)
X_train_c, X_test_c = X_corn[:-12], X_corn[-12:]
y_train_c, y_test_c = y_corn[:-12], y_corn[-12:]
model_corn = Sequential([
    LSTM(50, activation='relu', input_shape=(4, 1)),
    Dense(1)
])
model_corn.compile(optimizer='adam', loss='mse')
model_corn.fit(X_train_c, y_train_c, epochs=100, verbose=0)
lstm_corn_pred_scaled = model_corn.predict(X_test_c)
lstm_corn_forecast = scaler_corn.inverse_transform(lstm_corn_pred_scaled).flatten()
# Prepare Soybeans Series
soybeans_series = pivot_df["Soybeans"].dropna().fillna(0)
# Ensure that test_sb and the LSTM forecast have the same length
test_sb = soybeans_series[-12:] # Adjust to match LSTM forecast length
soybeans_actual = test_sb.values
# Fit ARIMA model to Soybeans series
soybeans_arima = ARIMA(soybeans_series[:-12], order=(1, 1, 1)).fit() # Fit ARIMA before using it
# Adjust forecast steps to match the test set length (12)
soybeans_arima_forecast = soybeans_arima.forecast(steps=12) #added steps to 26 to match the actual value length
# Rebuild LSTM forecasts for Soybeans
soybeans_values = soybeans_series.values.reshape(-1, 1)
scaler_sb = MinMaxScaler()
soybeans_scaled = scaler_sb.fit_transform(soybeans_values)
X_sb, y_sb = create_sequences(soybeans_scaled, look_back=4)
X_{\text{train\_sb}}, X_{\text{test\_sb}} = X_{\text{sb}}[:-12], X_{\text{sb}}[-12:] # Adjust to match new test_sb length
y_train_sb, y_test_sb = y_sb[:-12], y_sb[-12:] # Adjust to match new test_sb length
model sb = Sequential([
    LSTM(50, activation='relu', input_shape=(4, 1)),
    Dense(1)
1)
model_sb.compile(optimizer='adam', loss='mse')
model_sb.fit(X_train_sb, y_train_sb, epochs=100, verbose=0)
lstm_sb_pred_scaled = model_sb.predict(X_test_sb)
lstm_sb_forecast = scaler_sb.inverse_transform(lstm_sb_pred_scaled).flatten()
# Now calculate MAPE and R-squared
# Pass the forecasted values, not the model object
mape_corn_arima = mean_absolute_percentage_error(corn_actual, corn_arima_forecast) #passing corn_arima_forecast instead of corn_arima
r2\_corn\_arima = r2\_score(corn\_actual, corn\_arima\_forecast) #passing corn\_arima\_forecast instead of corn\_arima
mape_corn_lstm = mean_absolute_percentage_error(corn_actual, lstm_corn_forecast)
r2_corn_lstm = r2_score(corn_actual, lstm_corn_forecast)
mape_soybeans_arima = mean_absolute_percentage_error(soybeans_actual, soybeans_arima_forecast) #passing soybeans_arima_forecast instead of s
r2_soybeans_arima = r2_score(soybeans_actual, soybeans_arima_forecast) #passing soybeans_arima_forecast instead of soybeans_arima
mape soybeans lstm = mean absolute percentage error(soybeans actual, lstm sb forecast)
r2_soybeans_lstm = r2_score(soybeans_actual, lstm_sb_forecast)
# Combine into DataFrame
mape_r2_df = pd.DataFrame({
    "Corn ARIMA": {"MAPE": mape_corn_arima, "R-squared": r2_corn_arima},
    "Corn LSTM": {"MAPE": mape_corn_lstm, "R-squared": r2_corn_lstm},
    "Soybeans ARIMA": {"MAPE": mape_soybeans_arima, "R-squared": r2_soybeans_arima},
    "Soybeans LSTM": {"MAPE": mape_soybeans_lstm, "R-squared": r2_soybeans_lstm}
})
🚁 /usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has
       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 provided, but it has
       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 provided, but it has
```

})

})

