Project No# 02

Market Price Prediction

SUBMITTED BY: SYED IRTIZA ABBAS ZAIDI

Market Price Prediction

- Developing a time series machine learning model for forecasting market trends.
- Predicting commodity quantities and prices for future months.

Objective

- Develop a robust time series machine learning model.
- Forecast market trends based on historical data.
- Enable proactive decision-making for stakeholders regarding production, procurement, pricing strategies, and resource allocation.

Data Description

- **Columns:**
  - **market:** Market or commodity.
  - **month:** Month of recorded data.
  - **year:** Year of recorded data.
  - **quantity:** Commodity traded/available.
  - **priceMin:** Minimum price during the month.
  - **priceMax:** Maximum price during the month.
  - **priceMod:** Mode price during the month.
  - **state:** State or region of the market.
  - **city:** City of the market.
  - **date:** Specific date of recorded data.

Data Preprocessing

- **Import Libraries:** pandas, numpy, matplotlib, seaborn, sklearn, etc.
- **Load Data:** Read CSV file.
- **Data Cleaning:**
  - Convert date to datetime format and set as index.
  - Handle missing values and duplicates.
  - Encode categorical variables using LabelEncoder.
  - Resample data to monthly frequency.

```python
# Importing Libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from scipy.stats import zscore
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.preprocessing import MinMaxScaler
import tensorflow
from keras.models import Sequential
from keras.layers import LSTM, Dense
from statsmodels.tsa.seasonal import seasonal_decompose
from sklearn.metrics import mean_absolute_error, mean_squared_error

# Ensure that plots are displayed inline within the Jupyter Notebook
%matplotlib inline

import warnings

# Ignore warnings
warnings.filterwarnings('ignore')
```

✓ 2m 58.7s

Data Preprocessing

- **Load the "Market Price Prediction" Dataset:**

```
# Load the "Market Price Prediction" Dataset
df = pd.read_csv("MarketPricePrediction.csv")
```

✓ 0.7s

```
df.head()
```

✓ 0.2s

	market	month	year	quantity	priceMin	priceMax	priceMod	state	city	date
0	ABOHAR(PB)	January	2005	2350	404	493	446	PB	ABOHAR	January-2005
1	ABOHAR(PB)	January	2006	900	487	638	563	PB	ABOHAR	January-2006
2	ABOHAR(PB)	January	2010	790	1283	1592	1460	PB	ABOHAR	January-2010
3	ABOHAR(PB)	January	2011	245	3067	3750	3433	PB	ABOHAR	January-2011
4	ABOHAR(PB)	January	2012	1035	523	686	605	PB	ABOHAR	January-2012

Data Preprocessing

- **Information of Dataset:**

```
# Information of dataset:
df.info()
```

✓ 0.3s

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10227 entries, 0 to 10226
Data columns (total 10 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   market    10227 non-null  object
 1   month     10227 non-null  object
 2   year      10227 non-null  int64
 3   quantity  10227 non-null  int64
 4   priceMin  10227 non-null  int64
 5   priceMax  10227 non-null  int64
 6   priceMod  10227 non-null  int64
 7   state     10227 non-null  object
 8   city      10227 non-null  object
 9   date      10227 non-null  object
dtypes: int64(5), object(5)
memory usage: 799.1+ KB
```

Data Preprocessing

- **Convert "date" column to datetime format:**

```
# Convert "date" column to datetime format
df['date'] = pd.to_datetime(df['date'])
```
0.5s

- **Set "date" column as the index:**

```
# Set "date" column as the index
df.set_index('date', inplace=True)
```
0.0s

- **Now "date" column is the index:**

```
# Now "date" column is the index
df.head()
```
0.1s

	market	month	year	quantity	priceMin	priceMax	priceMod	state	city
date									
2005-01-01	ABOHAR(PB)	January	2005	2350	404	493	446	PB	ABOHAR
2006-01-01	ABOHAR(PB)	January	2006	900	487	638	563	PB	ABOHAR
2010-01-01	ABOHAR(PB)	January	2010	790	1283	1592	1460	PB	ABOHAR
2011-01-01	ABOHAR(PB)	January	2011	245	3067	3750	3433	PB	ABOHAR
2012-01-01	ABOHAR(PB)	January	2012	1035	523	686	605	PB	ABOHAR

Data Preprocessing

- **Summary Statisics:**

```python
# Summary Statisics:
df.describe()
```

0.4s

	year	quantity	priceMin	priceMax	priceMod
count	10227.000000	1.022700e+04	10227.000000	10227.000000	10227.000000
mean	2009.022294	7.660488e+04	646.944363	1212.760731	984.284345
std	4.372841	1.244087e+05	673.121850	979.658874	818.471498
min	1996.000000	2.000000e+01	16.000000	145.000000	80.000000
25%	2006.000000	8.898000e+03	209.000000	557.000000	448.000000
50%	2009.000000	2.746000e+04	440.000000	923.000000	747.000000
75%	2013.000000	8.835650e+04	828.000000	1527.000000	1248.000000
max	2016.000000	1.639032e+06	6000.000000	8192.000000	6400.000000

- **Handling missing values & Check for missing values:**

```python
# Handling missing values & Check for missing values
missing_values = df.isnull().sum()
print("Missing Values:\n", missing_values)
```

0.0s

```
Missing Values:
 market      0
month       0
year        0
quantity    0
priceMin    0
priceMax    0
priceMod    0
state       0
city        0
dtype: int64
```

Data Preprocessing

- **Encoding categorical variables:**

