INTRODUCTION TO TIME SERIES ANALYSIS IN PYTHON

Introduction to the Course

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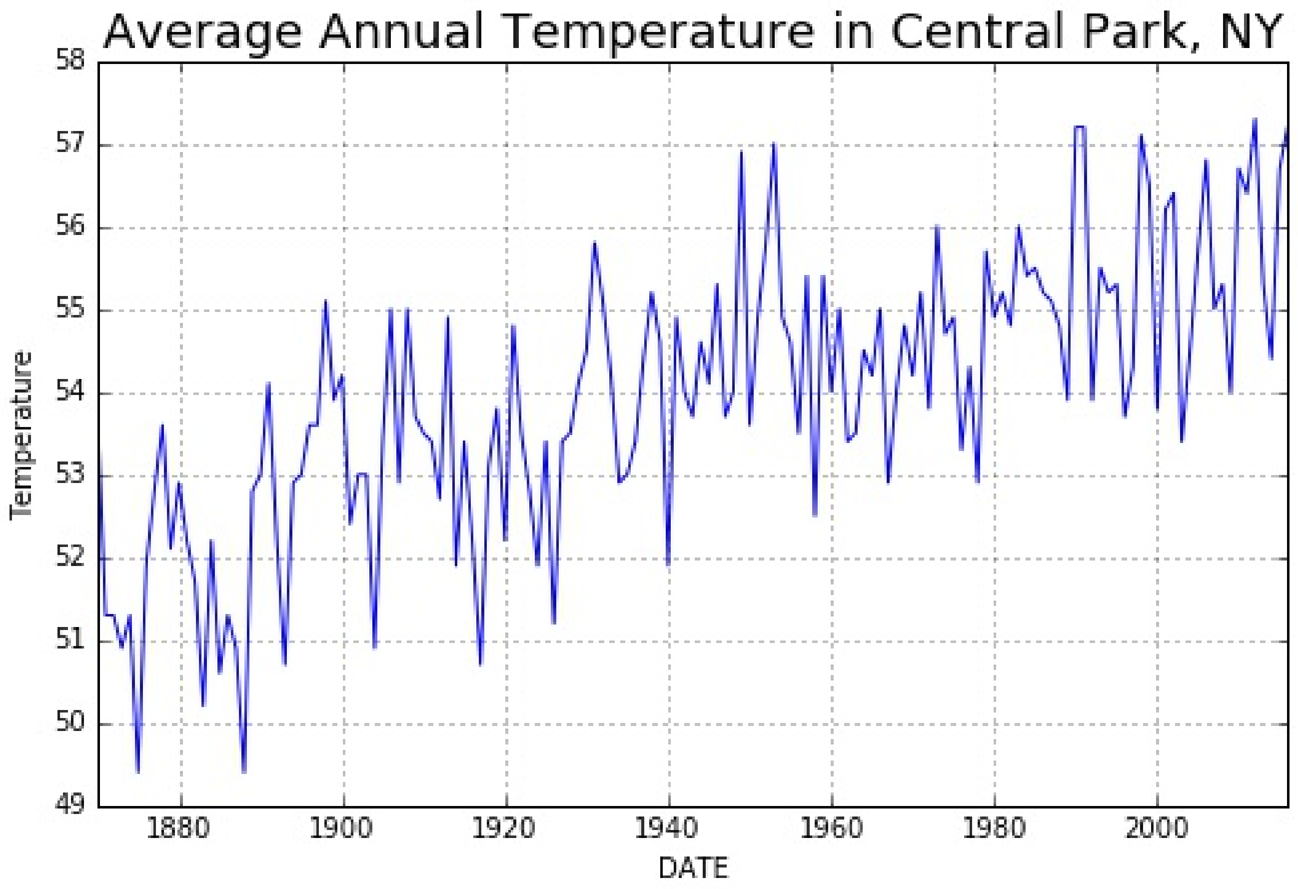
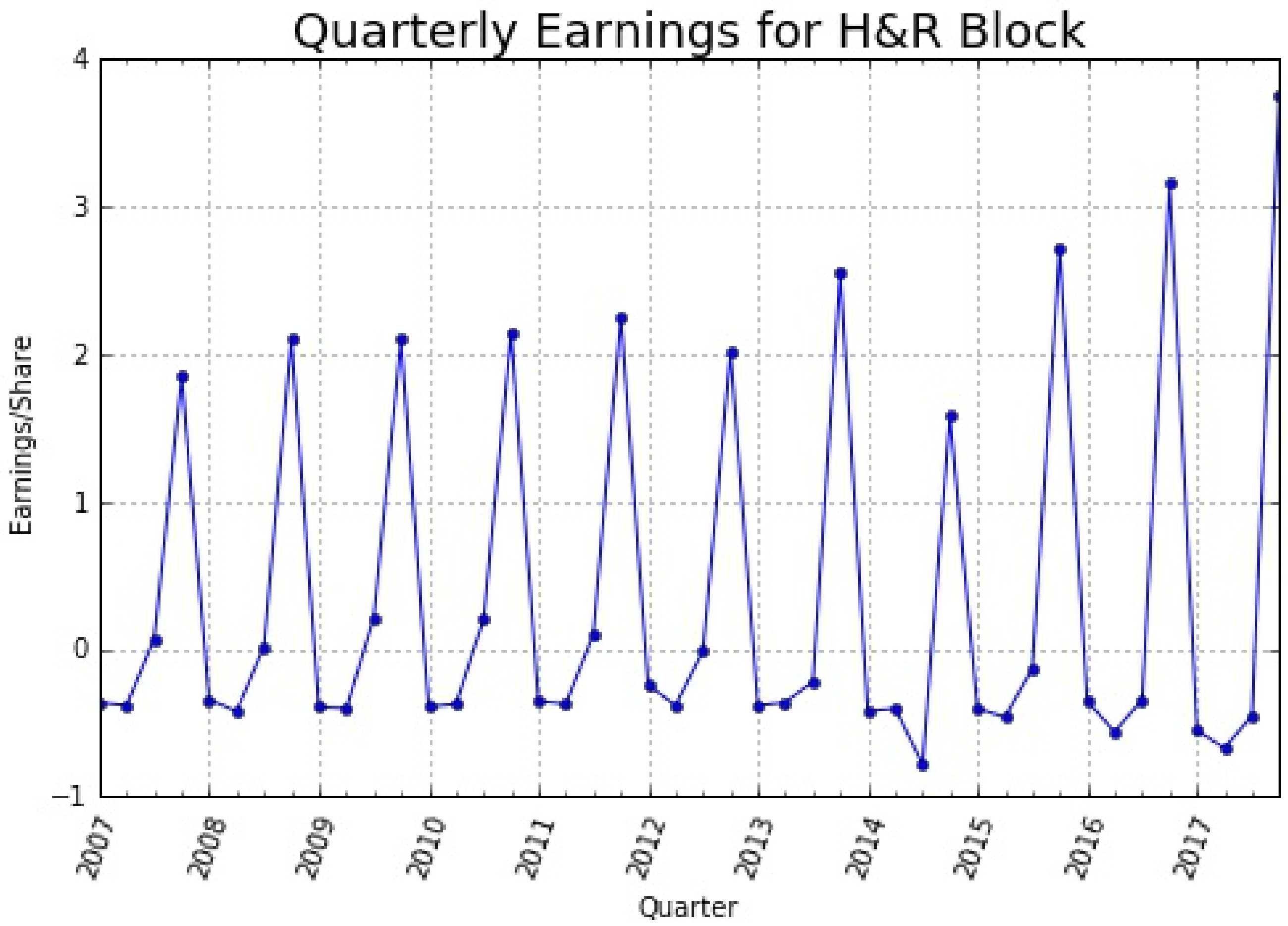
Example of Time Series: Google Trends