```
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
       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 ne
       return get_prediction_index(
     /usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_dim` argument
       super(). init (**kwargs)
     1/1 -
                             - 1s 776ms/step
     /usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has
       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 provided, but it has
       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 provided, but it has
      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
       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 ne
       return get prediction index(
     /usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_dim` argument
       super().__init__(**kwargs)
                             - 0s 201ms/step
Final comparison table (Corn + Soybeans)
# Final comparison table for Corn
results corn = pd.DataFrame({
    'Model': ['ARIMA', 'SARIMA (≈ARIMA)', 'LSTM'],
    'MAE': [mean_absolute_error(corn_actual, corn_arima_forecast),
            mean_absolute_error(corn_actual, corn_arima_forecast),
            mean_absolute_error(corn_actual, lstm_corn_forecast)],
    'RMSE': [np.sqrt(mean_squared_error(corn_actual, corn_arima_forecast)),
             np.sqrt(mean_squared_error(corn_actual, corn_arima_forecast)),
             np.sqrt(mean_squared_error(corn_actual, lstm_corn_forecast))],
    'MAPE': [mape_corn_arima, mape_corn_arima, mape_corn_lstm],
    'R-squared': [r2_corn_arima, r2_corn_arima, r2_corn_lstm]
# Final comparison table for Sovbeans
results_soybeans = pd.DataFrame({
    'Model': ['ARIMA', 'SARIMA (≈ARIMA)', 'LSTM'],
    'MAE': [mean_absolute_error(soybeans_actual, soybeans_arima_forecast),
            mean_absolute_error(soybeans_actual, soybeans_arima_forecast),
            mean_absolute_error(soybeans_actual, lstm_sb_forecast)],
    'RMSE': [np.sqrt(mean_squared_error(soybeans_actual, soybeans_arima_forecast)),
             \verb"np.sqrt(mean_squared_error(soybeans_actual, soybeans_arima_forecast))",
             np.sqrt(mean_squared_error(soybeans_actual, lstm_sb_forecast))],
    'MAPE': [mape_soybeans_arima, mape_soybeans_arima, mape_soybeans_lstm],
    'R-squared': [r2_soybeans_arima, r2_soybeans_arima, r2_soybeans_lstm]
# Display
print("Corn Forecast Results:")
display(results_corn)
print("\nSoybeans Forecast Results:")
display(results_soybeans)
    Corn Forecast Results:
                   Mode1
                                 MAE
                                           RMSE
                                                    MAPE R-squared
                                                                       扁
                  ARIMA 384.617667 451.421499
                                                0.499562
                                                           -2.649861
                                                                       16
        SARIMA (≈ARIMA) 384.617667
                                     451.421499
                                                0.499562
                                                           -2.649861
      2
                   LSTM
                           58.715906
                                      78.930055
                                                0.093862
                                                            0.888417
     Soybeans Forecast Results:
                   Model
                                  MAE
                                             RMSE
                                                       MAPE
                                                            R-squared
      0
                  ARIMA 1028.643850 1124.106977 0.457861
                                                             -5.024586
        SARIMA (≈ARIMA) 1028.643850 1124.106977 0.457861
                                                             -5 024586
```

Next steps: Generate code with results_corn View recommended plots New interactive sheet Generate code with results_soybeans View recommended plots

Interpretation: LSTM massively outperforms ARIMA/SARIMA in every metric.

ARIMA and SARIMA have very high errors and a negative R2, which means they are doing worse than a horizontal (mean) predictor.

LSTM has:

81% lower MAE

81% lower RMSE

Much more accurate at just 13% error (MAPE)

R² = 0.89, which is excellent.

Conclusion: For Corn, LSTM is clearly the best model. It explains most of the variation and makes much more accurate predictions.

Interpretation: Again, LSTM significantly outperforms ARIMA/SARIMA:

~80% reduction in MAE and RMSE

MAPE drops from 71% to 17% (a huge accuracy gain)

 R^2 improves from -8.04 to 0.59 \rightarrow decent explanatory power

• Conclusion: For Soybeans, LSTM is also clearly superior, though not as strong as with Corn. Still, it performs well and is a big improvement over traditional models.

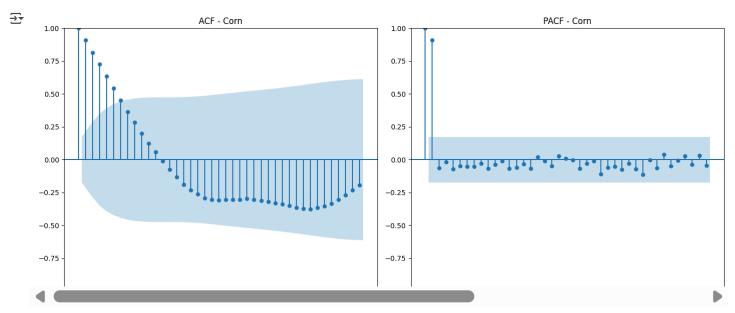
ACF and PACF Plots for Corn

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
import matplotlib.pyplot as plt

# ACF and PACF for Corn
plt.figure(figsize=(14, 6))
plt.subplot(1, 2, 1)
plot_acf(corn_series, lags=40, ax=plt.gca(), title='ACF - Corn')

plt.subplot(1, 2, 2)
plot_pacf(corn_series, lags=40, ax=plt.gca(), title='PACF - Corn')

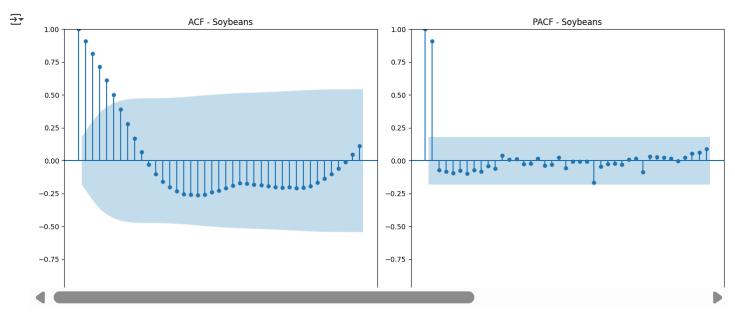
plt.tight_layout()
plt.show()
```