```
# Encode categorical variables
label_encoder = LabelEncoder()
df['market'] = label_encoder.fit_transform(df['market'])
df['state'] = label_encoder.fit_transform(df['state'])
df['city'] = label_encoder.fit_transform(df['city'])
```
✓ 0.0s

- **Select numeric columns for resampling:**

```
# Select numeric columns for resampling
numeric_columns = df.select_dtypes(include=[np.number]).columns
monthly_data = df[numeric_columns].resample('M').mean()
```
✓ 0.5s

Exploratory Data Analysis (EDA)

- **Price Trends:** Plot priceMin, priceMax, and priceMod over time.
- **Quantity Trends:** Plot quantity over time.
- **Time Series Decomposition:**
  - Decompose quantity into trend, seasonal, and residual components.
  - Identify monthly seasonality and residuals.

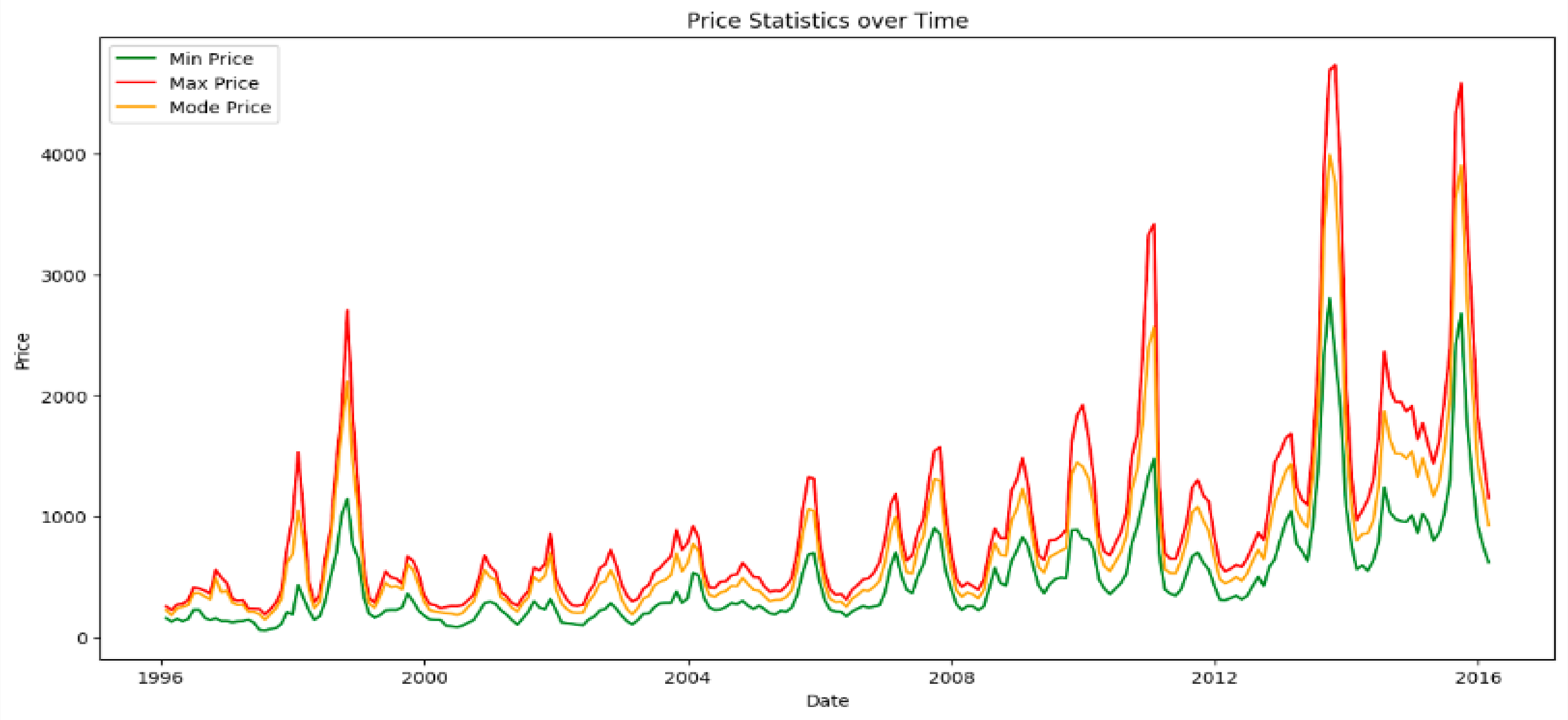
- **Scatter Plots:**
  - Quantity vs priceMin.
  - Quantity vs priceMod.
  - Quantity vs priceMax.
- **Anomaly Detection:**
  - Use Z-score for detecting anomalies in quantity.
  - Highlight anomalies on time series plot.

Exploratory Data Analysis (EDA)

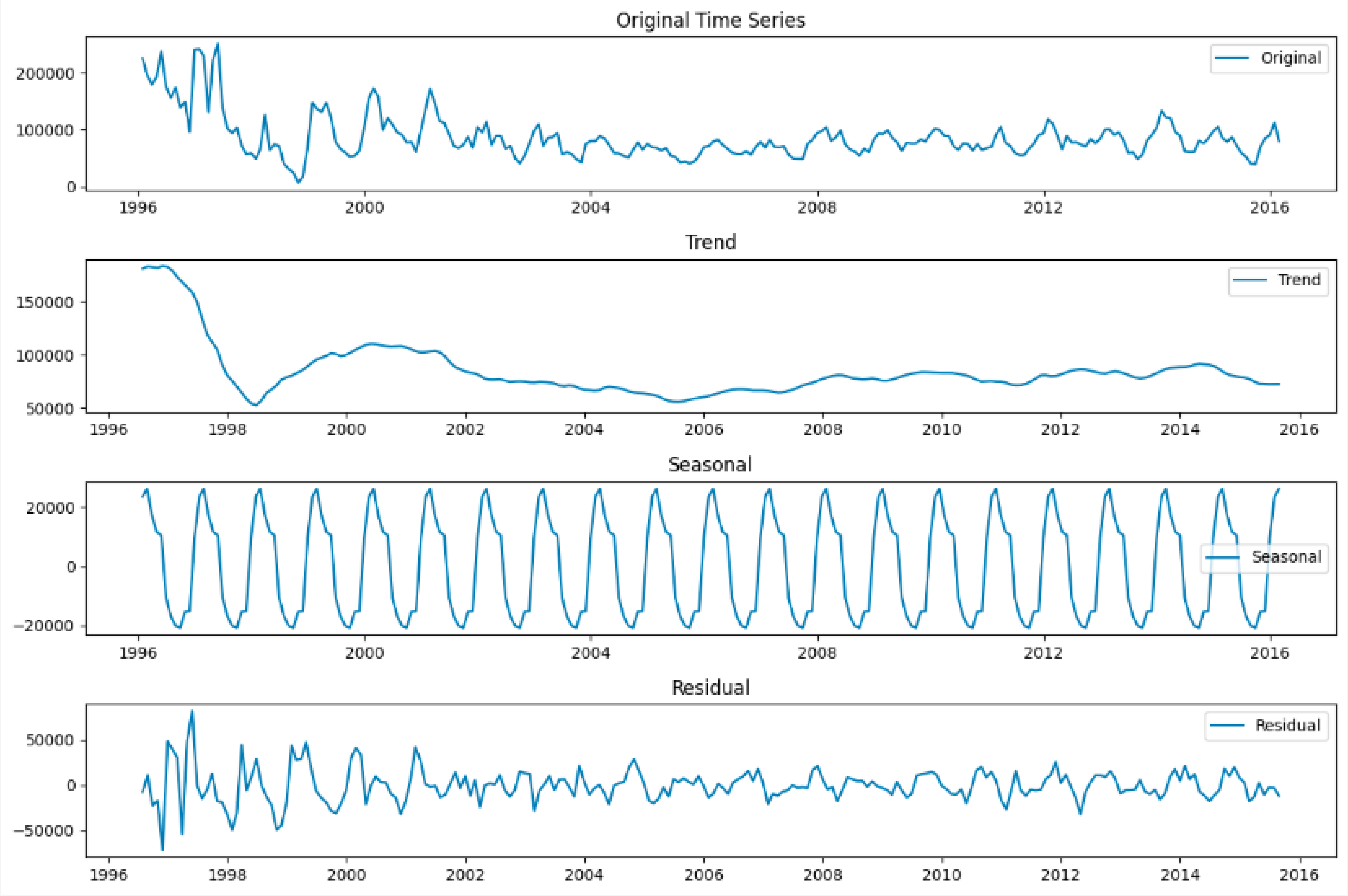
- **Plotting the price statistics over time:**