time series analysis deals with data that is ordered in time.

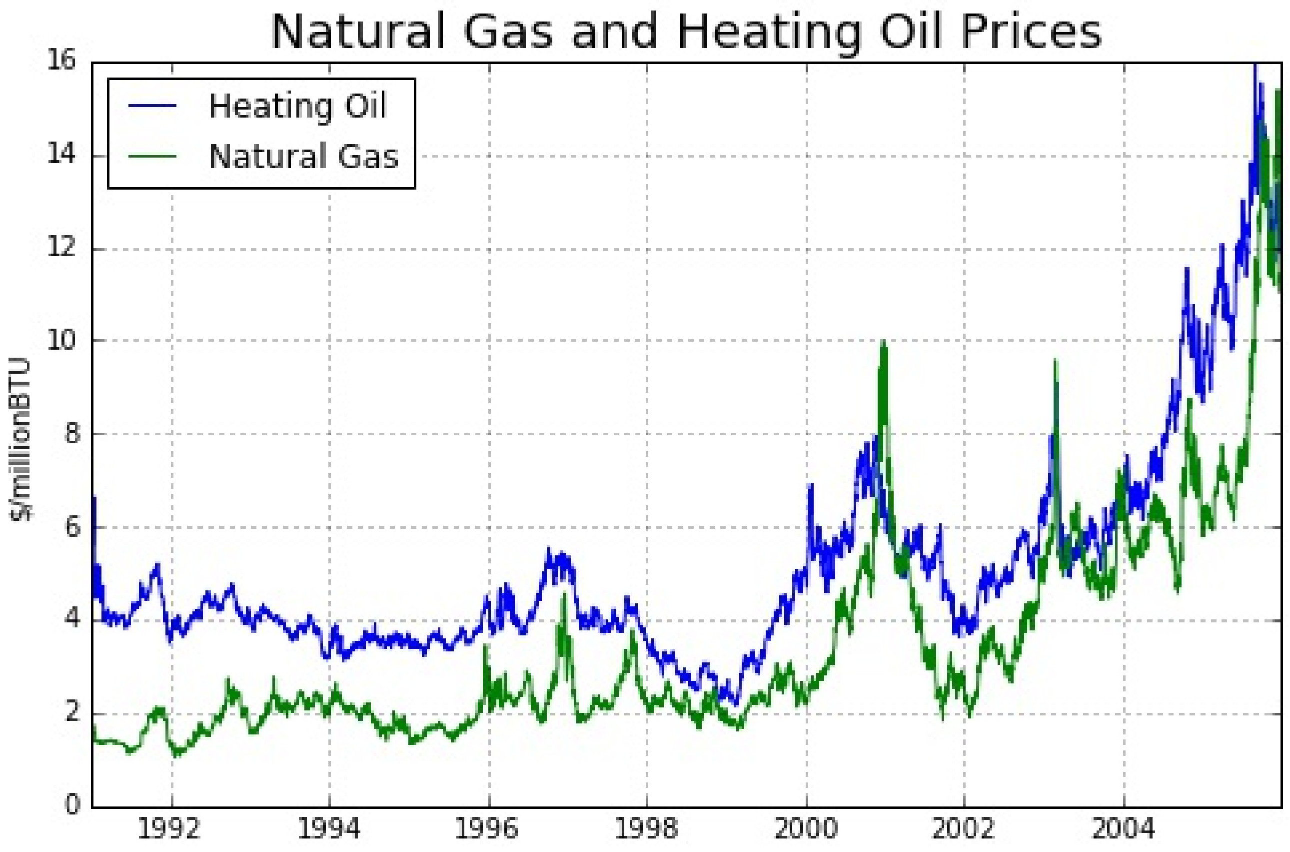
Example of Time Series: Climate Data



Example of Time Series: Quarterly Earnings Data



Example of Multiple Series: Natural Gas and Heating Oil



Goals of Course

- Learn about time series models
- Fit data to a times series model
- Use the models to make forecasts of the future
- Learn how to use the relevant statistical packages in Python
- Provide concrete examples of how these models are used