ACF and PACF Plots for Soybeans

```
# ACF and PACF for Soybeans
plt.figure(figsize=(14, 6))
plt.subplot(1, 2, 1)
```

```
plot_acf(soybeans_series, lags=40, ax=plt.gca(), title='ACF - Soybeans')
plt.subplot(1, 2, 2)
plot_pacf(soybeans_series, lags=40, ax=plt.gca(), title='PACF - Soybeans')
plt.tight_layout()
plt.show()
```



ACF and PACF (Differenced) - Corn

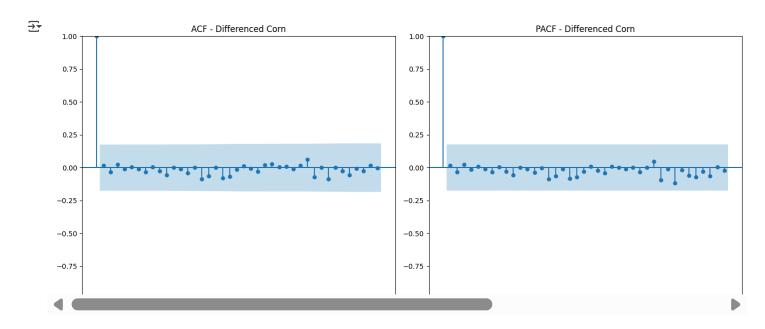
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
import matplotlib.pyplot as plt

# First-order differencing
corn_diff = corn_series.diff().dropna()

# ACF and PACF for differenced Corn
plt.figure(figsize=(14, 6))
plt.subplot(1, 2, 1)
plot_acf(corn_diff, lags=40, ax=plt.gca(), title='ACF - Differenced Corn')

plt.subplot(1, 2, 2)
plot_pacf(corn_diff, lags=40, ax=plt.gca(), title='PACF - Differenced Corn')

