

Stock_ARIMA

November 29, 2024

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[269]: import yfinance as yf
import pandas as pd
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.stats.diagnostic import acorr_ljungbox
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from sklearn.metrics import mean_squared_error
from pmdarima import auto_arima
import numpy as np

# Step 1: Fetch Apple stock data
apple_data = yf.download("AAPL", start="2024-08-01", end="2024-11-20")
apple_close = apple_data["Close"]

# Step 2: Train-Test Split
train_size = int(len(apple_close) * 0.90)
train, test = apple_close[:train_size], apple_close[train_size:]

# Plot train and test sets
plt.figure(figsize=(12, 6))
plt.plot(train, label="Train Data")
plt.plot(test, label="Test Data", color="orange")
plt.title("Train-Test Split")
plt.xlabel("Date")
plt.ylabel("Price")
plt.legend()
plt.show()

# Step 3: Option to Apply Exponential Smoothing with Custom Parameters
use_smoothing = True # Set to True to apply exponential smoothing

# Set custom parameters for Exponential Smoothing
alpha = .5 # Smoothing level (overall data)
beta = 0 # Smoothing for the trend
gamma = 0 # Smoothing for seasonality (set None if no seasonality)
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if use_smoothing:
    print("Applying exponential smoothing to the trend...")
    model = ExponentialSmoothing(
        train,
        trend="add",
        seasonal="add",
        seasonal_periods=3
    )
    smoothed_fit = model.fit(smoothing_level=alpha, smoothing_slope=beta,
    ↪smoothing_seasonal=gamma, optimized=False)
    smoothed_train = smoothed_fit.fittedvalues
    print("Exponential Smoothing Parameters:")
    print(f"Alpha (Level): {alpha}, Beta (Trend): {beta}, Gamma (Seasonality):
    ↪{gamma}")
else:
    smoothed_train = train

# Plot smoothed data (if applicable)
if use_smoothing:
    plt.figure(figsize=(12, 6))
    plt.plot(train, label="Original Train Data", color="blue", alpha=0.5)
    plt.plot(smoothed_train, label="Smoothed Train Data", color="red")
    plt.title("Exponential Smoothing Applied to Train Data")
    plt.xlabel("Date")
    plt.ylabel("Price")
    plt.legend()
    plt.show()

# Step 4: Augmented Dickey-Fuller Test with Iterative Differencing
def adf_test(series):
    """Perform Augmented Dickey-Fuller test."""
    result = adfuller(series)
    return result[1] # Return p-value

# Check stationarity and difference iteratively
differenced_train = smoothed_train.copy()
d = 0
while adf_test(differenced_train) > 0.05: # p-value > 0.05 means non-stationary
    print(f"Data is non-stationary (p-value = {adf_test(differenced_train):.
    ↪5f}). Differencing applied.")
    differenced_train = differenced_train.diff().dropna()
    d += 1

print(f"Data is stationary after {d} differencing step(s) (p-value =
    ↪{adf_test(differenced_train):.5f}).")

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# Plot the stationary series
plt.figure(figsize=(12, 6))
plt.plot(differenced_train, label="Stationary Series")
plt.title("Stationary Series After Differencing")
plt.xlabel("Date")
plt.ylabel("Differenced Values")
plt.legend()
plt.show()

# Step 5: ACF and PACF Plots (Stationary Data)
fig, ax = plt.subplots(1, 2, figsize=(15, 5))
plot_acf(differenced_train, ax=ax[0], lags=6, title="ACF (Stationary Data)")
plot_pacf(differenced_train, ax=ax[1], lags=6, title="PACF (Stationary Data)")
plt.tight_layout()
plt.show()

# # Step 6: Use auto_arima for Reference
# print("Running auto_arima to determine optimal parameters...")
# auto_arima_model = auto_arima(
#     smoothed_train,
#     seasonal=True,
#     m=12, # Seasonality period
#     trace=True,
#     error_action="ignore",
#     suppress_warnings=True,
#     stepwise=True
# )
# print(f"Auto ARIMA Results: {auto_arima_model.summary()}")

# Step 7: Fit SARIMA Model (Manual Parameters)
model = SARIMAX(smoothed_train, order=(1, 1, 1), seasonal_order=(1, 1, 2, 3),
    enforce_stationarity=False, enforce_invertibility=False)
sarima_fit = model.fit(dispatch=False)

