Financial Annalytics LA3

April 5, 2025

| Name | Tufan Kundu |
|-------------|--------------------------|
| Reg No. | 24MDT0184 |
| Course Name | Financial Analytics Lab |
| Course Code | PMDS610P |
| Assessment | Lab Digital Assessment 3 |

1 Problem Statement

You are given historical daily closing prices of the NIFTY 50 index from the National Stock Exchange of India (NSE). Your task is to analyze and forecast stock prices using an Regression model with time series error.

1.0.1 Importing the necessary libraries

```
import numpy as np
import pandas as pd
import yfinance as yf
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.arima.model import ARIMA
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_percentage_error
import warnings
warnings.filterwarnings('ignore')
```

```
# -----
# 2.1 Data Preprocessing
# ------
nifty = yf.download("^NSEI", start="2019-01-01", end="2024-01-01")
nifty = nifty[['Close']]
nifty.index = pd.to_datetime(nifty.index)
print("Missing values before handling:", nifty['Close'].isna().sum())
nifty.dropna(inplace=True)
print("Missing values after handling:", nifty['Close'].isna().sum())
```

YF.download() has changed argument auto_adjust default to True

```
[******** 100%********** 1 of 1 completed
   Missing values before handling: Ticker
   ^NSEI
   dtype: int64
   Missing values after handling: Ticker
   ^NSET
   dtype: int64
[4]: # -----
    # 2.2 Stationarity Check
    # -----
    def adf_test(series):
       result = adfuller(series)
       print(f"ADF Statistic: {result[0]:.4f}")
       print(f"p-value: {result[1]:.4f}")
       return result[1]
    p_val = adf_test(nifty['Close'])
    if p_val > 0.05:
       print("Series is non-stationary. Applying first-order differencing...")
       nifty_diff = nifty['Close'].diff().dropna()
       adf_test(nifty_diff)
    else:
       print("Series is stationary.")
       nifty_diff = nifty['Close']
   ADF Statistic: -0.1888
   p-value: 0.9398
   Series is non-stationary. Applying first-order differencing...
   ADF Statistic: -12.2918
   p-value: 0.0000
[5]: # -----
    # 2.3 Model Selection & Training
    # -----
    nifty['Time'] = np.arange(len(nifty))
    split = int(len(nifty) * 0.8)
    train = nifty.iloc[:split]
    test = nifty.iloc[split:]
    X_train = train[['Time']]
    y_train = train['Close']
    X_test = test[['Time']]
    y_test = test['Close']
```

```
lr = LinearRegression()
    lr.fit(X_train, y_train)
    y_pred_train = lr.predict(X_train)
    residuals = y_train - y_pred_train
[6]: # Check stationarity of residuals
    adf_residuals = adfuller(residuals)
    print(f"\nADF Test on Residuals:")
    print(f"ADF Statistic: {adf_residuals[0]}")
    print(f"p-value: {adf_residuals[1]}")
    # Fit ARMA model to residuals (ARIMA with d=0)
    arma_model = ARIMA(residuals, order=(2, 0, 2)).fit()
    print("\nARMA Model Summary:")
    print(arma_model.summary())
   ADF Test on Residuals:
   ADF Statistic: -2.1465498132914145
   p-value: 0.22621307051827794
   ARMA Model Summary:
                                SARIMAX Results
   ______
   Dep. Variable:
                                 ^NSEI No. Observations:
                                                                         985
   Model:
                       ARIMA(2, 0, 2) Log Likelihood
                                                                  -6406.601
   Date:
                     Sat, 05 Apr 2025 AIC
                                                                   12825.201
   Time:
                              15:43:41 BIC
                                                                   12854.557
                                     O HQIC
                                                                   12836.367
   Sample:
                                 - 985
   Covariance Type:
                                                P>|z|
                          std err
                                                           [0.025
                                                                      0.9751
               0.0011 688.632 1.66e-06 1.000 -1349.693 1349.696
0.1253 0.168 0.747 0.455 -0.204 0.454
   const
   ar.L1
   ar.L2
                           0.166
                                     5.199
                                               0.000
               0.8611
                                                           0.536
                                                                      1.186
                            0.171
   ma.L1
                0.8673
                                      5.082
                                               0.000
                                                            0.533
                                                                       1.202
                          0.025 -0.707
693 795 37.653
              -0.0175
   ma.L2
                                               0.480
                                                           -0.066
                                                                       0.031
                                     37.653
             2.612e+04
                                                 0.000
                                                         2.48e+04
                                                                    2.75e+04
   Ljung-Box (L1) (Q):
                                      0.00
                                             Jarque-Bera (JB):
   1446.83
   Prob(Q):
                                      0.98
                                             Prob(JB):
   0.00
   Heteroskedasticity (H):
                                      1.16
                                             Skew:
```

```
-0.92
   Prob(H) (two-sided):
                                  0.18 Kurtosis:
   8.65
   Warnings:
   [1] Covariance matrix calculated using the outer product of gradients (complex-
   step).
[7]: # -----
    # 2.4 Model Evaluation
    # -----
    y_pred_reg = lr.predict(X_test).ravel()
    residuals_forecast = arma_model.forecast(steps=len(X_test))
    y_pred_final = y_pred_reg + residuals_forecast.values
    mse = mean_squared_error(y_test, y_pred_final)
    mape = mean_absolute_percentage_error(y_test, y_pred_final)
    print(f"\nModel Evaluation:")
    print(f"Mean Squared Error (MSE): {mse:.2f}")
    print(f"Mean Absolute Percentage Error (MAPE): {mape * 100:.2f}%")
   Model Evaluation:
   Mean Squared Error (MSE): 590709.10
   Mean Absolute Percentage Error (MAPE): 3.45%
[8]: # -----
    # 2.5 Forecasting Future Prices
    # -----
    future_time = np.arange(len(nifty), len(nifty) + 30).reshape(-1, 1)
    future_reg = lr.predict(future_time).ravel()
    future_resid = arma_model.forecast(steps=30)
    forecast = future_reg + future_resid.values
    forecast_dates = pd.date_range(start=nifty.index[-1] + pd.Timedelta(days=1),_
     →periods=30, freq='B')
    # Display Forecasted Future Prices
    # -----
    forecast_df = pd.DataFrame({
       'Date': forecast_dates,
       'Forecasted_Close_Price': forecast
```

forecast_df.set_index('Date', inplace=True)

})

```
print("\nForecasted NIFTY 50 Closing Prices for the Next 30 Business Days:")
print(forecast_df.round(2))
```

```
Forecasted NIFTY 50 Closing Prices for the Next 30 Business Days:
```

```
Forecasted_Close_Price
Date
2024-01-01
                           20367.45
2024-01-02
                           20373.51
2024-01-03
                           20388.89
2024-01-04
                           20396.16
2024-01-05
                           20410.43
2024-01-08
                           20418.60
2024-01-09
                           20432.04
2024-01-10
                           20440.88
2024-01-11
                           20453.69
2024-01-12
                           20463.03
2024-01-15
                           20475.35
2024-01-16
                           20485.06
2024-01-17
                           20497.00
2024-01-18
                           20506.98
2024-01-19
                           20518.64
2024-01-22
                           20528.82
                           20540.26
2024-01-23
2024-01-24
                           20550.58
2024-01-25
                           20561.84
2024-01-26
                           20572.26
2024-01-29
                           20583.39
2024-01-30
                           20593.88
2024-01-31
                           20604.90
2024-02-01
                           20615.44
                           20626.37
2024-02-02
2024-02-05
                           20636.93
2024-02-06
                           20647.79
                           20658.37
2024-02-07
2024-02-08
                           20669.17
2024-02-09
                           20679.76
# Visualization (Focus on last few weeks)
```

```
[9]: # ------
# Visualization (Focus on last few weeks)
# -------
last_n_days = 60
start_date = nifty.index[-last_n_days]

plt.figure(figsize=(12, 6))
```

```
plt.plot(nifty.index[-last_n_days:], nifty['Close'][-last_n_days:],__
 ⇔label='Historical Prices', color='blue')
plt.plot(test.index[-len(y_pred_final):], y_pred_final, label='Test_□
 ⇔Predictions', color='orange')
plt.plot(forecast_dates, forecast, label='30-Day Forecast', color='green',

slinestyle='--')
plt.xlabel("Date")
plt.ylabel("NIFTY 50 Closing Price")
plt.title("NIFTY 50 Forecasting - Regression with Time Series Error (Last 12_{\sqcup}
 →Weeks)")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.xticks(rotation=45)
plt.xlim(start_date, forecast_dates[-1])
plt.show()
```