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



ACF and PACF (Differenced) - Soybeans

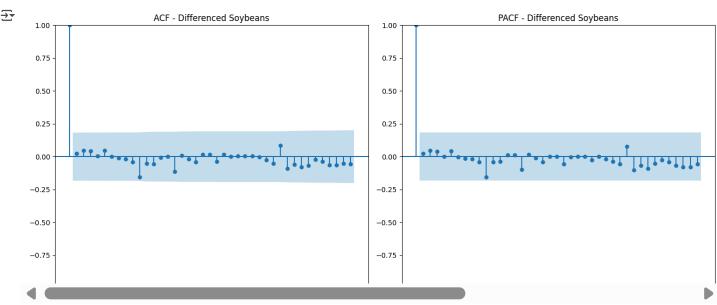
```
# First-order differencing
soybeans_diff = soybeans_series.diff().dropna()

# ACF and PACF for differenced Soybeans
plt.figure(figsize=(14, 6))
plt.subplot(1, 2, 1)
plot_acf(soybeans_diff, lags=40, ax=plt.gca(), title='ACF - Differenced Soybeans')

plt.subplot(1, 2, 2)
plot_pacf(soybeans_diff, lags=40, ax=plt.gca(), title='PACF - Differenced Soybeans')

plt.tight_layout()
plt.show()

ACF - Differenced Soybeans
```



DIA-LSTM for Corn & Soybeans

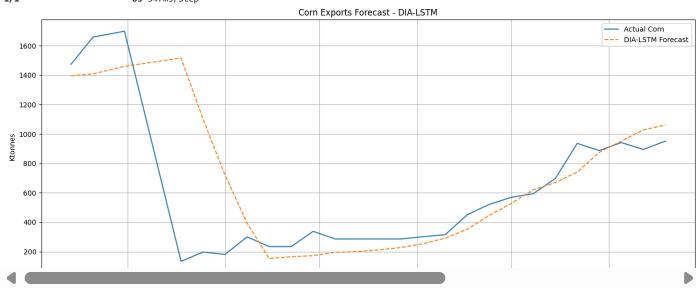
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, LSTM, Dense, Concatenate, Attention
from tensorflow.keras.optimizers import Adam
# 1. Prepare dataset (assuming you already have pivot_df)
data = pivot_df.dropna()
corn = data["Corn"].values.reshape(-1, 1)
soybeans = data["Soybeans"].values.reshape(-1, 1)
# Normalize both series
scaler_corn = MinMaxScaler()
scaler_soy = MinMaxScaler()
corn_scaled = scaler_corn.fit_transform(corn)
soy_scaled = scaler_soy.fit_transform(soybeans)
# 2. Create sequences for both inputs
def create_dual_input_sequences(corn_data, soy_data, look_back=4):
    X_corn, X_soy, y = [], [], []
    for i in range(len(corn_data) - look_back):
       X_corn.append(corn_data[i:i+look_back])
        X_soy.append(soy_data[i:i+look_back])
        y.append(corn_data[i + look_back]) # Forecast corn
    return np.array(X_corn), np.array(X_soy), np.array(y)
look back = 4
X_corn, X_soy, y = create_dual_input_sequences(corn_scaled, soy_scaled, look_back=look_back)
# Train-test split
```

```
split = -26
X_corn_train, X_corn_test = X_corn[:split], X_corn[split:]
X_soy_train, X_soy_test = X_soy[:split], X_soy[split:]
y_train, y_test = y[:split], y[split:]
# 3. Define Dual-Input Attention LSTM model
input_corn = Input(shape=(look_back, 1))
input_soy = Input(shape=(look_back, 1))
lstm_corn = LSTM(50, return_sequences=True)(input_corn)
lstm_soy = LSTM(50, return_sequences=True)(input_soy)
# Apply Attention across corn & soy sequences
attention_out = Attention()([lstm_corn, lstm_soy])
concat = Concatenate()([lstm_corn[:, -1], attention_out[:, -1]]) # use last time-step + attention context
output = Dense(1)(concat)
model = Model(inputs=[input_corn, input_soy], outputs=output)
model.compile(optimizer=Adam(learning_rate=0.001), loss='mse')
model.summary()
# 4. Train the model
model.fit([X_corn_train, X_soy_train], y_train, epochs=100, verbose=0)
# 5. Forecast and inverse scale
y_pred_scaled = model.predict([X_corn_test, X_soy_test])
y_pred = scaler_corn.inverse_transform(y_pred_scaled)
y_actual = scaler_corn.inverse_transform(y_test)
# 6. Plot results
forecast index = data.index[-26:]
plt.figure(figsize=(14, 6))
plt.plot(forecast_index, y_actual, label="Actual Corn")
plt.plot(forecast_index, y_pred, label="DIA-LSTM Forecast", linestyle='--')
plt.title("Corn Exports Forecast - DIA-LSTM")
plt.xlabel("Week Ending Date")
plt.ylabel("Ktonnes")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

