DATS 6313 – Time Series Analysis & Modeling
Instructor: Reza Jafari
Lab #3
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1 – Abstract:

This lab pertains to implementing the Autocorrelation function program using python and applying it to real world data by accessing time series datasets regarding stock value for 6 major companies using the yahoo API.

2 – Introduction:

This experiment was performed to increase understanding of what the autocorrelation metric represents, how to interpret it, and what it looks like visually when plotted amongst the data points.

3 – Method, Theory, and Procedures:

Autocorrelation measures the linear relationship between lagged values of time series. The notation used for autocorrelation is τk which shows the linear relationship between yt and yt−k . Ry (τ) is an estimated autocorrelation for stationary time series y(t). It just depends on the lagged values of time series. The following formula is used to find Ry (τ):

$$\hat{R}_y(\tau) = \frac{\sum_{t=\tau+1}^{T}(y_t - \overline{y})(y_{t-\tau} - \overline{y})}{\sum_{t=1}^{T}(y_t - \overline{y})^2}$$

In the first question, we manually find the autocorrelation of the provided y(t): [3, 9, 27, 81,243] and calculate the ACF for lag 0, 1, 2, 3, and 4 ($ry(0)$, $ry(1)$, $ry(2)$, $ry(3)$, $ry(4)$). Next, we create a function in python to calculate the ACF and plot it accordingly. The following figures represent the functions used to find and plot ACF:

```python
def autocorrelation(x):
    n = len(x)
    variance = x.var()
    x = x - x.mean()
    r = np.correlate(x, x, mode='full')[-n:]
    assert np.allclose(r, np.array([(x[:n - k] * x[-(n - k):]).sum() for k in range(n)]))
    result = r / (variance * (np.arange(n, 0, -1)))
    return result

def autocorrelation_plot(x, lag=1):
    n = len(x)
    variance = x.var()
    x = x - x.mean()
    r = np.correlate(x, x, mode='full')[-n:]
    assert np.allclose(r, np.array([(x[:n - k] * x[-(n - k):]).sum() for k in range(n)]))
    result = r / (variance * (np.arange(n, 0, -1)))

    plt.acorr(result, maxlags = lag)
    plt.title('Autocorrelation')
    plt.ylabel('Magnitude')
    plt.xlabel('Lags')
    plt.grid(True)
    plt.show()
```

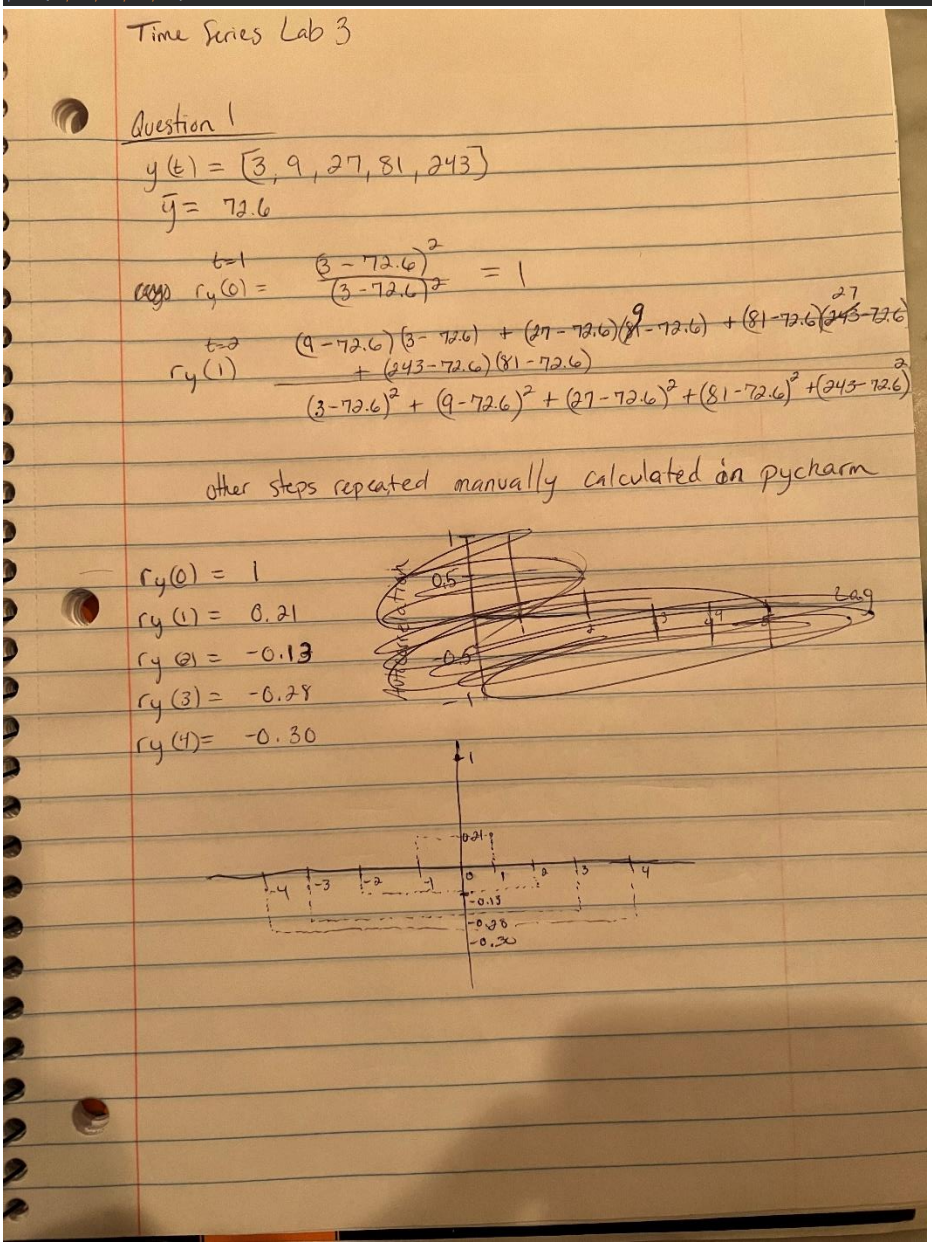
The data used to experiment with calculating and plotting the ACF was gathered by accessing stock value information using the yahoo API. The company stocks and code to access the API are as follows:

stocks = ['AAPL','ORCL', 'TSLA', 'IBM','YELP', 'MSFT']
import pandas_datareader as web web.DataReader('AAPL', data_source='yahoo', start=, end=)

4 – Answers to Lab Questions:

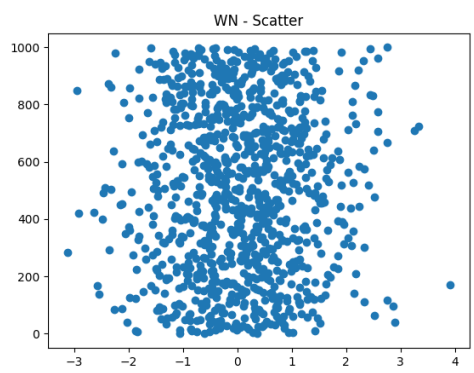
1.

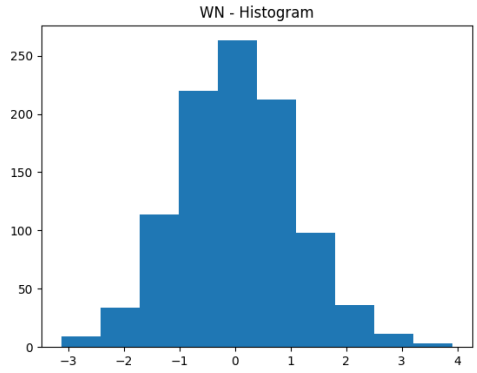
```
# question 1
y1 = 3
y2 = 9
y3 = 27
y4 = 81
y5 = 243
ymean = 72.6

r0 = (y1 - ymean)**2 // (y1 - ymean)**2
r1 = ((y2-ymean)*(y1-ymean) + (y3-ymean)*(y2-ymean) + (y4-ymean)*(y3-ymean) + (y5-ymean)*(y4-ymean)) / ((y1-ymean)**2+(y2-ymean)**2+(y3-ymean)**2+(y4-ymean)**2+(y5-ymean)**2)
r2 = ((y3-ymean)*(y1-ymean) + (y4-ymean)*(y2-ymean) + (y5-ymean)*(y3-ymean)) / ((y1-ymean)**2 + (y2-ymean)**2 + (y3-ymean)**2 + (y4-ymean)**2 + (y5-ymean)**2)
r3 = ((y4-ymean)*(y1-ymean) + (y5-ymean)*(y2-ymean)) / ((y1-ymean)**2 + (y2-ymean)**2 + (y3-ymean)**2 + (y4-ymean)**2 + (y5-ymean)**2)
r4 = ((y5-ymean)*(y1-ymean)) / ((y1-ymean)**2 + (y2-ymean)**2 + (y3-ymean)**2 + (y4-ymean)**2 + (y5-ymean)**2)
print(r0, r1, r2, r3, r4)
```



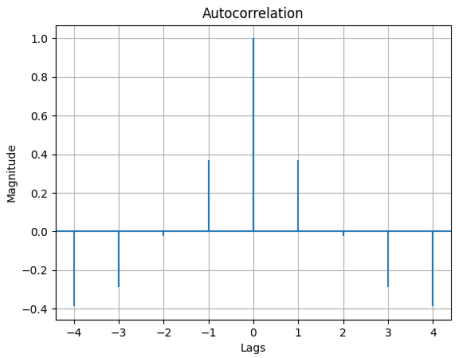
Please don’t dock points for manually calculating question 1 in pycharm 😊

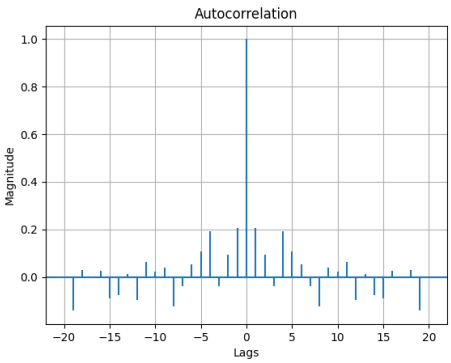
2. The following scatter and histogram plots represent the white noise data generated:





3. The following images show the code used to calculate and plot the ACF as well as the plots asked for:

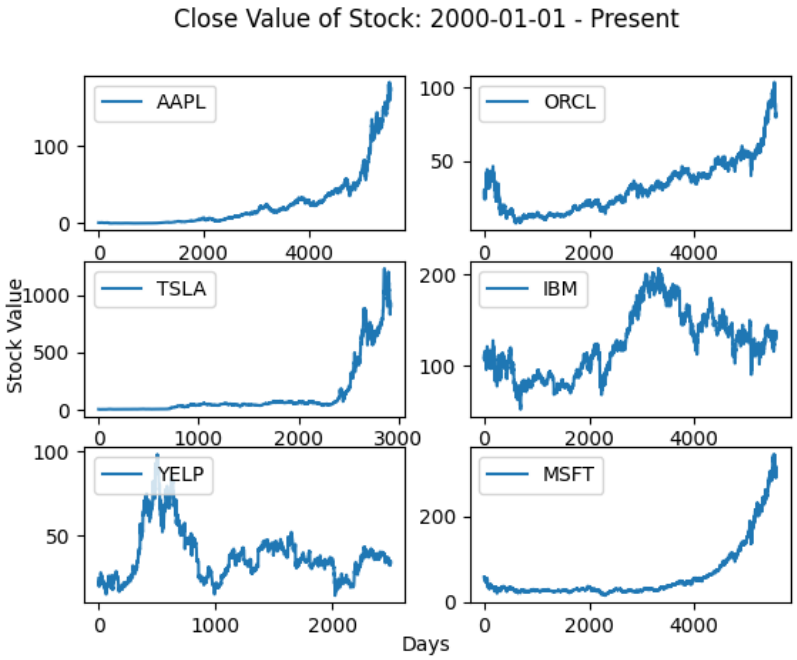


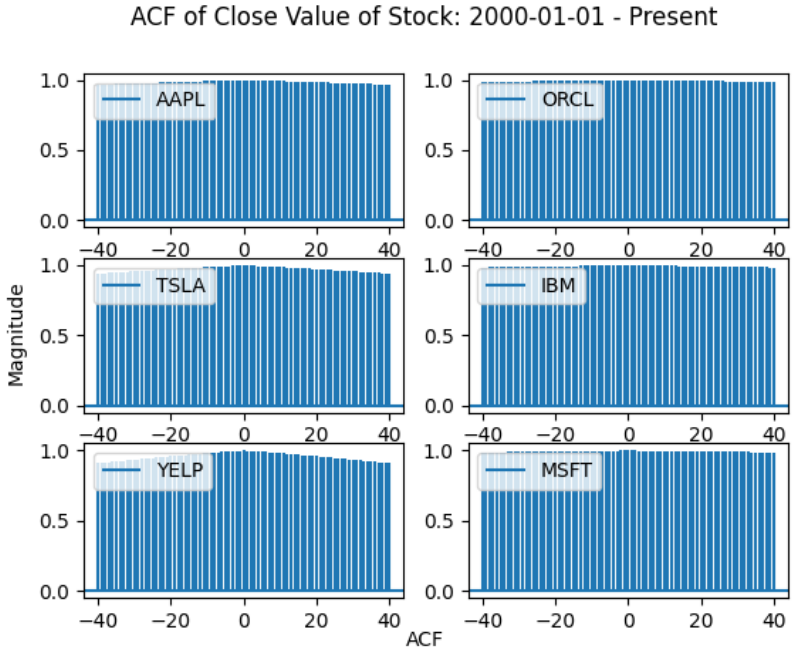



```python
def autocorrelation_plot(x, lag=1):
    n = len(x)
    variance = x.var()
    x = x - x.mean()
    r = np.correlate(x, x, mode='full')[-n:]
    assert np.allclose(r, np.array([(x[:n - k] * x[-(n - k):]).sum() for k in range(n)]))
    result = r / (variance * (np.arange(n, 0, -1)))

    plt.acorr(result, maxlags=lag)
    plt.title('Autocorrelation')
    plt.ylabel('Magnitude')
    plt.xlabel('Lags')
    plt.grid(True)
    plt.show()


#autocorrelation(np.array[3,9,27,81,243])
autocorrelation_plot(x, lag=4)
autocorrelation_plot(x, lag=20)
```

The scatter and histogram plots show that the data is normalized. The ACF plot shows that there is no correlation between the error of each plotted point from the white noise data.

4.


Close Value of Stock: 2000-01-01 - Present
AAPL
ORCL
TSLA
IBM
YELP
MSFT
Stock Value
Days


ACF of Close Value of Stock: 2000-01-01 - Present
AAPL
ORCL
TSLA
IBM
YELP
MSFT
Magnitude
ACF

5. 1. If the ACF is slowly decaying, that means future values of the series are correlated / heavily affected by past values.
    a. Data is non-stationary.

    2. If the ACF is fast decaying, that means future values of the series are not correlated / heavily affected by past values.
    b. Data is stationary.

5 – Conclusion:

The ACF is beneficial in time series analysis as it allows us to measure the linear relationship between lagged values of time series. It is helpful in determining if data is stationary or not.

6 – Appendix

```
import numpy as np
import matplotlib.pyplot as plt
import pandas_datareader as web
from datetime import datetime

# question 1
y1 = 3
y2 = 9
y3 = 27
y4 = 81
y5 = 243
ymean = 72.6

r0 = (y1 - ymean)**2 // (y1 - ymean)**2
r1 = ((y2-ymean)*(y1-ymean) + (y3-ymean)*(y2-ymean) + (y4-ymean)*(y3-ymean) +
(y5-ymean)*(y4-ymean)) / ((y1-ymean)**2+(y2-ymean)**2+(y3-ymean)**2+(y4-
ymean)**2+(y5-ymean)**2)
r2 = ((y3-ymean)*(y1-ymean) + (y4-ymean)*(y2-ymean) + (y5-ymean)*(y3-ymean))
/ ((y1-ymean)**2 + (y2-ymean)**2 + (y3-ymean)**2 + (y4-ymean)**2 + (y5-
ymean)**2)
r3 = ((y4-ymean)*(y1-ymean) + (y5-ymean)*(y2-ymean)) / ((y1-ymean)**2 + (y2-
ymean)**2 + (y3-ymean)**2 + (y4-ymean)**2 + (y5-ymean)**2)
r4 = ((y5-ymean)*(y1-ymean)) / ((y1-ymean)**2 + (y2-ymean)**2 + (y3-ymean)**2
+ (y4-ymean)**2 + (y5-ymean)**2)
print(r0, r1, r2, r3, r4)

# question 2
x = np.random.normal(loc=0, scale=1, size=1000)
y = np.arange(0,1000)

plt.scatter(x,y)
plt.title('WN - Scatter')
plt.show()

plt.hist(x)
plt.title('WN - Histogram')
plt.show()
```

```
# question 3
def autocorrelation(x):
    n = len(x)
    variance = x.var()
    x = x - x.mean()
    r = np.correlate(x, x, mode='full')[-n:]
    assert np.allclose(r, np.array([(x[:n - k] * x[-(n - k):]).sum() for k in
range(n)]))
    result = r / (variance * (np.arange(n, 0, -1)))
    return result

def autocorrelation_plot(x, lag=1):
    n = len(x)
    variance = x.var()
    x = x - x.mean()
    r = np.correlate(x, x, mode='full')[-n:]
    assert np.allclose(r, np.array([(x[:n - k] * x[-(n - k):]).sum() for k in
range(n)]))
    result = r / (variance * (np.arange(n, 0, -1)))

    plt.acorr(result, maxlags = lag)
    plt.title('Autocorrelation')
    plt.ylabel('Magnitude')
    plt.xlabel('Lags')
    plt.grid(True)
    plt.show()


autocorrelation_plot(np.array([3,9,27,81,243]), lag=4)
autocorrelation_plot(x, lag=20)

'''
The scatter and histogram plots show that the data is normalized
The ACF plot shows that there is no correlation between the error
of each plotted point from the white noise data.
'''

# question 4
start = datetime(2000, 1, 1)
end = datetime(2022, 2, 5)

AAPL = web.DataReader('AAPL', data_source='yahoo', start=start, end=end)
ORCL = web.DataReader('ORCL', data_source='yahoo', start=start, end=end)
TSLA = web.DataReader('TSLA', data_source='yahoo', start=start, end=end)
IBM = web.DataReader('IBM', data_source='yahoo', start=start, end=end)
YELP = web.DataReader('YELP', data_source='yahoo', start=start, end=end)
MSFT = web.DataReader('MSFT', data_source='yahoo', start=start, end=end)

print(AAPL.head())
#print(np.array(AAPL['Close']))
#print(autocorrelation(np.array(AAPL['Close'])))


fig, ax = plt.subplots(3, 2)
ax1, ax2, ax3, ax4, ax5, ax6 = ax.flatten()
fig.suptitle('Close Value of Stock: 2000-01-01 - Present')
ax1.plot(np.arange(len(AAPL['Close'])), AAPL['Close'], label='AAPL')
```

```
ax1.legend(loc='upper left')
ax2.plot(np.arange(len(ORCL['Close'])), ORCL['Close'], label='ORCL')
ax2.legend(loc='upper left')
ax3.plot(np.arange(len(TSLA['Close'])), TSLA['Close'], label='TSLA')
ax3.legend(loc='upper left')
ax4.plot(np.arange(len(IBM['Close'])), IBM['Close'], label='IBM')
ax4.legend(loc='upper left')
ax5.plot(np.arange(len(YELP['Close'])), YELP['Close'],  label='YELP')
ax5.legend(loc='upper left')
ax6.plot(np.arange(len(MSFT['Close'])), MSFT['Close'], label='MSFT')
ax6.legend(loc='upper left')
fig.text(0.5, 0.04, 'Days', ha='center')
fig.text(0.04, 0.5, 'Stock Value', va='center', rotation='vertical')

plt.show()

fig1, ax = plt.subplots(3, 2)
ax1, ax2, ax3, ax4, ax5, ax6 = ax.flatten()
fig1.suptitle('ACF of Close Value of Stock: 2000-01-01 - Present')
ax1.acorr(autocorrelation(np.array(AAPL['Close'])), maxlags = 40,
label='AAPL')
ax1.legend(loc='upper left')
ax2.acorr(autocorrelation(np.array(ORCL['Close'])), maxlags = 40,
label='ORCL')
ax2.legend(loc='upper left')
ax3.acorr(autocorrelation(np.array(TSLA['Close'])), maxlags = 40,
label='TSLA')
ax3.legend(loc='upper left')
ax4.acorr(autocorrelation(np.array(IBM['Close'])), maxlags = 40, label='IBM')
ax4.legend(loc='upper left')
ax5.acorr(autocorrelation(np.array(YELP['Close'])), maxlags = 40,
label='YELP')
ax5.legend(loc='upper left')
ax6.acorr(autocorrelation(np.array(MSFT['Close'])), maxlags = 40,
label='MSFT')
ax6.legend(loc='upper left')
fig1.text(0.5, 0.04, 'ACF', ha='center')
fig1.text(0.04, 0.5, 'Magnitude', va='center', rotation='vertical')

plt.show()
```