



## INTRODUCTION TO TIME SERIES ANALYSIS IN PYTHON

# Autocorrelation Function

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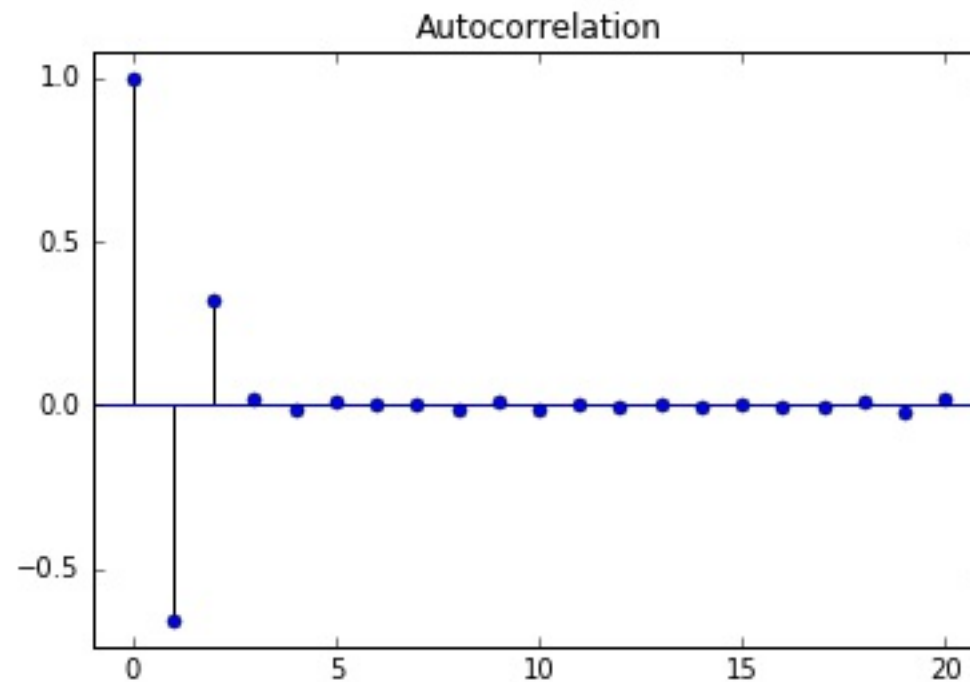
# Autocorrelation Function

sample autocorrelation function (or ACF) shows not only the lag-one, but the entire autocorrelation function for different lags.

- Autocorrelation Function (ACF): The autocorrelation as a function of the lag
  - Equals one at lag-zero
  - Interesting information beyond lag-one
- any significant non-zero autocorrelations implies that the series can be forecast from the past.

# ACF Example 1: Simple Autocorrelation Function

- Can use last two values in series for forecasting

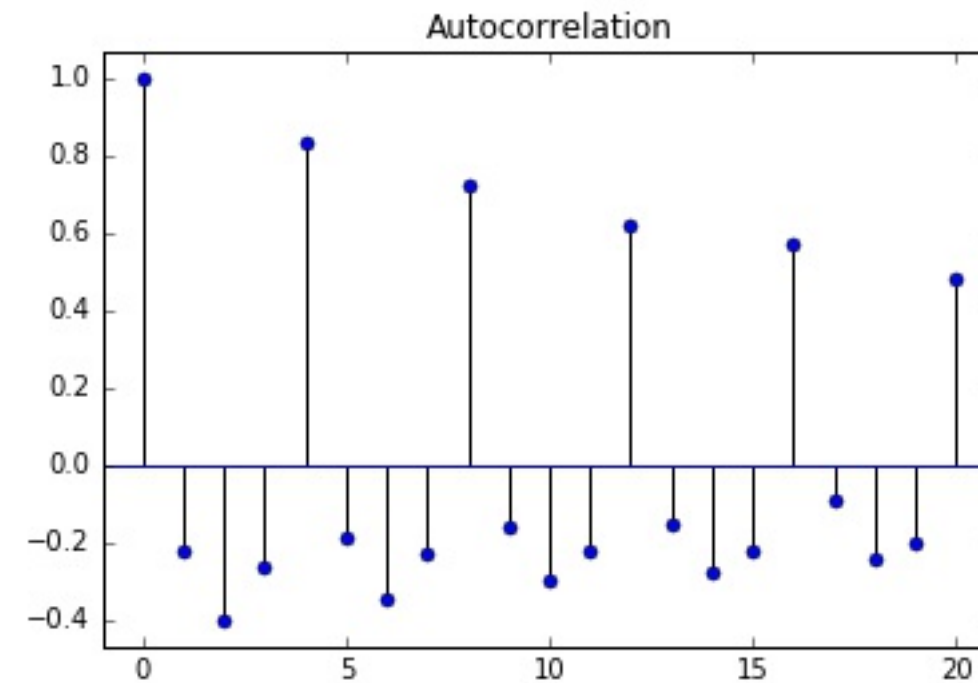
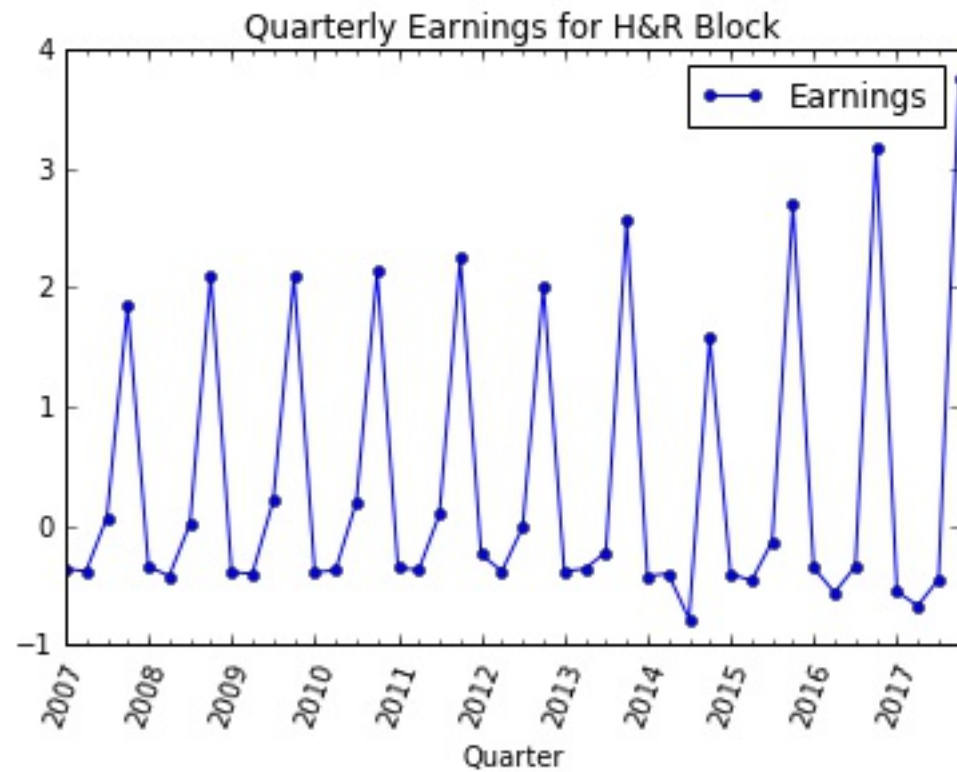