```
# Plotting the price statistics over time
plt.figure(figsize=(14, 7))
plt.plot(monthly_data['priceMin'], label='Min Price', color='green')
plt.plot(monthly_data['priceMax'], label='Max Price', color='red')
plt.plot(monthly_data['priceMod'], label='Mode Price', color='orange')
plt.title('Price Statistics over Time')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()
plt.show()
```

✓ 1.7s



Exploratory Data Analysis (EDA)



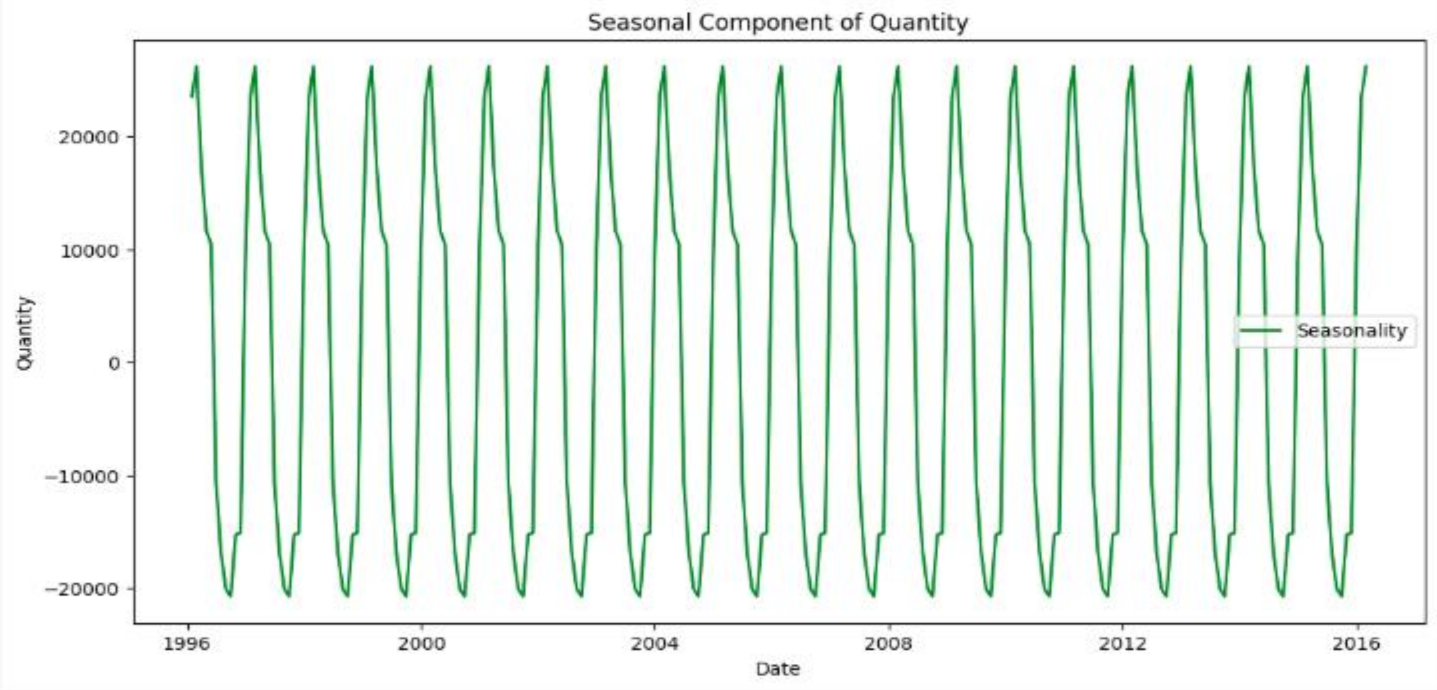
Exploratory Data Analysis (EDA)

- **Identify seasonality**

Monthly Seasonality - Quantity:

```
# Monthly Seasonality - Quantity
plt.figure(figsize=(12, 6))
plt.plot(seasonal, label='Seasonality', color='green')
plt.title('Seasonal Component of Quantity')
plt.xlabel('Date')
plt.ylabel('Quantity')
plt.legend()
plt.show()
```

✓ 0.5s

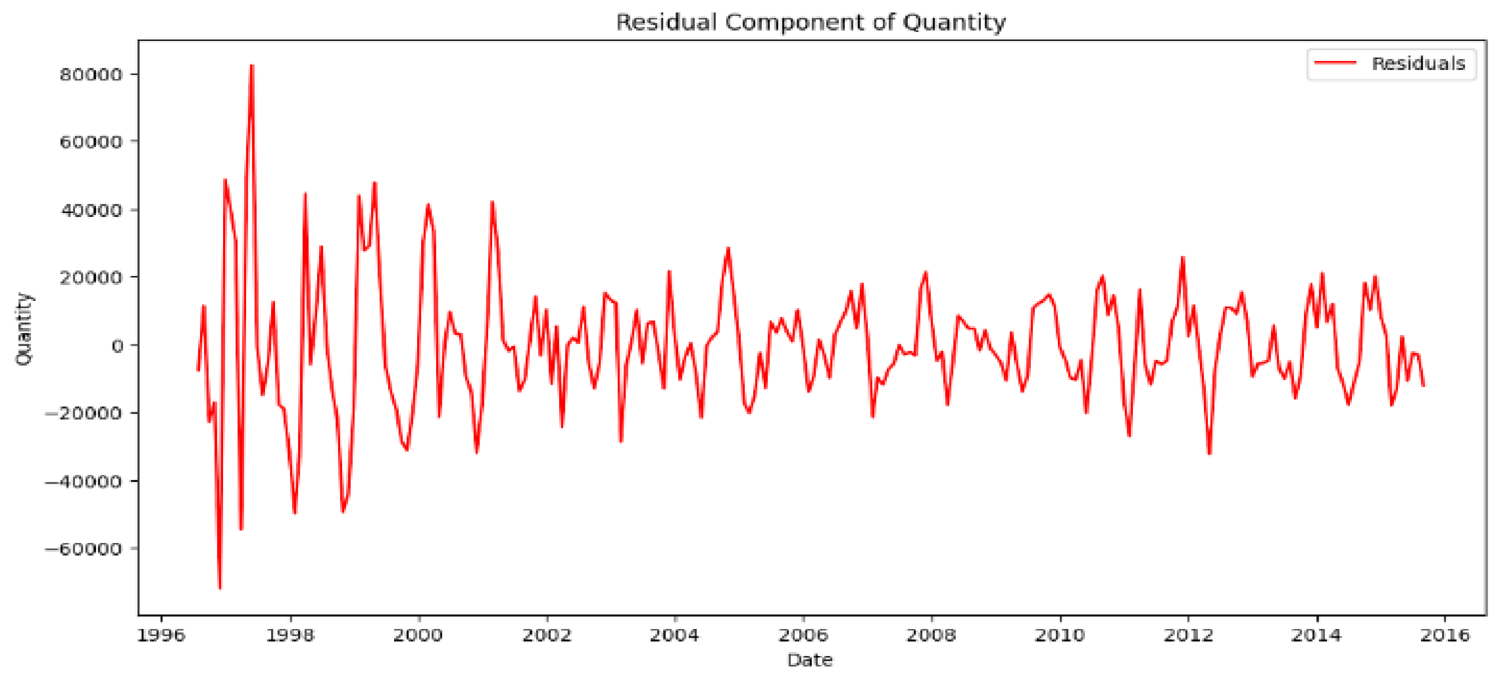


Exploratory Data Analysis (EDA)

- **Explore Residuals:**

```python
# Residual Component of Quantity
plt.figure(figsize=(12, 6))
plt.plot(residual, label='Residuals', color='red')
plt.title('Residual Component of Quantity')
plt.xlabel('Date')
plt.ylabel('Quantity')
plt.legend()
plt.show()
```

✓ 0.5s



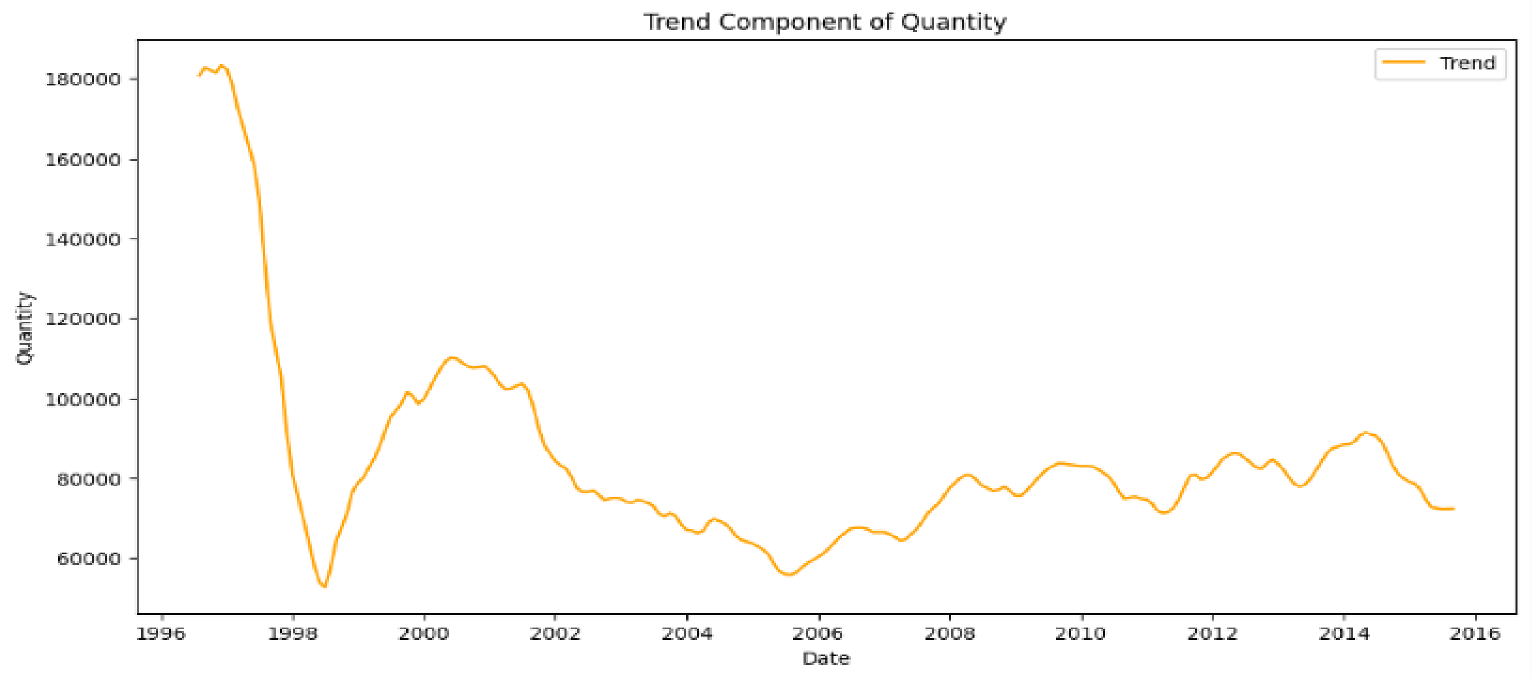
Exploratory Data Analysis (EDA)

- **Explore Trends:**

Trends Component of Quantity:

```
# Trends Component of Quantity
plt.figure(figsize=(12, 6))
plt.plot(trend, label='Trend', color='orange')
plt.title('Trend Component of Quantity')
plt.xlabel('Date')
plt.ylabel('Quantity')
plt.legend()
plt.show()
```

✓ 0.8s



Exploratory Data Analysis (EDA)

- **Z-score for Anomaly Detection:**

```
# Z - Score for Anomaly Detection
df['quantity_zscore'] = zscore(df['quantity'])
anomalies = df[np.abs(df['quantity_zscore']) > 3]
print("Anomalies based on Z-score:")
anomalies.head()
```

✓ 0.2s