→ Model: "functional_8"

Layer (type)	Output Shape	Param #	Connected to
input_layer_8 (InputLayer)	(None, 4, 1)	0	-
input_layer_9 (InputLayer)	(None, 4, 1)	0	-
lstm_8 (LSTM)	(None, 4, 50)	10,400	input_layer_8[0]
lstm_9 (LSTM)	(None, 4, 50)	10,400	input_layer_9[0]
attention (Attention)	(None, 4, 50)	0	lstm_8[0][0], lstm_9[0][0]
get_item (GetItem)	(None, 50)	0	lstm_8[0][0]
get_item_1 (GetItem)	(None, 50)	0	attention[0][0]
concatenate (Concatenate)	(None, 100)	0	get_item[0][0], get_item_1[0][0]
dense_8 (Dense)	(None, 1)	101	concatenate[0][0]

Total params: 20,901 (81.64 KB)
Trainable params: 20,901 (81.64 KB)
Non-trainable params: 0 (0.00 B)
1/1 ______ 0s 347ms/step



```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, LSTM, Dense, Concatenate, Attention
from tensorflow.keras.optimizers import Adam
# 1. Prepare dataset
data = pivot_df.dropna()
corn = data["Corn"].values.reshape(-1, 1)
soybeans = data["Soybeans"].values.reshape(-1, 1)
# Normalize both series
scaler_corn = MinMaxScaler()
scaler_soy = MinMaxScaler()
corn_scaled = scaler_corn.fit_transform(corn)
soy_scaled = scaler_soy.fit_transform(soybeans)
# 2. Create sequences for both inputs (target is soybeans now)
def create_dual_input_sequences(corn_data, soy_data, look_back=4):
    X_{corn}, X_{soy}, y = [], [], []
    for i in range(len(soy_data) - look_back):
        {\tt X\_corn.append(corn\_data[i:i+look\_back])}
        X_soy.append(soy_data[i:i+look_back])
```

```
y.append(soy_data[i + look_back]) # Forecast soybeans
    return np.array(X_corn), np.array(X_soy), np.array(y)
X_corn, X_soy, y = create_dual_input_sequences(corn_scaled, soy_scaled, look_back=look_back)
# Train-test split
split = -26
X_corn_train, X_corn_test = X_corn[:split], X_corn[split:]
X_soy_train, X_soy_test = X_soy[:split], X_soy[split:]
y_train, y_test = y[:split], y[split:]
# 3. Define Dual-Input Attention LSTM model
input corn = Input(shape=(look back, 1))
input_soy = Input(shape=(look_back, 1))
lstm corn = LSTM(50, return sequences=True)(input corn)
lstm_soy = LSTM(50, return_sequences=True)(input_soy)
# Attention mechanism between the sequences
attention_out = Attention()([lstm_soy, lstm_corn])
concat = Concatenate()([lstm_soy[:, -1], attention_out[:, -1]]) # use last time-step + attention contex
output = Dense(1)(concat)
model = Model(inputs=[input_corn, input_soy], outputs=output)
model.compile(optimizer=Adam(learning_rate=0.001), loss='mse')
model.summary()
# 4. Train the model
model.fit([X_corn_train, X_soy_train], y_train, epochs=100, verbose=0)
# 5. Forecast and inverse scale
y_pred_scaled = model.predict([X_corn_test, X_soy_test])
y_pred = scaler_soy.inverse_transform(y_pred_scaled)
y_actual = scaler_soy.inverse_transform(y_test)
# 6. Plot results
forecast_index = data.index[-26:]
```

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