Some Useful Pandas Tools

- Changing an index to datetime

convert index, often read in as a string into a datetime index

```
df.index = pd.to_datetime(df.index)
```

- Plotting data

```
df.plot()
```

- Slicing data by year

```
df['2012']
```

Some Useful Pandas Tools

- Join two DataFrames

```
df1.join(df2)
```

- Resample data (e.g. from daily to weekly)

```
df = df.resample(rule='W', how='last')
```

More pandas Functions

- Computing percent changes and differences of a time series

```
df['col'].pct_change()
df['col'].diff()
```

convert prices to returns

- pandas correlation method of Series

```
df['ABC'].corr(df['XYZ'])
```

- pandas autocorrelation

```
df['ABC'].autocorr()
```

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Let's practice!

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Correlation of Two Time Series

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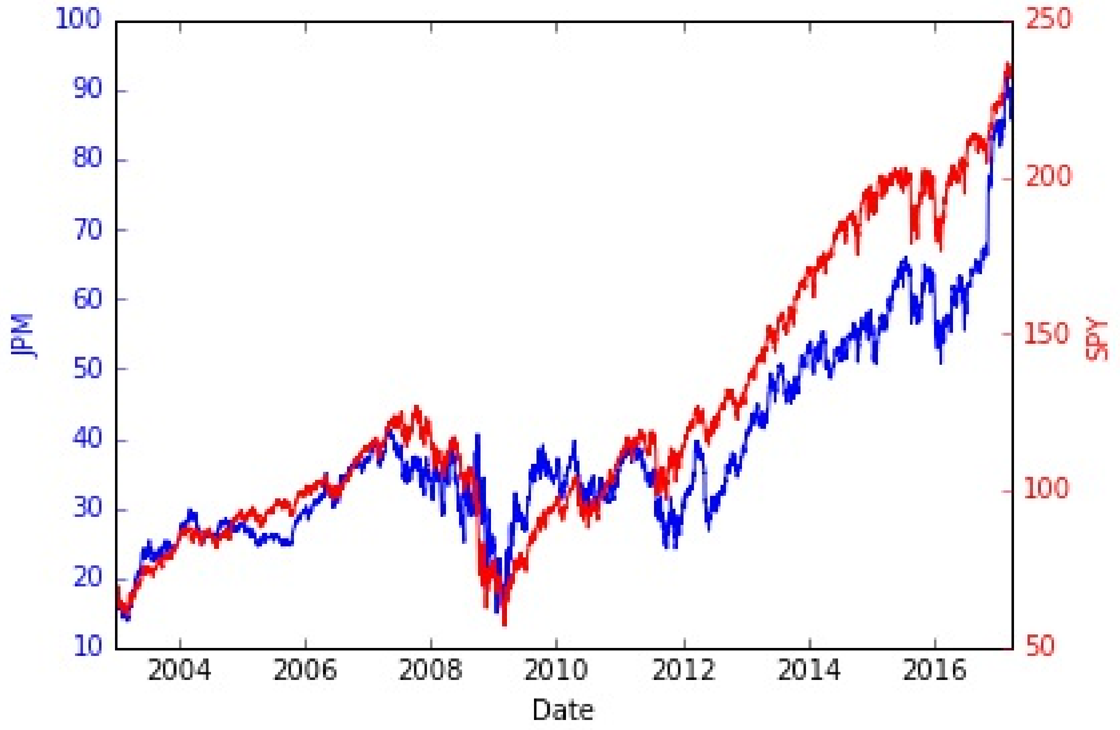
Correlation of Two Time Series