# Print model summary
print(sarima_fit.summary())

# Step 8: Residual Diagnostics
sarima_fit.plot_diagnostics(figsize=(12, 8))
plt.tight_layout()
plt.show()

# Step 9: Ljung-Box Test
ljung_box_results = acorr_ljungbox(sarima_fit.resid, lags=[10], return_df=True)
print("Ljung-Box Test Results:")
print(ljung_box_results)

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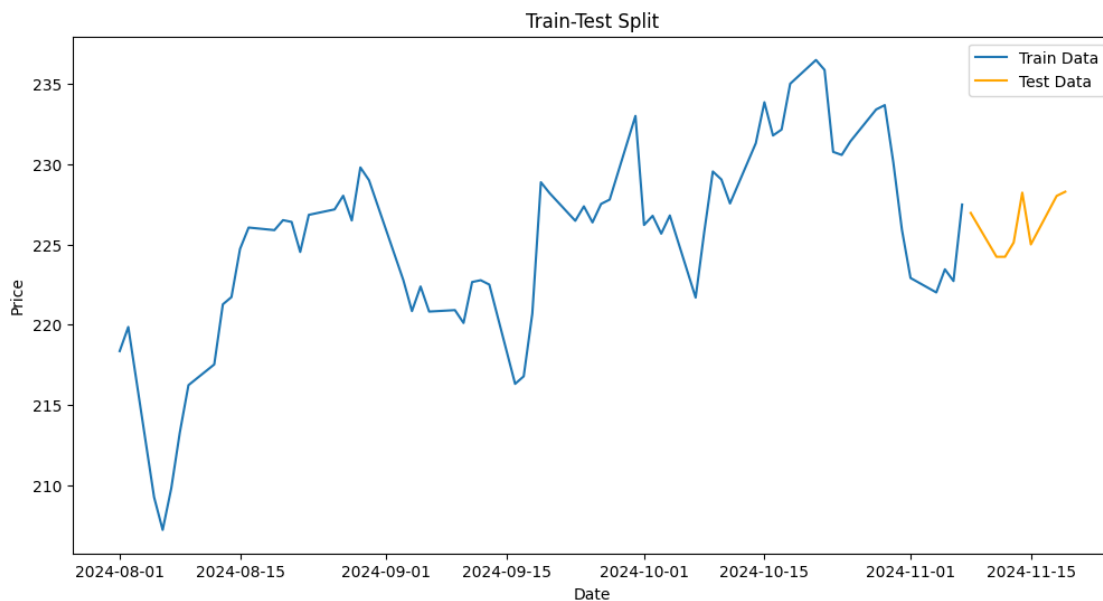
# Step 10: Forecast on Test Data
forecast = sarima_fit.get_forecast(steps=len(test))
forecast_values = forecast.predicted_mean
forecast_ci = forecast.conf_int()

# Plot Actual vs Forecasted
plt.figure(figsize=(12, 6))
plt.plot(train, label="Train Data", color="blue")
plt.plot(test, label="Test Data", color="orange")
plt.plot(test.index, forecast_values, label="Forecast", color="green",
         linestyle="--")
plt.fill_between(test.index, forecast_ci.iloc[:, 0], forecast_ci.iloc[:, 1],
         color="green", alpha=0.2, label="Confidence Interval")
plt.title("Actual vs Forecasted")
plt.xlabel("Date")
plt.ylabel("Price")
plt.legend()
plt.show()