this autocorrelation function implies that u can forecast the next value of the series from the last 2 values, since lag-one and lag-two autocorrelations differ from zero.



# ACF Example 2: Seasonal Earnings

- Earnings for H&R Block
- ACF for H&R Block



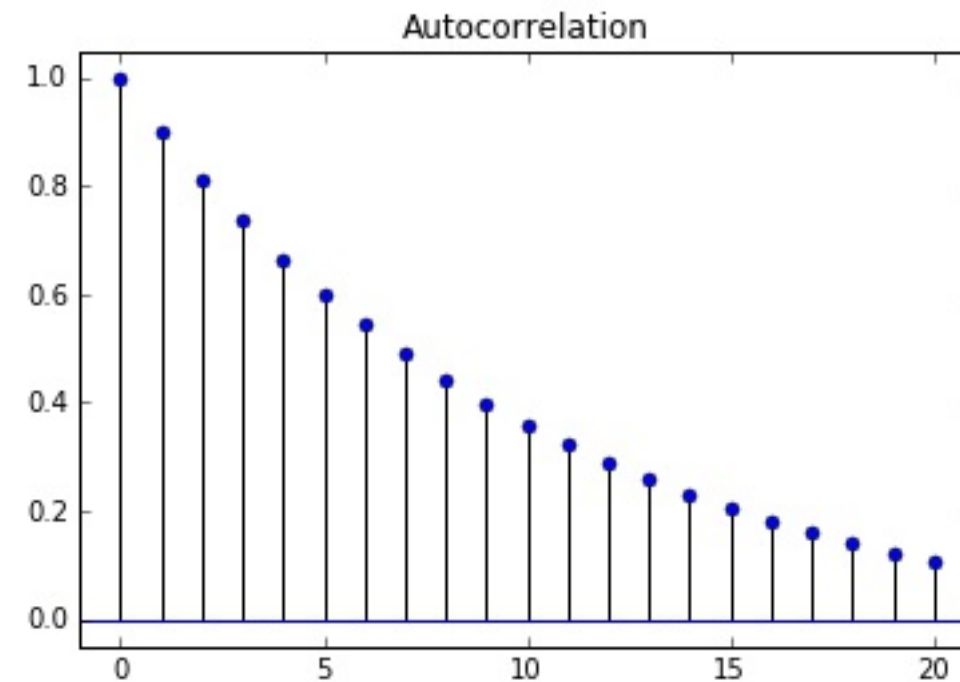
autocorrelation function on the right shows strong autocorrelation at lags 4, 8, 12, 16 and 20



# ACF Example 3: Useful for Model Selection

- Model selection

ACF can also be useful for selecting a parsimonious model for fitting data.



# Plot ACF in Python

- Import module:

```
from statsmodels.graphics.tsaplots import plot_acf
```

- Plot the ACF:

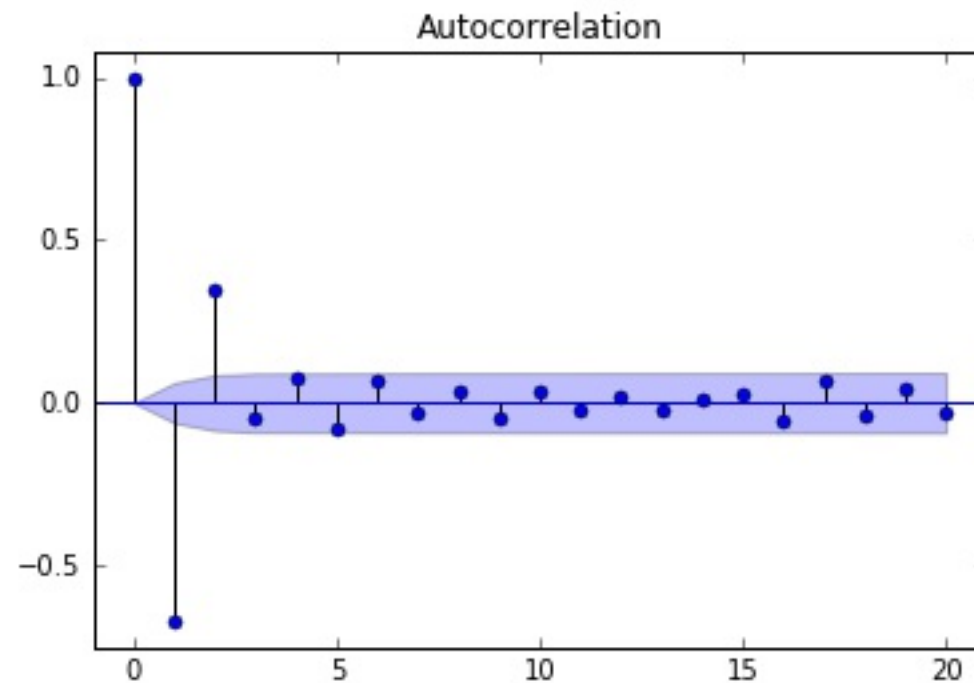
```
plot_acf(x, lags= 20, alpha=0.05)
```

how many lags of the acf will be plotted

alpha: set the width of confidence interval



# Confidence Interval of ACF



ACF plot that contains confidence interval for each lag, which is the blue region



# Confidence Interval of ACF

- Argument alpha sets the width of confidence interval
- Example: alpha=0.05
  - 5% chance that if true autocorrelation is zero, it will fall outside blue band
- Confidence bands are wider if:
  - Alpha lower
  - Fewer observations
- Under some simplifying assumptions, 95% confidence bands are  $\pm 2/\sqrt{N}$   
*approximation the width of 95% confidence interval*
- If you want no bands on plot, set alpha=1 *no confidence interval*





# ACF Values Instead of Plot

extract ACF numerical values

```
from statsmodels.tsa.stattools import acf
print(acf(x))

[ 1.          -0.6765505   0.34989905 -0.01629415 -0.02507013  0.01930354
 -0.03186545  0.01399904 -0.03518128  0.02063168 -0.02620646 -0.00509828
 ...
 0.07191516 -0.12211912  0.14514481 -0.09644228  0.05215882]
```



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**Let's practice!**



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# White Noise

general definition, white noise is a series with  $\text{mean}=\text{const}$ ,  $\text{variance}=\text{const}$ , zero autocorrelation at all lags.

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# What is White Noise?

- White Noise is a series with:
  - Constant mean
  - Constant variance
  - Zero autocorrelations at all lags
- Special Case: if data has normal distribution, then *Gaussian White Noise*



# Simulating White Noise

- It's very easy to generate white noise

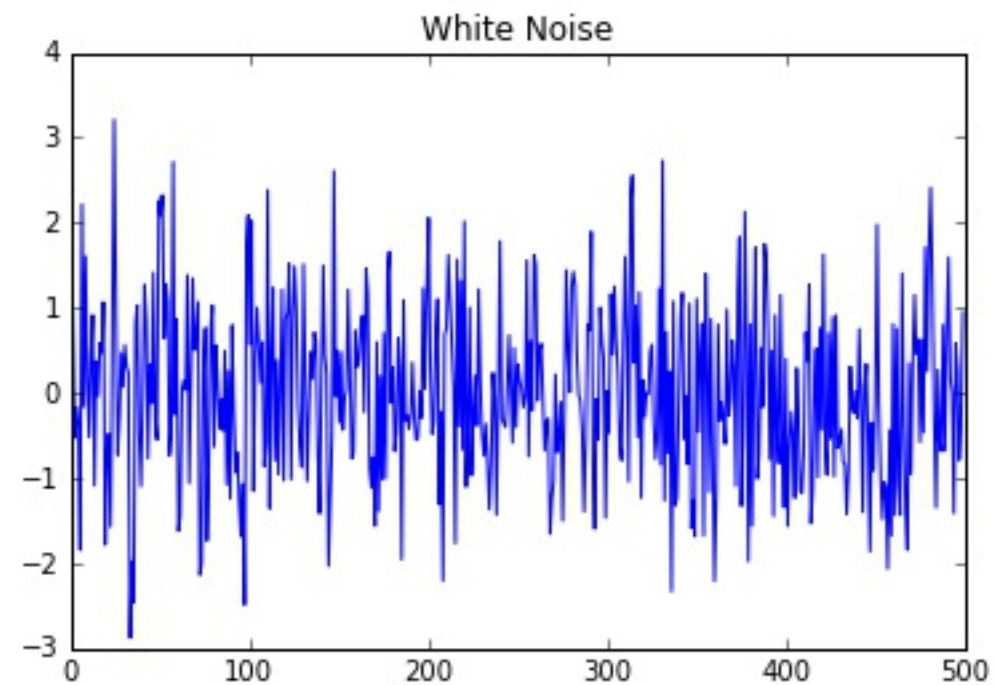
```
import numpy as np  
noise = np.random.normal(loc=0, scale=1, size=500)
```

loc is mean  
scale is std



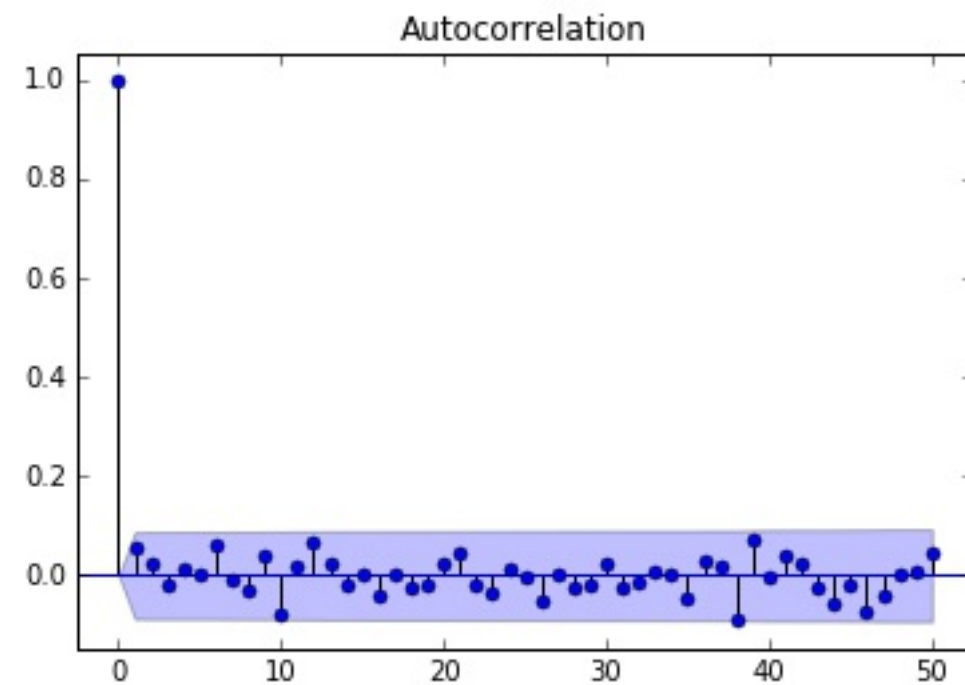
# What Does White Noise Look Like?

```
plt.plot(noise)
```



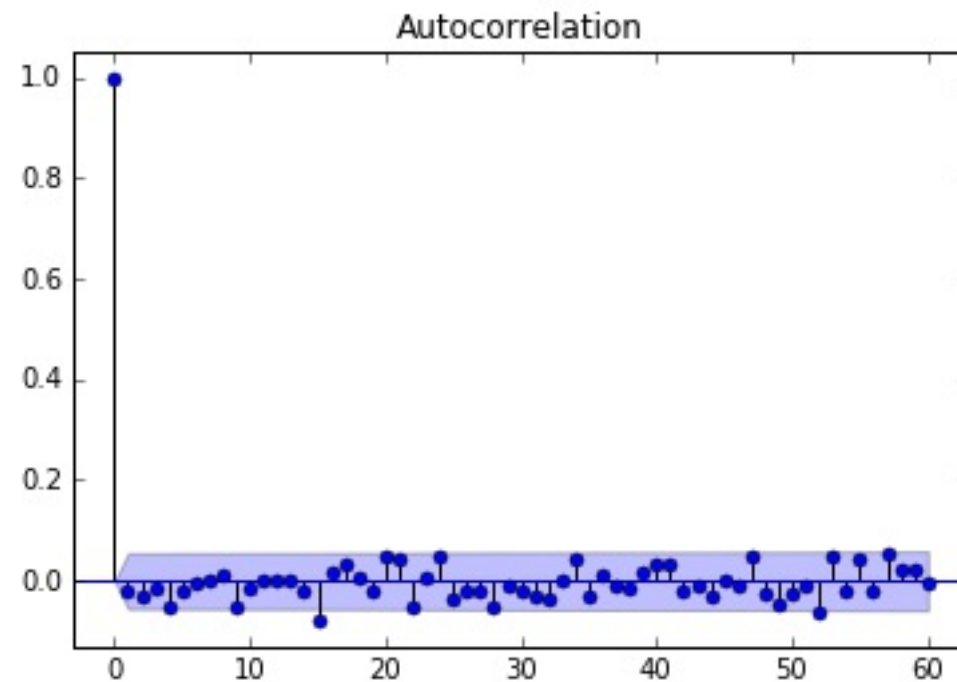
# Autocorrelation of White Noise

```
plt_acf(noise, lags=50)
```



# Stock Market Returns: Close to White Noise

- Autocorrelation Function for the S&P500



notice that there are pretty much no lags where autocorrelation is significantly different from zero.





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# Random Walk

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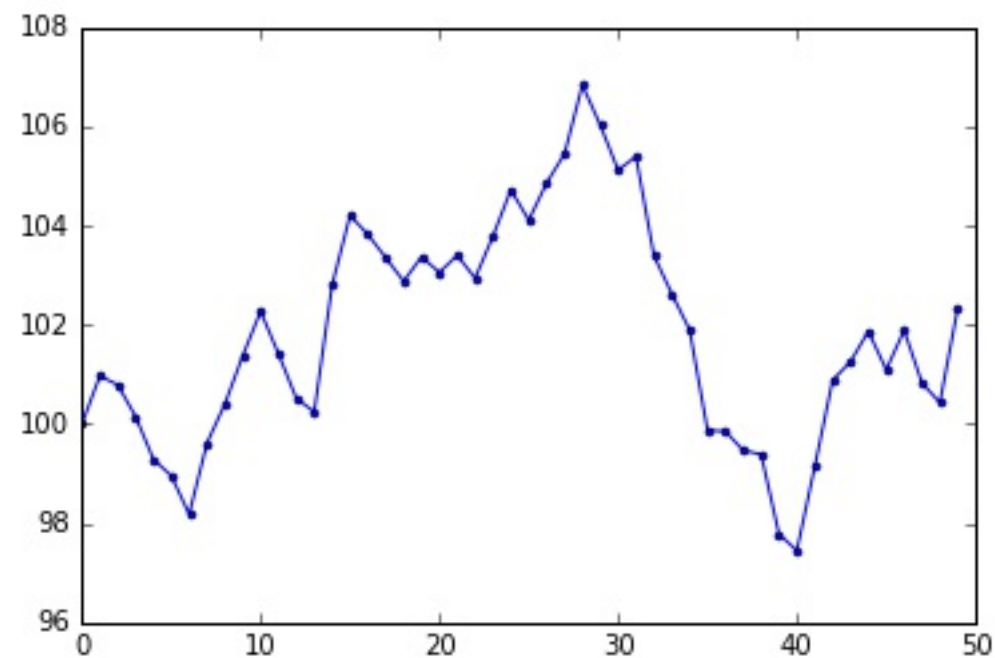


# What is a Random Walk?

- Today's Price = Yesterday's Price + Noise

$$P_t = P_{t-1} + \epsilon_t$$

- Plot of simulated data



# What is a Random Walk?

- Today's Price = Yesterday's Price + Noise

$$P_t = P_{t-1} + \epsilon_t$$

- Change in price is white noise

incidentally, if prices are in logs, then the difference in log prices is one way to measure returns.

$$P_t - P_{t-1} = \epsilon_t$$

bottom line is that if stock prices follow a random walk then stock returns are white noise.

- Can't forecast a random walk
- Best forecast for tomorrow's price is today's price



# What is a Random Walk?

- Today's Price = Yesterday's Price + Noise

$$P_t = P_{t-1} + \epsilon_t$$

- Random walk with drift: prices on average drift by  $\mu$  every period

$$P_t = \mu + P_{t-1} + \epsilon_t$$

- Change in price is white noise with non-zero mean:

$$P_t - P_{t-1} = \mu + \epsilon_t$$

returns are still white noise, but with an average return of  $\mu$  instead of zero

# Statistical Test for Random Walk

- Random walk with drift

to test whether a series follows a random walk, u can regress current prices on lagged prices.

$$P_t = \mu + P_{t-1} + \epsilon_t$$

- Regression test for random walk     **Ho: series is a random walk**

$$P_t = \alpha + \beta P_{t-1} + \epsilon_t$$

if slope (beta) coefficient is not significant different from one.  
Can not reject Ho.

- Test:

$$H_0 : \beta = 1 \text{ (random walk)}$$

$$H_1 : \beta < 1 \text{ (not random walk)} \quad \text{if slope coeff is significantly less than one, reject Ho}$$



# Statistical Test for Random Walk

- Regression test for random walk

identical way to do that test is to regress the difference in prices on the lagged price.

$$P_t = \alpha + \beta P_{t-1} + \epsilon_t$$

test slope coeff whether it is zero.

- Equivalent to

$$P_t - P_{t-1} = \alpha + \beta P_{t-1} + \epsilon_t$$

- Test:

$$H_0 : \beta = 0 \text{ (random walk)}$$

$$H_1 : \beta < 0 \text{ (not random walk)}$$



# Statistical Test for Random Walk

- Regression test for random walk

$$P_t - P_{t-1} = \alpha + \beta P_{t-1} + \epsilon_t$$

- Test:

$$H_0 : \beta = 0 \text{ (random walk)}$$

$$H_1 : \beta < 0 \text{ (not random walk)}$$

- This test is called the **Dickey-Fuller** test
- If you add more lagged changes on the right hand side, it's the **Augmented Dickey-Fuller** test





# ADF Test in Python

- Import module from statsmodels

```
from statsmodels.tsa.stattools import adfuller
```

- Run Augmented Dickey-Test

```
adfuller(x)
```



# Example: Is the S&P500 a Random Walk?

- Run Augmented Dickey-Fuller Test on SPX data

```
results = adfuller(df['SPX'])
```

- Print p-value

```
print(results[1])  
0.782253808587 = p-value --> can not reject Ho
```

main output is p-value of the test.

- Print full results

p-value < 5% --> reject Ho (95% confidence)

```
print(results)  
(-0.91720490331127869, test statistic  
0.78225380858668414,  
0,  
1257, no of observations  
{ '1%': -3.4355629707955395, critical values of test statistic  
'10%': -2.567995644141416,  
'5%': -2.8638420633876671},  
10161.888789598503)
```



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# Stationarity

in its strictest sense, it means that the joint distribution of the observations do not depend on time.

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# What is Stationarity?

- **Strong stationarity:** entire distribution of data is time-invariant
- **Weak stationarity:** mean, variance and autocorrelation are time-invariant (i.e., for autocorrelation,  $\text{corr}(X_t, X_{t-\tau})$  is only a function of  $\tau$ )

less restrictive version of stationary (easier to test) is weak stationary.

$\text{corr}(X_t, X(t-\tau))$  is only a function of lag  $\tau$ , not a function of time.



# Why Do We Care?

a process is not stationary, it becomes difficult to model.

- If parameters vary with time, too many parameters to estimate
- Can only estimate a parsimonious model with a few parameters

modeling involves estimating a set of parameters, if a process is not stationary, the parameters are different at each point in time, there are too many parameters to estimate.

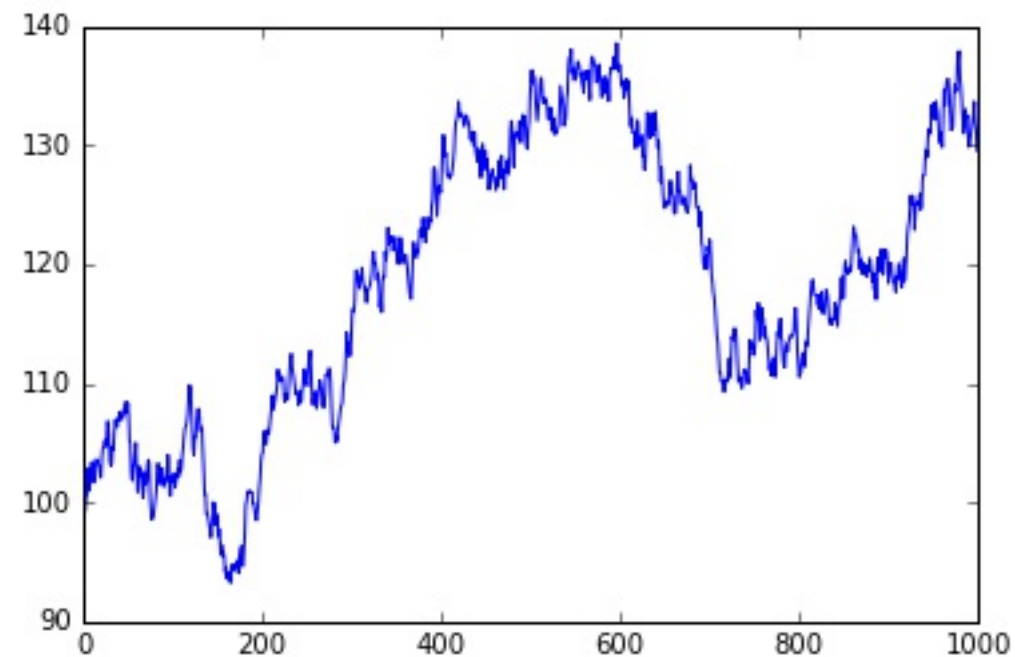
End up having more parameters than actual data

stationary is necessary for a parsimonious model, one with a smaller set of parameter to estimate



# Examples of Nonstationary Series

- Random Walk



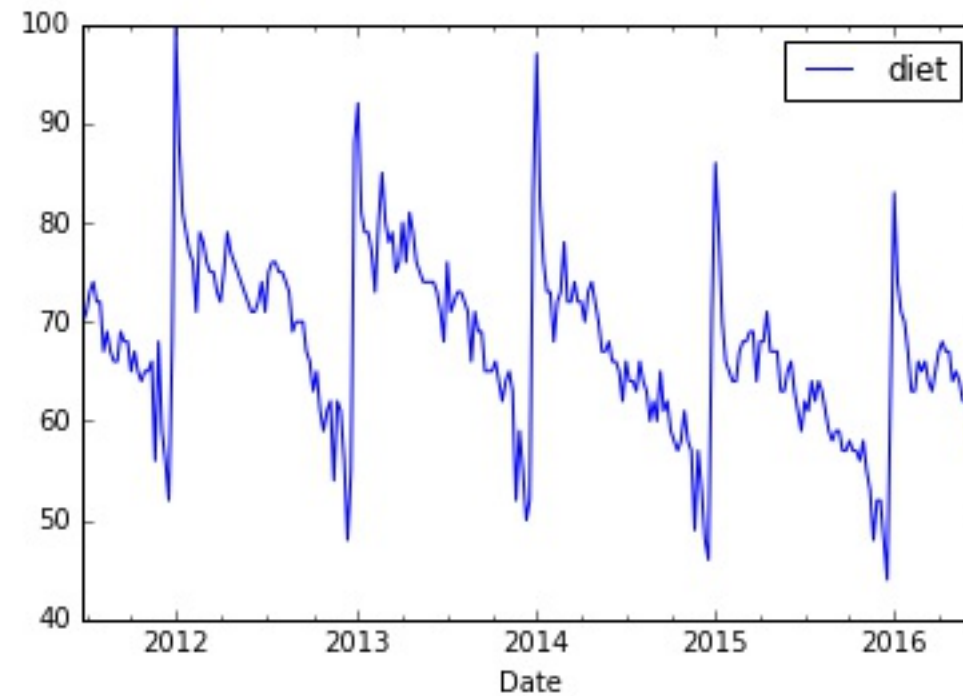
variance grows with time.  
EX: stock prices are a random walk,  
uncertainty about prices tomorrow  
is much less than the uncertainty  
10 years from now.



# Examples of Nonstationary Series

- Seasonality in series

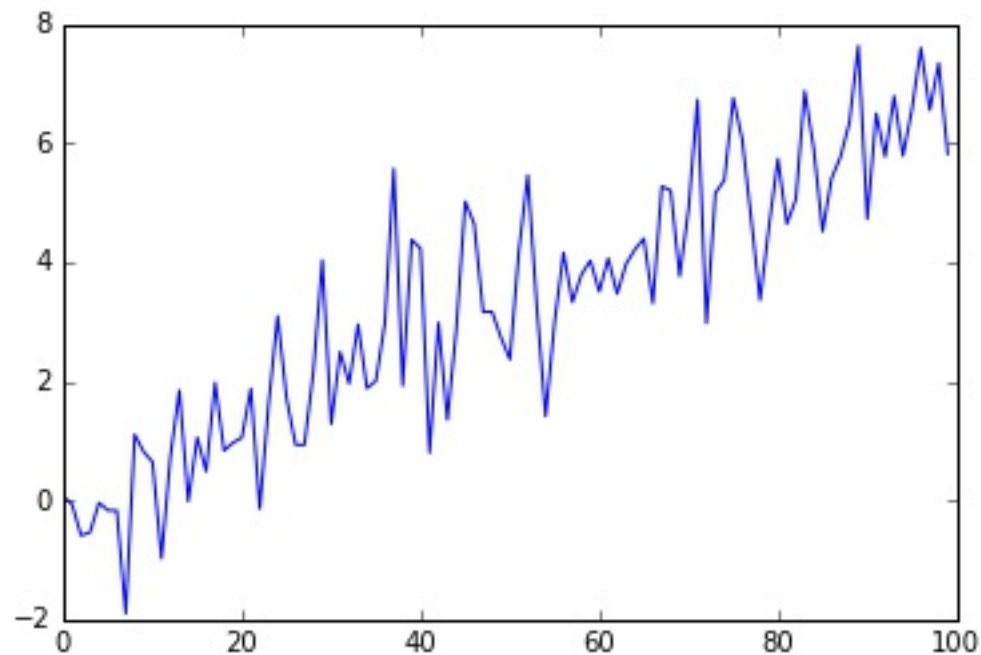
mean varies with time of the year.





# Examples of Nonstationary Series

- Change in Mean or Standard Deviation over time



here is white noise, which would ordinarily be a stationary process,

but mean increases over time, make it non-stationary.