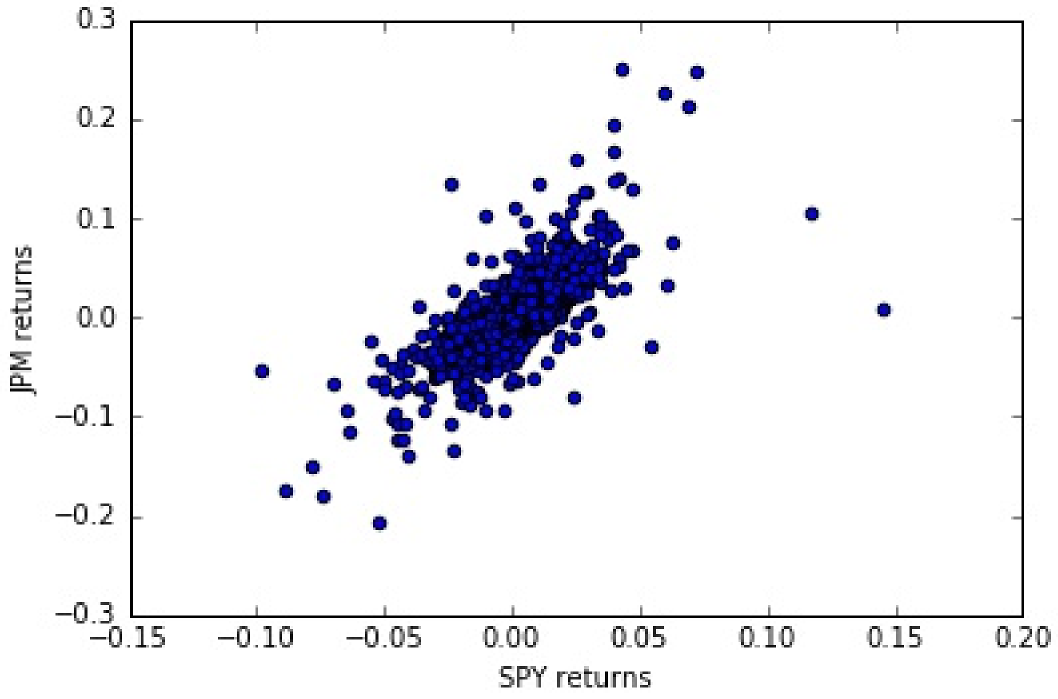
- Plot of S&P500 and JPMorgan stock



Correlation of Two Time Series

- Scatter plot of S&P500 and JP Morgan returns

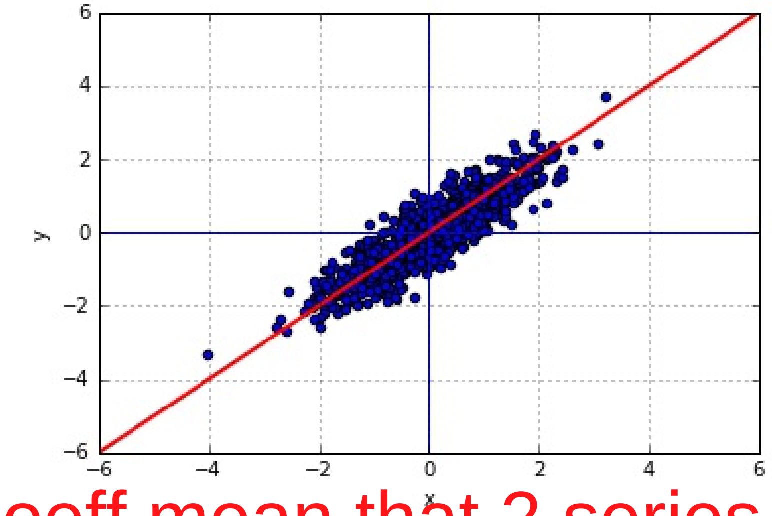
--> visualize the relationship btw the two time series



More Scatter Plots

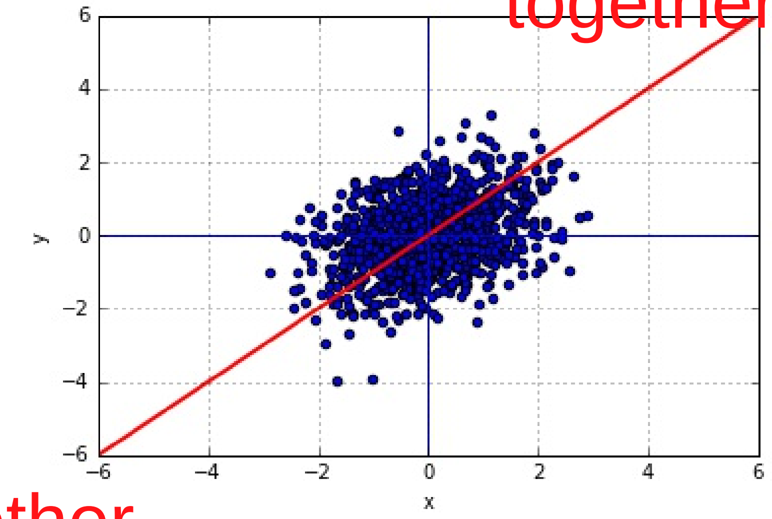
correlation coefficient is a measure of how much two series vary together