# Step 11: Calculate RMSE
rmse = np.sqrt(mean_squared_error(test, forecast_values))
print(f"RMSE on Test Data: {rmse}")

```

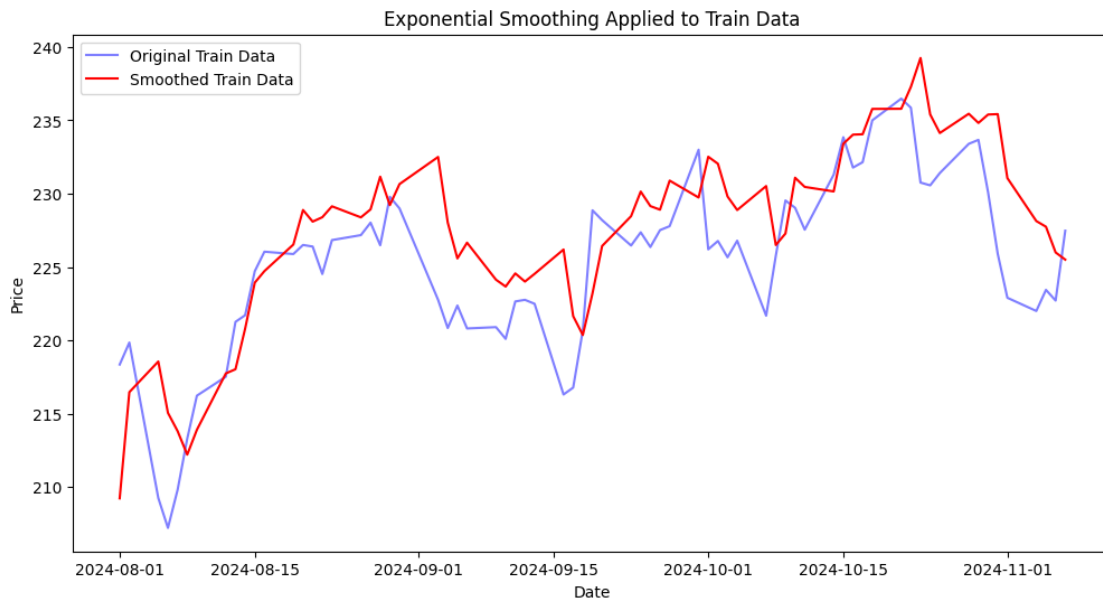
[*****100%*****] 1 of 1 completed



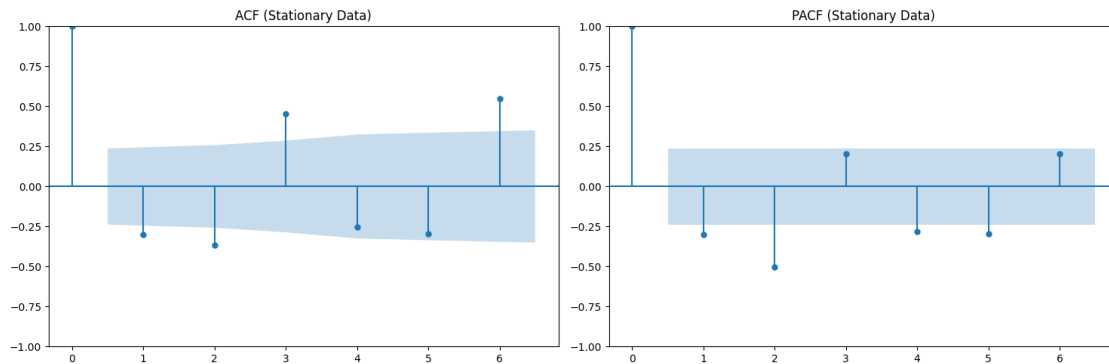
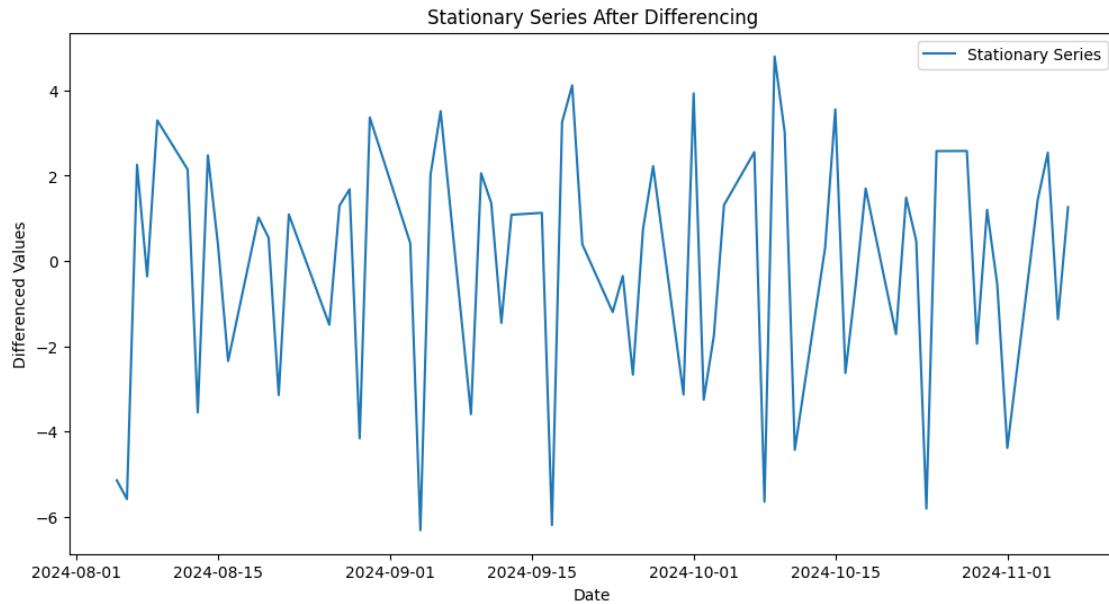
Applying exponential smoothing to the trend...
Exponential Smoothing Parameters:

Alpha (Level): 0.5, Beta (Trend): 0, Gamma (Seasonality): 0