```
Anomalies based on Z-score:
```

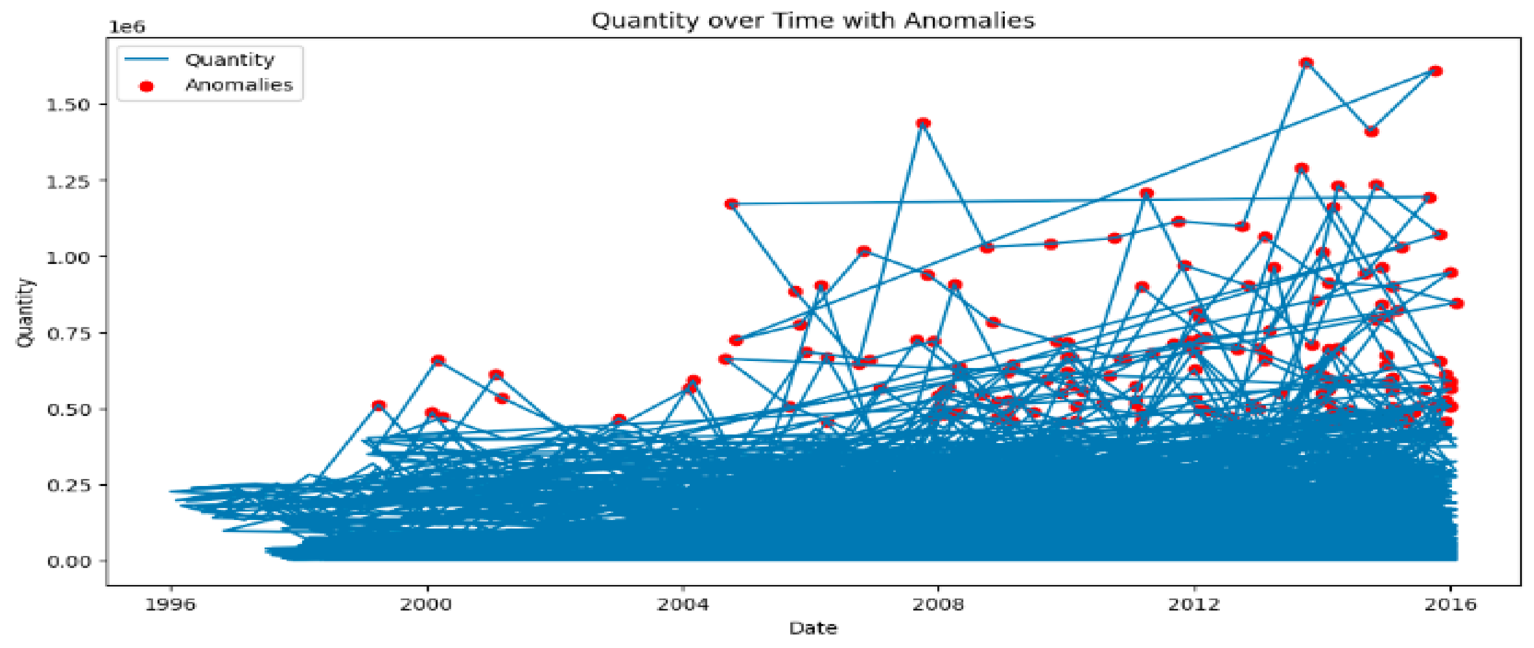
	market	month	year	quantity	priceMin	priceMax	priceMod	state	city	quantity_zscore
date										
2014-03-01	3	March	2014	453107	100	960	598	14	3	3.026481
2014-12-01	3	December	2014	474988	127	2249	1175	14	3	3.202369
2012-01-01	9	January	2012	531906	161	736	583	12	9	3.659900
2014-01-01	9	January	2014	606710	404	1296	1094	12	9	4.261206
2015-01-01	9	January	2015	583681	313	1967	1602	12	9	4.076089

Exploratory Data Analysis (EDA)

- **Plot Anomalies:**
  - Highlight anomalies on the time series plot.

```
# Plot Anomalies:
# Highlight anomalies on the time series plot.
plt.figure(figsize=(12, 6))
plt.plot(df['quantity'], label='Quantity')
plt.scatter(anomalies.index, anomalies['quantity'], color='red', label='Anomalies')
plt.title('Quantity over Time with Anomalies')
plt.xlabel('Date')
plt.ylabel('Quantity')
plt.legend()
plt.show()
```

✓ 0.9s



Feature Engineering

- **Lagged Variables:** Create lagged features for quantity and priceMod.
- **Rolling Statistics:** Create rolling mean features for quantity and priceMod.
- **Seasonal Indicators:** Create indicators based on month and quarter.
- **Handling NaNs:** Drop rows with NaN values resulting from lagged variables and rolling statistics.

Feature Engineering

- Creating relevant features such as lagged variables, rolling statistics, and seasonal indicators.

```python
# Lagged variables
# Create lagged variables for 'quantity' and 'priceMod'
lags = [1, 3, 6, 12]  # Define the lag periods
for lag in lags:
    df[f'quantity_lag_{lag}'] = df['quantity'].shift(lag)
    df[f'priceMod_lag_{lag}'] = df['priceMod'].shift(lag)

# Rolling statistics
# Create rolling statistics for 'quantity' and 'priceMod'
windows = [3, 6, 12]  # Define the window sizes
for window in windows:
    df[f'quantity_roll_mean_{window}'] = df['quantity'].rolling(window=window).mean()
    df[f'priceMod_roll_mean_{window}'] = df['priceMod'].rolling(window=window).mean()

# Seasonal indicators
# Create seasonal indicators based on month or quarter
df['month'] = df.index.month
df['quarter'] = df.index.quarter
data = pd.get_dummies(df, columns=['month', 'quarter'], drop_first=True)

# Drop rows with NaN values resulting from lagged variables and rolling statistics
df.dropna(inplace=True)

# Print the first few rows of the dataset with engineered features
print("Dataset with Engineered Features.")
df.head()
```

✓ 0.3s