- Correlation = 0.9



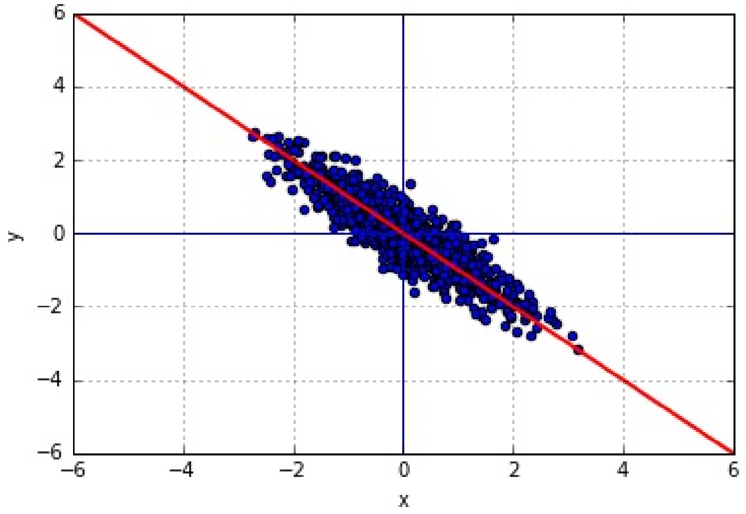
- Correlation = 0.4

low correlation means they vary together , but there is a weak association



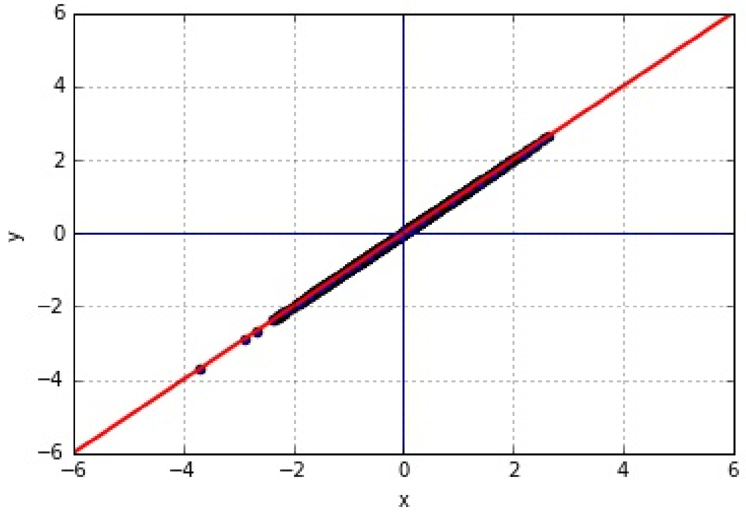
high corr coeff mean that 2 series strongly vary together

- Correlation = -0.9



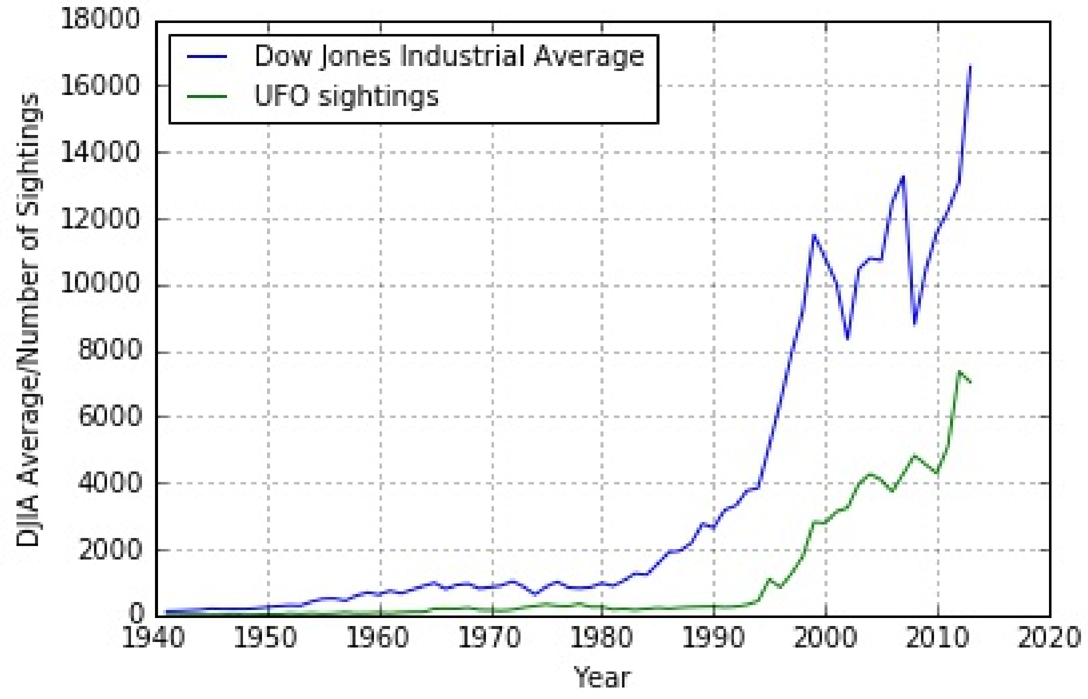
- Corelation = 1.0

perfect linear relationship with no deviations



Common Mistake: Correlation of Two Trending Series

- Dow Jones Industrial Average and UFO Sightings (www.nuforc.org)



even if 2 series are totally unrelated, u could still get a very high correlation

--> it should look at the correlation of their *returns*, not their levels

- Correlation of levels: 0.94
- Correlation of percent changes: ≈ 0

Example: Correlation of Large Cap and Small Cap Stocks

- Start with stock prices of SPX (large cap) and R2000 (small cap)
- First step: Compute percentage changes of both series

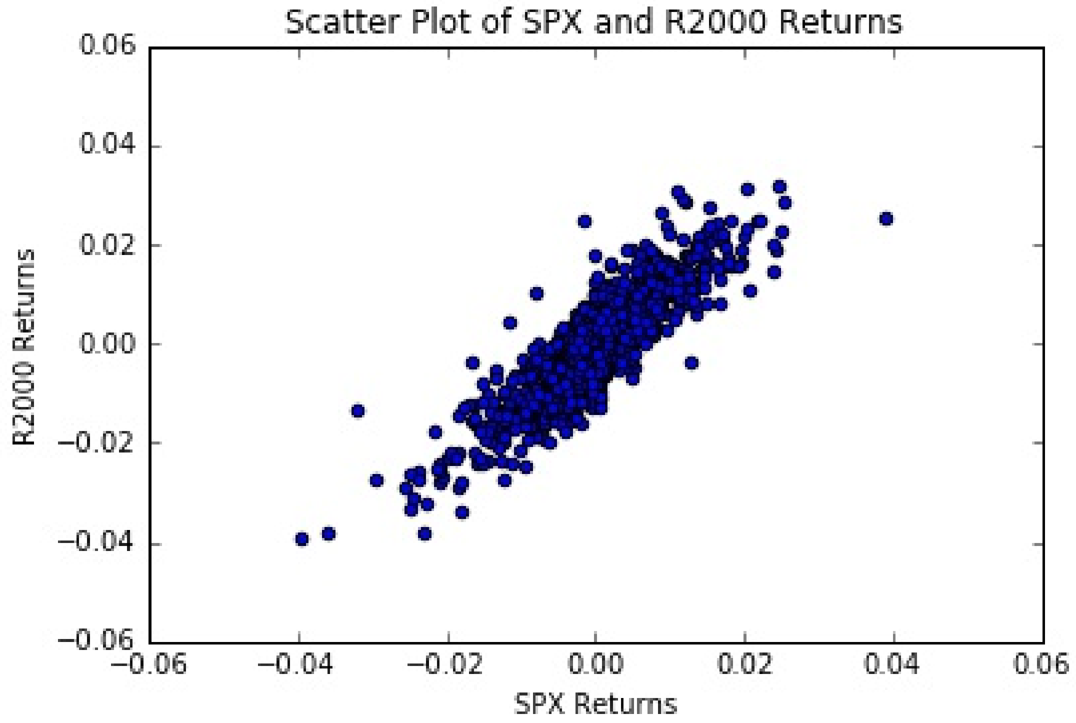
gives the returns of these series instead of prices

```
df['SPX_Ret'] = df['SPX_Prices'].pct_change()
df['R2000_Ret'] = df['R2000_Prices'].pct_change()
```

Example: Correlation of Large Cap and Small Cap Stocks

- Visualize correlation with scattter plot

```
plt.scatter(df['SPX_Ret'], df['R2000_Ret'])
plt.show()
```



Example: Correlation of Large Cap and Small Cap Stocks

- Use pandas correlation method for Series

```
correlation = df['SPX_Ret'].corr(df['R2000_Ret'])
print("Correlation is: ", correlation)

Correlation is: 0.868
```

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Simple Linear Regressions

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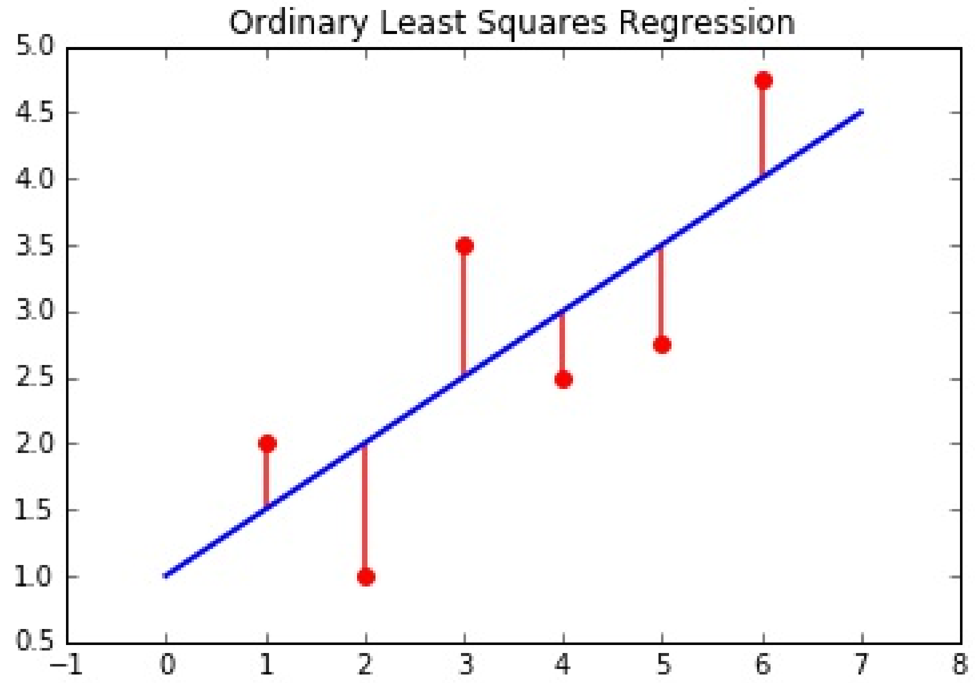
What is a Regression?

- **Simple linear regression**: (best fit y and x)
  x and y can be 2 time series.

$$y_t = \alpha + \beta x_t + \epsilon_t$$

What is a Regression?

- **Ordinary Least Squares (OLS)** minimize the sum of squared distances btw data points and the regression line



Python Packages to Perform Regressions

- In statsmodels:

```
import statsmodels.api as sm
sm.OLS(y, x).fit()
```

- In numpy:

```
np.polyfit(x, y, deg=1)
```

- In pandas:

```
pd.ols(y, x)
```

- In scipy:

```
from scipy import stats
stats.linregress(x, y)
```

- Beware that the order of x and y is not consistent across packages

Example: Regresssion of Small Cap Returns on Large Cap

- Import the statsmodels module

```
import statsmodels.api as sm
```

- As before, compute percentage changes in both series

```
df['SPX_Ret'] = df['SPX_Prices'].pct_change()
df['R2000_Ret'] = df['R2000_Prices'].pct_change()
```

- Add a constant to the DataFrame for the regression intercept

```
df = sm.add_constant(df)
```

need to add a column of ones as a dependent, right hand side variable. Because regression function assumes that if there is no constant column, then u want to run the regression without an intercept.
by adding a column of one, statsmodels will compute the regression coeff of that column as well, which can be interpreted as the intercept of the line

Regresssion Example (continued)

- Notice that the first row of returns is NaN

```
              SPX_Price  R2000_Price   SPX_Ret  R2000_Ret
Date
2012-11-01  1427.589966   827.849976       NaN        NaN
2012-11-02  1414.199951   814.369995 -0.009379  -0.016283
```

each return is computed from 2 prices,
so there is one less return than price

- Delete the row of NaN

```
df = df.dropna()
```

- Run the regression

y const x

```
results = sm.OLS(df['R2000_Ret'],df[['const','SPX_Ret']]).fit()
print(results.summary())
```

Regresssion Example (continued)

- Regression output

intercept
slope

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              R2000_Ret   R-squared:                       0.753
Model:                            OLS   Adj. R-squared:                  0.753
Method:                 Least Squares   F-statistic:                     3829.
Date:                Fri, 26 Jan 2018   Prob (F-statistic):               0.00
Time:                        13:29:55   Log-Likelihood:                 4882.4
No. Observations:                1257   AIC:                            -9761.
Df Residuals:                    1255   BIC:                            -9751.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [95.0% Conf. Int.]
------------------------------------------------------------------------------
const     -4.964e-05      0.000     -0.353      0.724        -0.000     0.000
SPX_Ret        1.1412      0.018     61.877      0.000         1.105     1.177
==============================================================================
Omnibus:                       61.950   Durbin-Watson:                   1.991
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              148.100
Skew:                           0.266   Prob(JB):                     6.93e-33
Kurtosis:                       4.595   Cond. No.                         131.
==============================================================================
```

- Intercept in results.params[0]
- Slope in results.params[1]

Regresssion Example (continued)

- Regression output

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              R2000_Ret   R-squared:                       0.753
Model:                            OLS   Adj. R-squared:                  0.753
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==============================================================================
```

Relationship Between R-Squared and Correlation

- $[\mathrm{corr}(x,y)]^2 = R^2$ (or R-squared) magnitude of the correlation is the square root of R^2
- $\mathrm{sign}(\mathrm{corr}) = \mathrm{sign}(\mathrm{regression\ slope})$
- In last example:
  - R-Squared = 0.753
  - Slope is positive
  - correlation = $+\sqrt{0.753} = 0.868$

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Autocorrelation

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What is Autocorrelation?

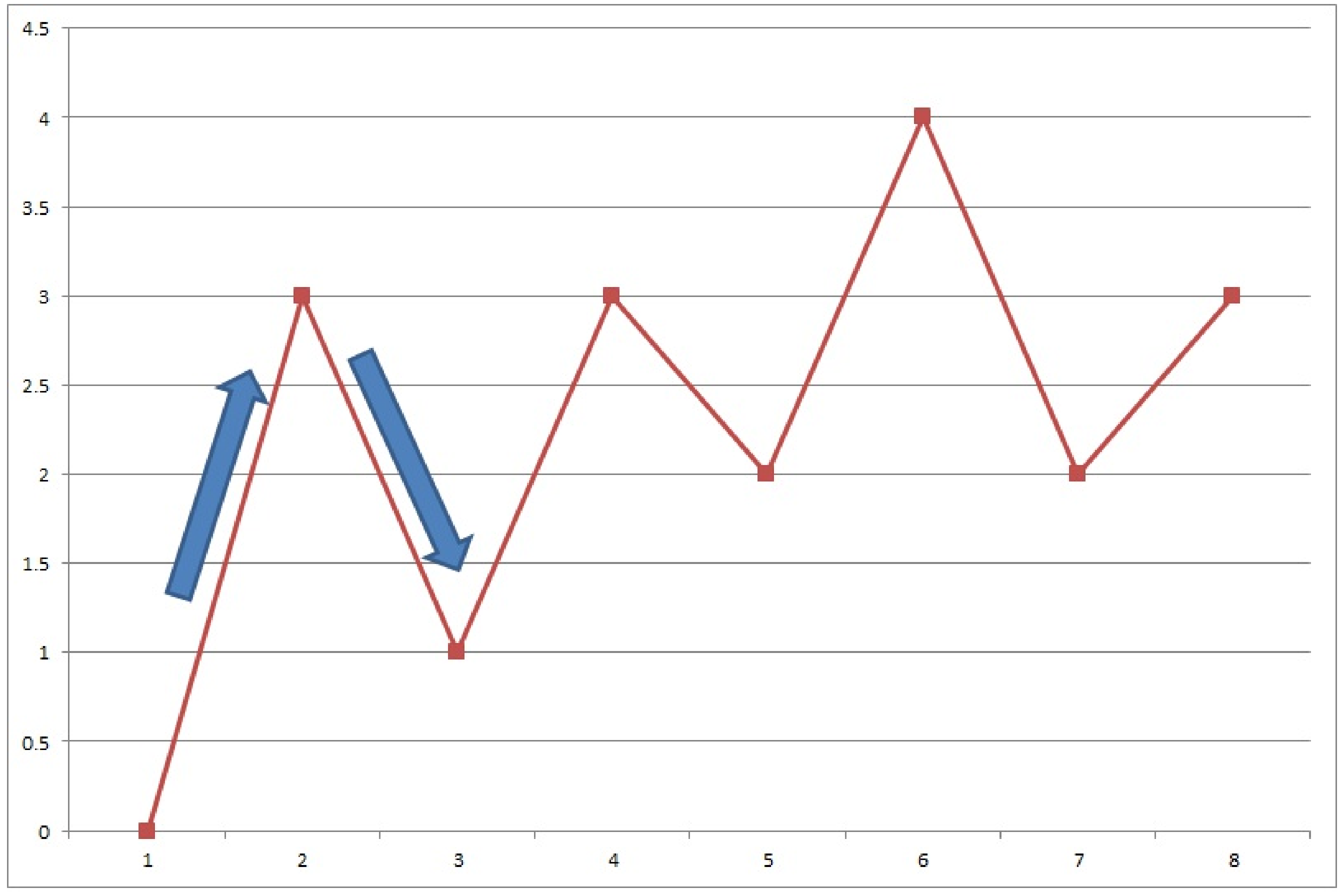
- Correlation of a time series with a lagged copy of itself

Series	Lagged Series
5	
10	5
15	10
20	15
25	20
⋮	⋮

- Lag-one autocorrelation = series's autocorrelation
- Also called **serial correlation**

Interpretation of Autocorrelation

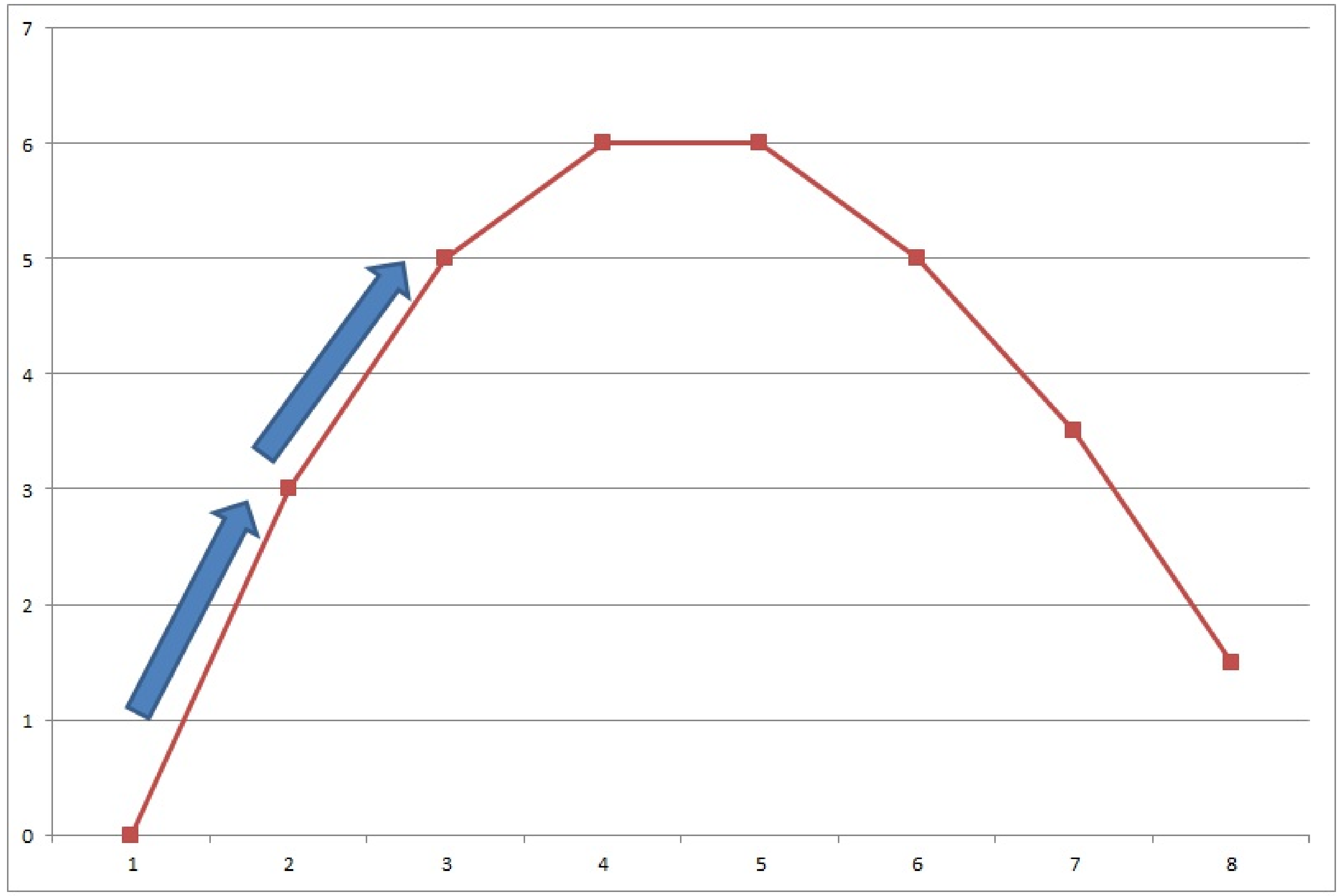
- **Mean Reversion** - Negative autocorrelation



with financial time series, when returns have a negative autocorrelation, we say it is "mean reverting"

Interpretation of Autocorrelation

- **Momentum**, or **Trend Following** - Positive autocorrelation



Traders Use Autocorrelation to Make Money

- Individual stocks
  - Historically have negative autocorrelation
  - Measured over short horizons (days)
  - Trading strategy: Buy losers and sell winners

to buy stocks that have dropped over the last week and sell stocks that have gone up

- Commodities and currencies
  - Historically have positive autocorrelation
  - Measured over longer horizons (months)
  - Trading strategy: Buy winners and sell losers

Example of Positive Autocorrelation: Exchange Rates

- Start with daily data of ¥/$ exchange rates in DataFrame df from FRED
- Convert index to datetime

```
df.index = pd.to_datetime(df.index)
```

- Downsample from daily to monthly data

```
df = df.resample(rule='M', how='last')
```

- Compute returns from prices

```
df['Return'] = df['Price'].pct_change()
```

- Compute autocorrelation

```
autocorrelation = df['Return'].autocorr()
print("The autocorrelation is: ",autocorrelation)
The autocorrelation is: 0.0567
```

so, this series exhibits some momentum

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