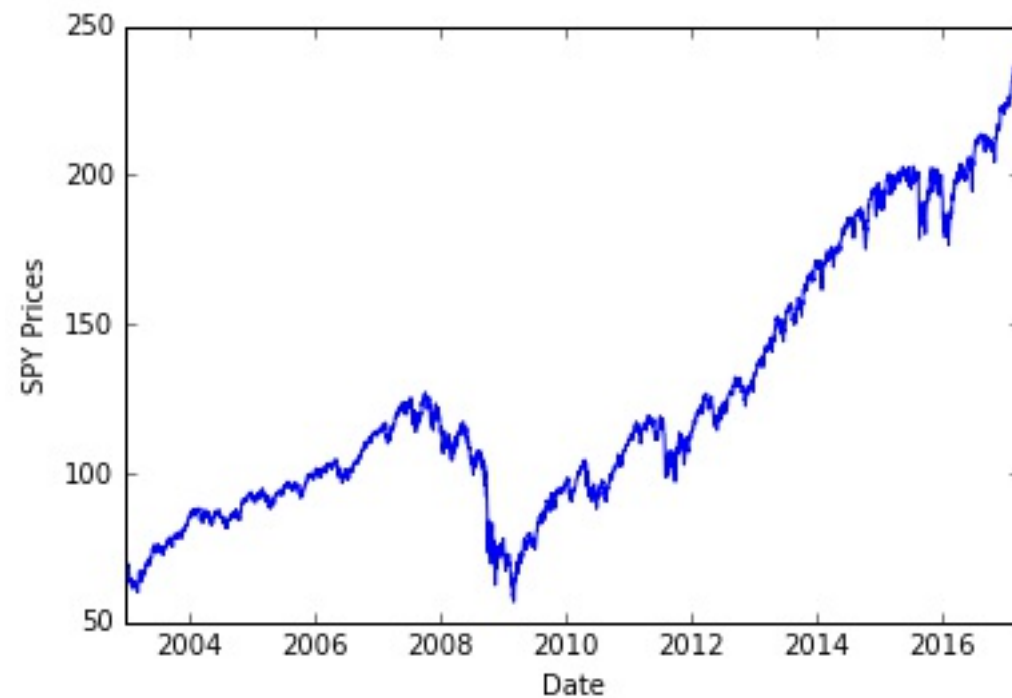


# Transforming Nonstationary Series Into Stationary Series

non-stationary

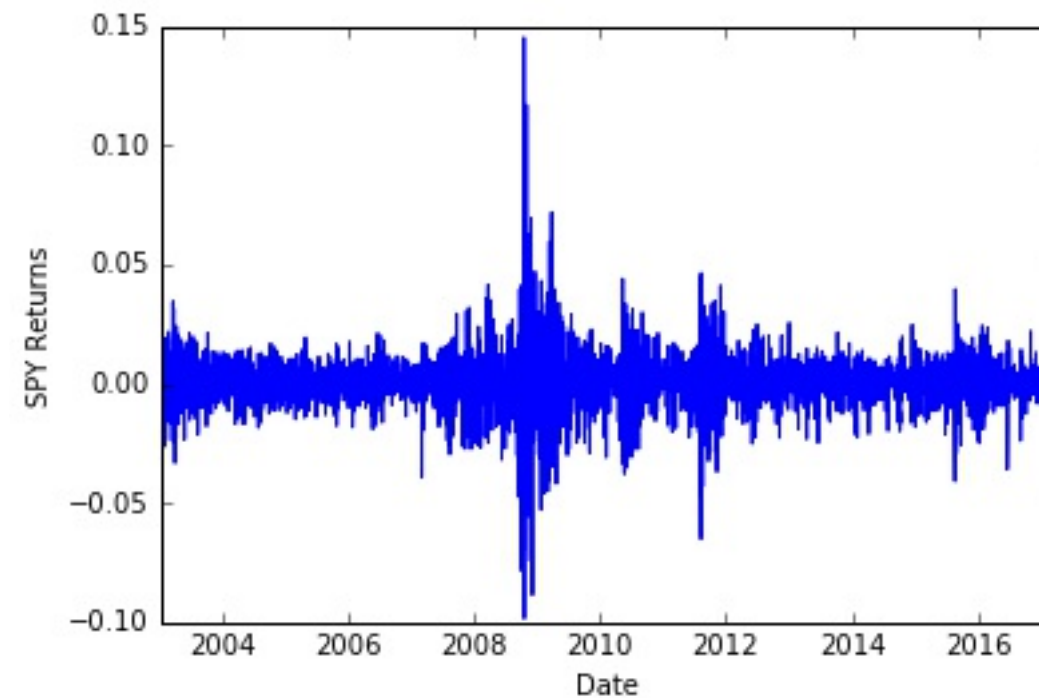
- Random Walk

```
plot.plot(SPY)
```



- First difference --> new series is white noise which is stationary

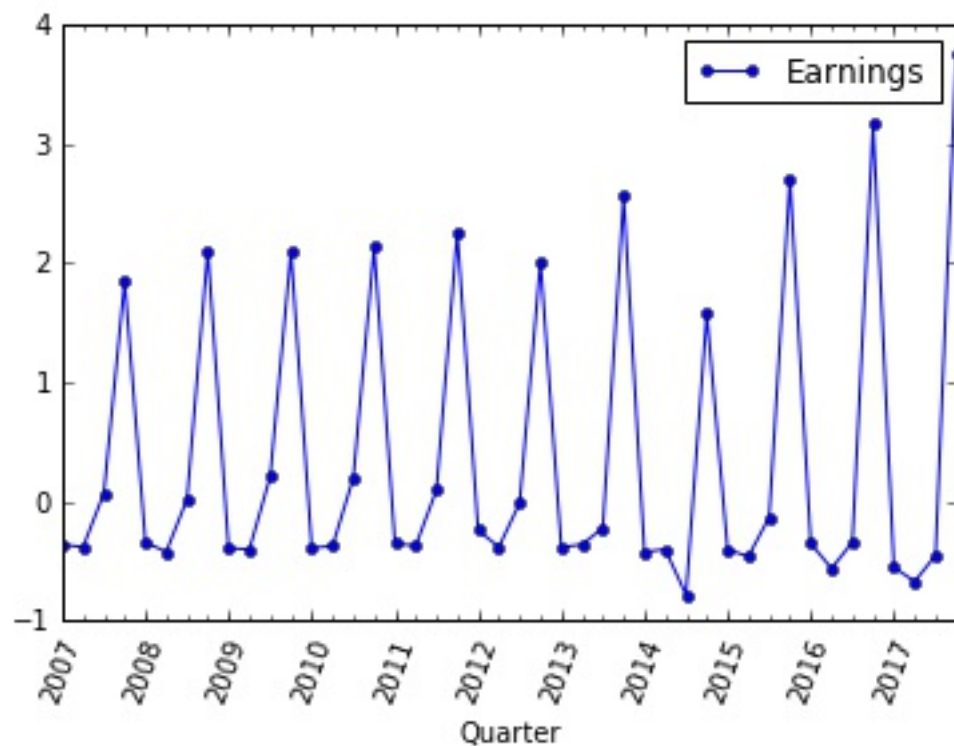
```
plot.plot(SPY.diff())
```



# Transforming Nonstationary Series Into Stationary Series

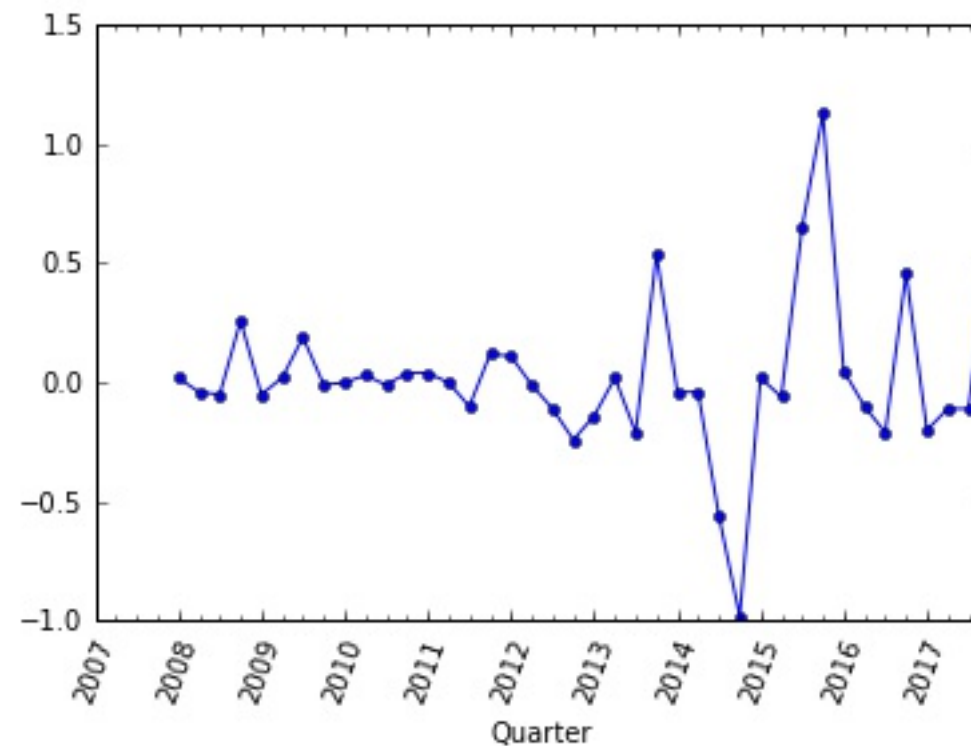
- Seasonality

```
plot.plot(HRB)
```



- Seasonal difference (take the difference with lag of 4)

```
plot.plot(HRB.diff(4))
```



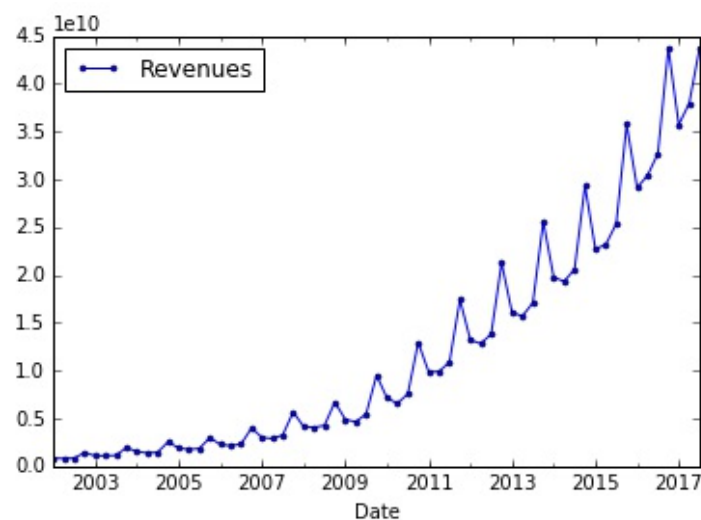
series looks stationary

# Transforming Nonstationary Series Into Stationary Series

need to make two transformations.

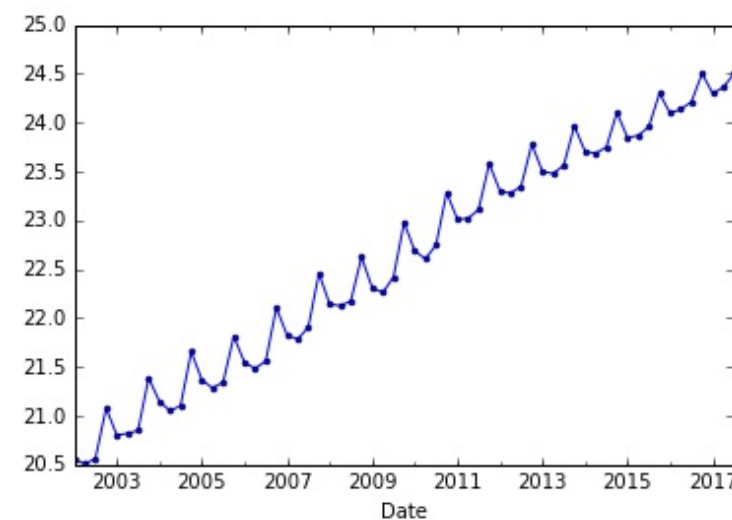
- AMZN Quarterly Revenues

```
plt.plot(AMZN)
```



- Log of AMZN Revenues (eliminate the exponential growth)

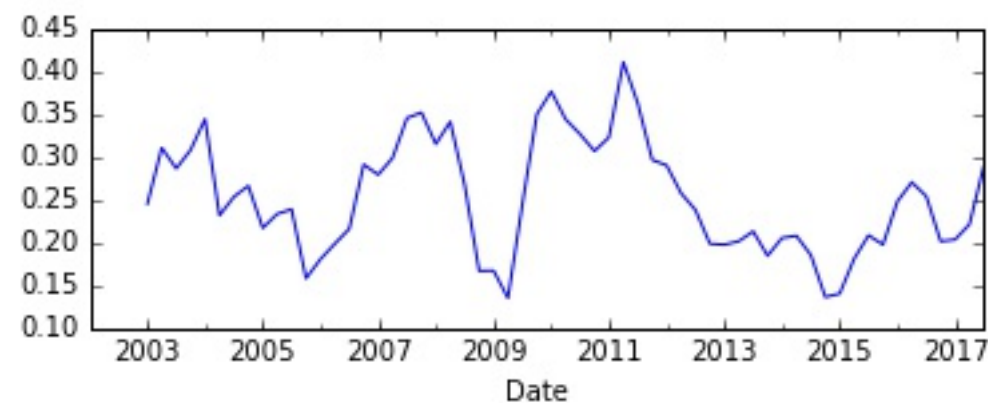
```
plt.plot(np.log(AMZN))
```



grow exponentially and strong seasonal pattern

- Log, then seasonal difference

```
plt.plot(np.log(AMZN).diff(4))
```



looks stationary



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