```
Dataset with Engineered Features.
```

	market	month	year	quantity	priceMin	priceMax	priceMod	state	city	quantity_zscore	...	priceMod_lag_6	quantity_lag_12	priceMod_lag_12	quantity_roll_mean_3	priceMod_roll_mean_3	quantity_roll_mean_6	priceMod_roll_mean_6	quantity_roll_mean_12	priceMod_roll_mean_12	q
date																					
2012-02-01	0	2	2012	675	510	650	570	16	0	-0.610356	...	1256.0	2350.0	446.0	510.000000	1005.666667	1005.833333	889.000000	843.333333	1188.000000	
2013-02-01	0	2	2013	845	1400	1843	1629	16	0	-0.608989	...	1613.0	900.0	563.0	606.666667	1108.000000	929.166667	891.666667	838.750000	1276.833333	
2014-02-01	0	2	2014	1115	831	1163	983	16	0	-0.606819	...	324.0	790.0	1460.0	878.333333	1060.666667	881.666667	1001.500000	865.833333	1237.083333	
2015-02-01	0	2	2015	1115	1200	1946	1688	16	0	-0.606819	...	380.0	245.0	3433.0	1025.000000	1433.333333	767.500000	1219.500000	938.333333	1091.666667	
2005-03-01	0	3	2005	900	281	357	322	16	0	-0.608547	...	1322.0	1035.0	605.0	1043.333333	997.666667	825.000000	1052.833333	927.083333	1068.083333	

5 rows × 25 columns

Model Selection and Training

- **Data Split:** Split data into training (80%) and testing (20%) sets.
- **Models:**
  - ARIMA: Train with order (5,1,0).
  - SARIMA: Train with order (1,1,1) and seasonal order (1,1,1,12).
  - LSTM: Scale data, create sequences, and train LSTM model.

Model Selection and Training

- Evaluating various time series forecasting models such as ARIMA, SARIMA, Prophet, and LSTM, selecting the most suitable one, and training it on the dataset.
- **Split the data into train and test sets:**

```
# Split the data into train and test sets
train_size = int(len(df) * 0.8)  # 80% train, 20% test
train_data, test_data = df.iloc[:train_size], df.iloc[train_size:]
```

6] ✓ 0.0s

- **ARIMA Model:**

```
# ARIMA model
arima_model = ARIMA(train_data['quantity'], order=(5,1,0))
arima_result = arima_model.fit()
```

7] ✓ 3.2s

+ Code + Markdown

- **SARIMA Model:**

```
# SARIMA model
sarima_model = SARIMAX(train_data['quantity'], order=(1, 1, 1), seasonal_order=(1, 1, 1, 12))
sarima_result = sarima_model.fit()
```

8] ✓ 1m 10.4s

- **LSTM Model:**

```
# LSTM model
scaler = MinMaxScaler()
train_scaled = scaler.fit_transform(train_data[['quantity', 'priceMod']])
test_scaled = scaler.transform(test_data[['quantity', 'priceMod']])
```

9] ✓ 7.1s

Model Selection and Training

```
def create_sequences(df, n_steps):
    X, y = [], []
    for i in range(len(df)):
        end_ix = i + n_steps
        if end_ix > len(df)-1:
            break
        seq_x, seq_y = df[i:end_ix, :], df[end_ix, :]
        X.append(seq_x)
        y.append(seq_y)
    return np.array(X), np.array(y)
```
✓ 0.7s

```
# Define number of time steps
n_steps = 12
X_train, y_train = create_sequences(train_scaled, n_steps)
X_test, y_test = create_sequences(test_scaled, n_steps)
```
✓ 1.8s

```
model = Sequential([
    LSTM(200, activation='relu', input_shape=(X_train.shape[1], X_train.shape[2])),
    Dense(2)
])
model.compile(optimizer='adam', loss='mse')
history = model.fit(X_train, y_train, epochs=100, batch_size=64, validation_data=(X_test, y_test), verbose=0)
```
✓ 30m 36.9s

Model Evaluation

- **Metrics:** Evaluate models using MAE, MSE, and RMSE.
- **ARIMA Model:**
  - MAE: [Value]
  - MSE: [Value]
  - RMSE: [Value]
- **SARIMA Model:**
  - MAE: [Value]
  - MSE: [Value]
  - RMSE: [Value]
- **LSTM Model:**
  - MAE: [Value]
  - MSE: [Value]
  - RMSE: [Value]

Model Evaluation

```
# Evaluate models
arima_predictions = arima_result.forecast(len(test_data))
sarima_predictions = sarima_result.get_forecast(len(test_data)).predicted_mean
lstm_predictions = model.predict(X_test)
```

✓ 4.2s

```
64/64 [==============================] - 2s 13ms/step
```

```
# Check lengths
print("Length of test_data.index:", len(test_data.index))
print("Length of ARIMA predictions:", len(arima_predictions))
print("Length of SARIMA predictions:", len(sarima_predictions))
print("Length of LSTM predictions:", len(lstm_predictions))

# Adjust the test_data.index to match the length of lstm_predictions
adjusted_index = test_data.index[-len(lstm_predictions):]
```

✓ 0.3s

```
Length of test_data.index: 2043
Length of ARIMA predictions: 2043
Length of SARIMA predictions: 2043
Length of LSTM predictions: 2031
```

Model Evaluation

- **Evaluate ARIMA Model:**

```
# Evaluate ARIMA model
arima_mae = mean_absolute_error(test_data['quantity'], arima_predictions)
arima_mse = mean_squared_error(test_data['quantity'], arima_predictions)
arima_rmse = np.sqrt(arima_mse)

print("ARIMA Model:")
print("MAE:", arima_mae)
print("MSE:", arima_mse)
print("RMSE:", arima_rmse)
```

0.3s

```
ARIMA Model:
MAE: 38797.42718695649
MSE: 7624129940.102239
RMSE: 87316.26389225686
```

- **Evaluate SARIMA Model:**

```
# Evaluate SARIMA model
sarima_mae = mean_absolute_error(test_data['quantity'], sarima_predictions)
sarima_mse = mean_squared_error(test_data['quantity'], sarima_predictions)
sarima_rmse = np.sqrt(sarima_mse)

print("SARIMA Model:")
print("MAE:", sarima_mae)
print("MSE:", sarima_mse)
print("RMSE:", sarima_rmse)
```

0.0s

```
SARIMA Model:
MAE: 74191.67578685867
MSE: 14552962529.719612
RMSE: 120635.66027389916
```

Model Evaluation

- **Evaluate LSTM Model:**

```
# Adjust the test_data to match the length of lstm_predictions
adjusted_test_data = test_data[-len(lstm_predictions):]

# Inverse transform the LSTM predictions
lstm_predictions_inverse = scaler.inverse_transform(lstm_predictions)[:, 0]

# Evaluate LSTM model
lstm_mae = mean_absolute_error(adjusted_test_data['quantity'], lstm_predictions_inverse)
lstm_mse = mean_squared_error(adjusted_test_data['quantity'], lstm_predictions_inverse)
lstm_rmse = np.sqrt(lstm_mse)

print(f'LSTM Mean Absolute Error: {lstm_mae}')
print(f'LSTM Mean Squared Error: {lstm_mse}')
print(f'LSTM Root Mean Squared Error: {lstm_rmse}')
```

✓ 0.1s

```
LSTM Mean Absolute Error: 27490.550929969195
LSTM Mean Squared Error: 3383204078.305734
LSTM Root Mean Squared Error: 58165.31679880833
```

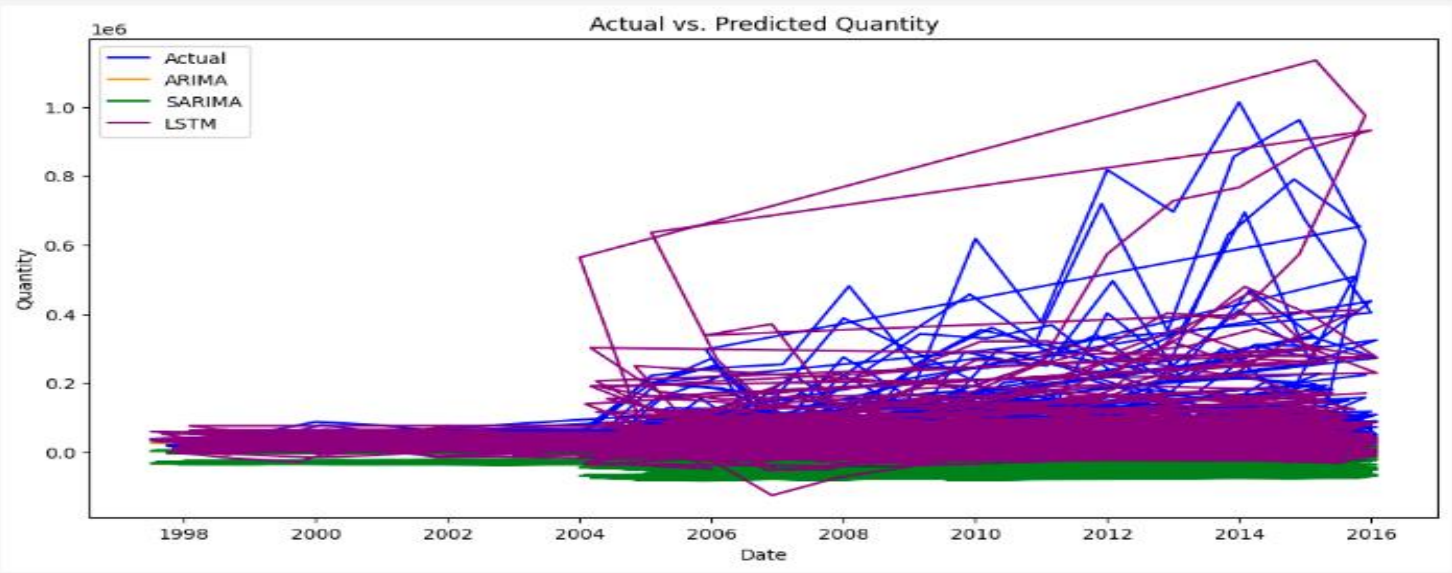
Results and Visualization

- Plot Actual vs. Predicted quantity for **ARIMA**, **SARIMA**, and **LSTM** models.
- Highlight the accuracy and comparison of models.

- **Plot Actual vs. Predicted values:**

```
# Actual vs Prediction values
plt.figure(figsize=(12, 6))
plt.plot(test_data.index, test_data['quantity'], label='Actual', color='blue')
plt.plot(test_data.index, arima_predictions, label='ARIMA', color='orange')
plt.plot(test_data.index, sarima_predictions, label='SARIMA', color='green')
plt.plot(adjusted_index, scaler.inverse_transform(lstm_predictions)[:, 0], label='LSTM', color='purple')
plt.title('Actual vs. Predicted Quantity')
plt.xlabel('Date')
plt.ylabel('Quantity')
plt.legend()
plt.show()
```

✓ 4.5s



Conclusion

- Summary of findings and model performance.
- Importance of the model for stakeholders.
- Future work and potential improvements.

Questions and Discussion

- Open the floor for any questions and discussion points from the audience.

Thank You