```
/Users/owner/miniconda3/lib/python3.8/site-  
packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has  
been provided, but it has no associated frequency information and so will be  
ignored when e.g. forecasting.  
    self._init_dates(dates, freq)  
/var/folders/gv/mxw7p1nn5_b2n6n_7wkjz2sw0000gn/T/ipykernel_11672/4156310572.py:4  
7: FutureWarning: the 'smoothing_slope' keyword is deprecated, use  
'smoothing_trend' instead.  
    smoothed_fit = model.fit(smoothing_level=alpha, smoothing_slope=beta,  
smoothing_seasonal=gamma, optimized=False)
```



Data is non-stationary (p-value = 0.18252). Differencing applied.
Data is non-stationary (p-value = 0.09948). Differencing applied.
Data is stationary after 2 differencing step(s) (p-value = 0.00380).



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/Users/owner/miniconda3/lib/python3.8/site-
packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has
been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
```

```
self._init_dates(dates, freq)
```

```
/Users/owner/miniconda3/lib/python3.8/site-
packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has
been provided, but it has no associated frequency information and so will be
ignored when e.g. forecasting.
```

```
self._init_dates(dates, freq)
```

SARIMAX Results

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Dep. Variable:

y No. Observations:

70

Model: SARIMAX(1, 1, 1)x(1, 1, [1, 2], 3) Log Likelihood
-104.269

Date: Fri, 29 Nov 2024 AIC
220.537

Time: 14:29:27 BIC
232.900

Sample: 0 HQIC
225.353

- 70
Covariance Type: opg

	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.2821	0.357	0.790	0.430	-0.418	0.982
ma.L1	0.2920	0.327	0.892	0.372	-0.349	0.933
ar.S.L3	-0.5229	0.462	-1.132	0.258	-1.429	0.383
ma.S.L3	-0.6595	1683.565	-0.000	1.000	-3300.386	3299.067
ma.S.L6	-0.3405	573.180	-0.001	1.000	-1123.752	1123.071
sigma2	1.9163	3226.202	0.001	1.000	-6321.323	6325.156

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Ljung-Box (L1) (Q): 0.20 Jarque-Bera (JB):

0.67

Prob(Q): 0.66 Prob(JB):

0.72

Heteroskedasticity (H): 1.00 Skew:

-0.09

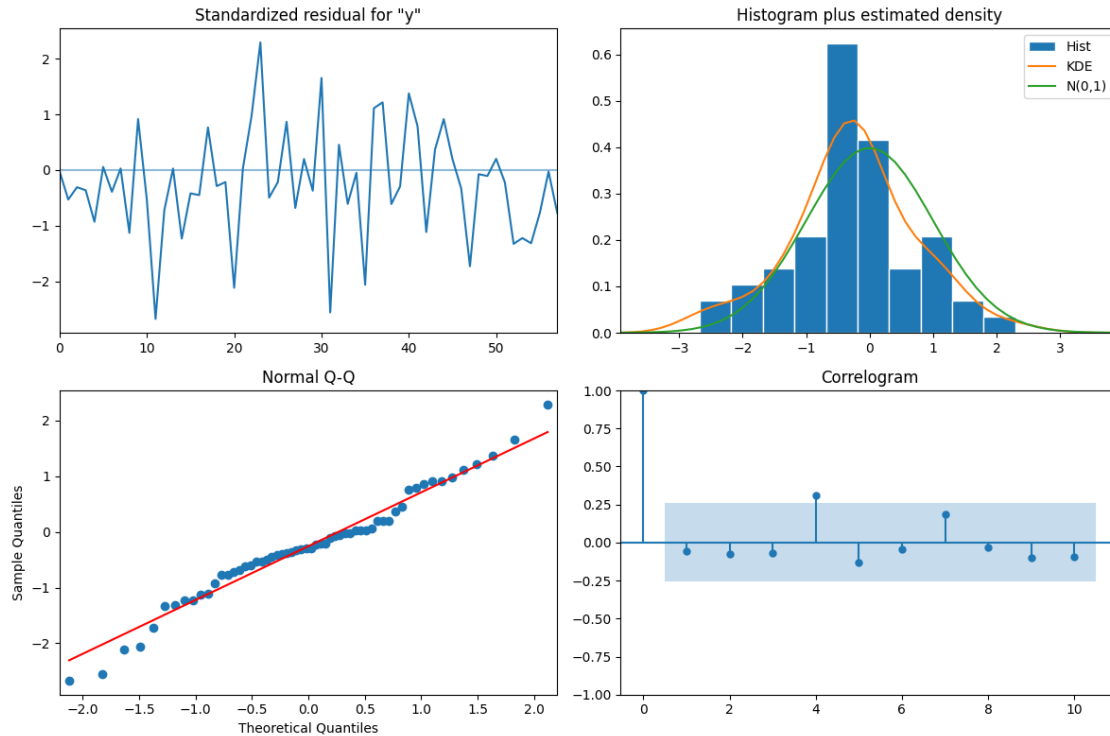
Prob(H) (two-sided): 0.99 Kurtosis:

3.49

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Warnings:

[1] Covariance matrix calculated using the outer product of gradients (complex-step).



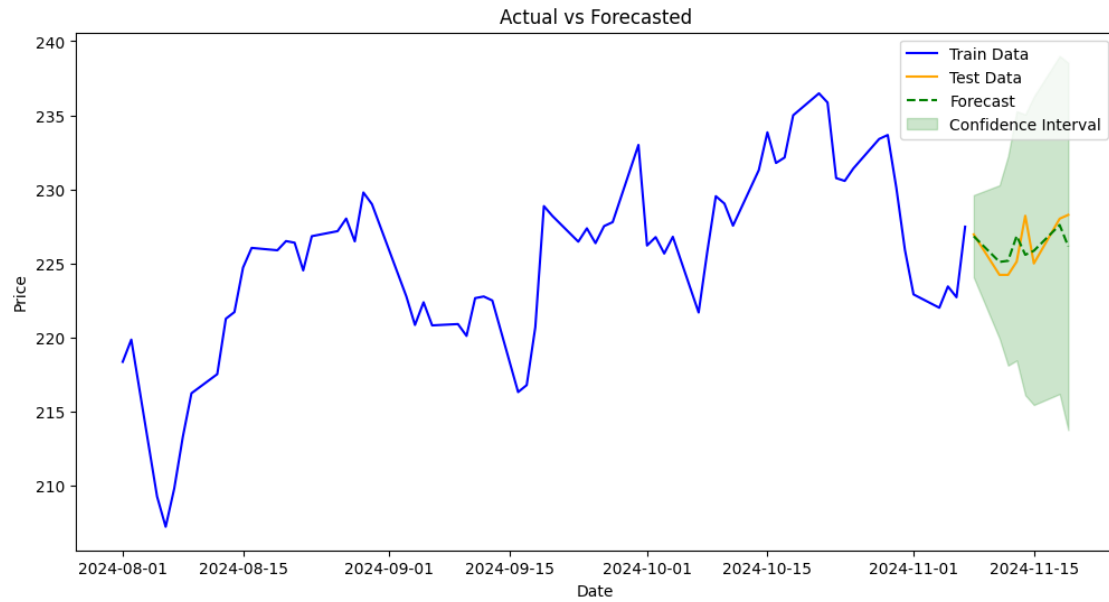
Ljung-Box Test Results:

	lb_stat	lb_pvalue
10	10.10785	0.431083

/Users/owner/miniconda3/lib/python3.8/site-packages/statsmodels/tsa/base/tsa_model.py:836: ValueWarning: No supported index is available. Prediction results will be given with an integer index beginning at `start`.

```
return get_prediction_index(
/Users/owner/miniconda3/lib/python3.8/site-packages/statsmodels/tsa/base/tsa_model.py:836: FutureWarning: No supported index is available. In the next version, calling this method in a model without a supported index will result in an exception.
```

```
return get_prediction_index(
```

RMSE on Test Data: 1.4621220810578681

[]: