# Rolling window functions with pandas

MANIPULATING TIME SERIES DATA IN PYTHON

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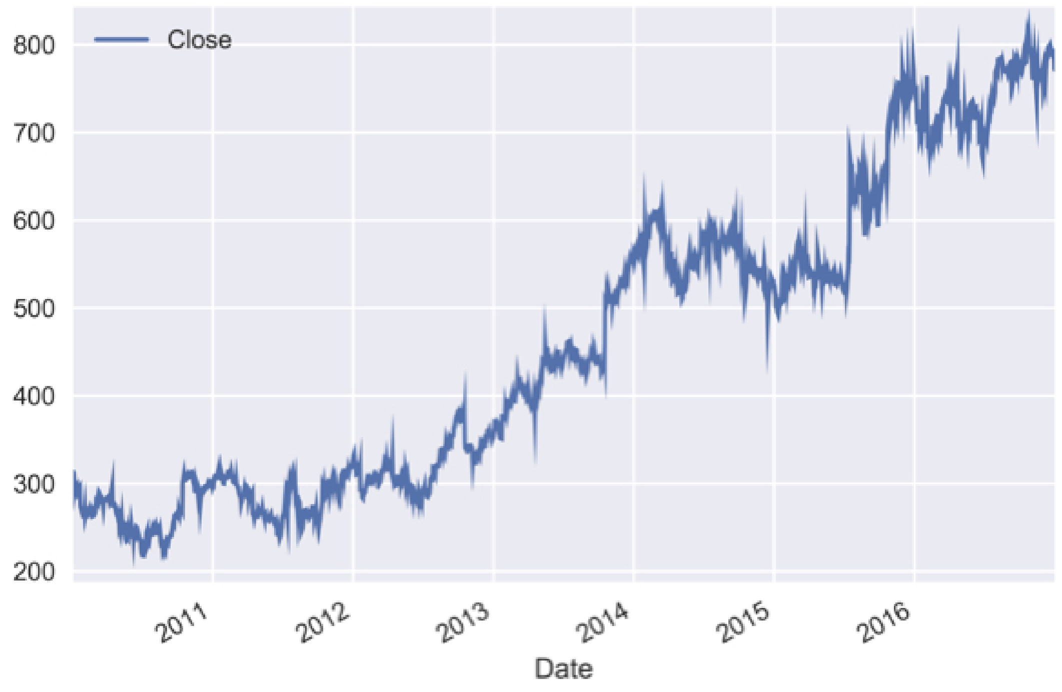
# Window functions in pandas

- Windows identify sub periods of your time series
- Calculate metrics for sub periods inside the window
- Create a new time series of metrics
- Two types of windows:
  - Rolling: same size, sliding (this video)
  - Expanding: contain all prior values (next video)

# Calculating a rolling average

```
data = pd.read_csv('google.csv', parse_dates=['date'], index_col='date')
```

```
DatetimeIndex: 1761 entries, 2010-01-04 to 2016-12-30
Data columns (total 1 columns):
price     1761 non-null float64
dtypes: float64(1)
```



# Calculating a rolling average

```
# Integer-based window size
data.rolling(window=30).mean() # fixed # observations
```

```
DatetimeIndex: 1761 entries, 2010-01-04 to 2017-05-24
Data columns (total 1 columns):
price    1732 non-null float64
dtypes: float64(1)
```

- `window=30` : # business days
- `min_periods` : choose value < 30 to get results for first days

# Calculating a rolling average

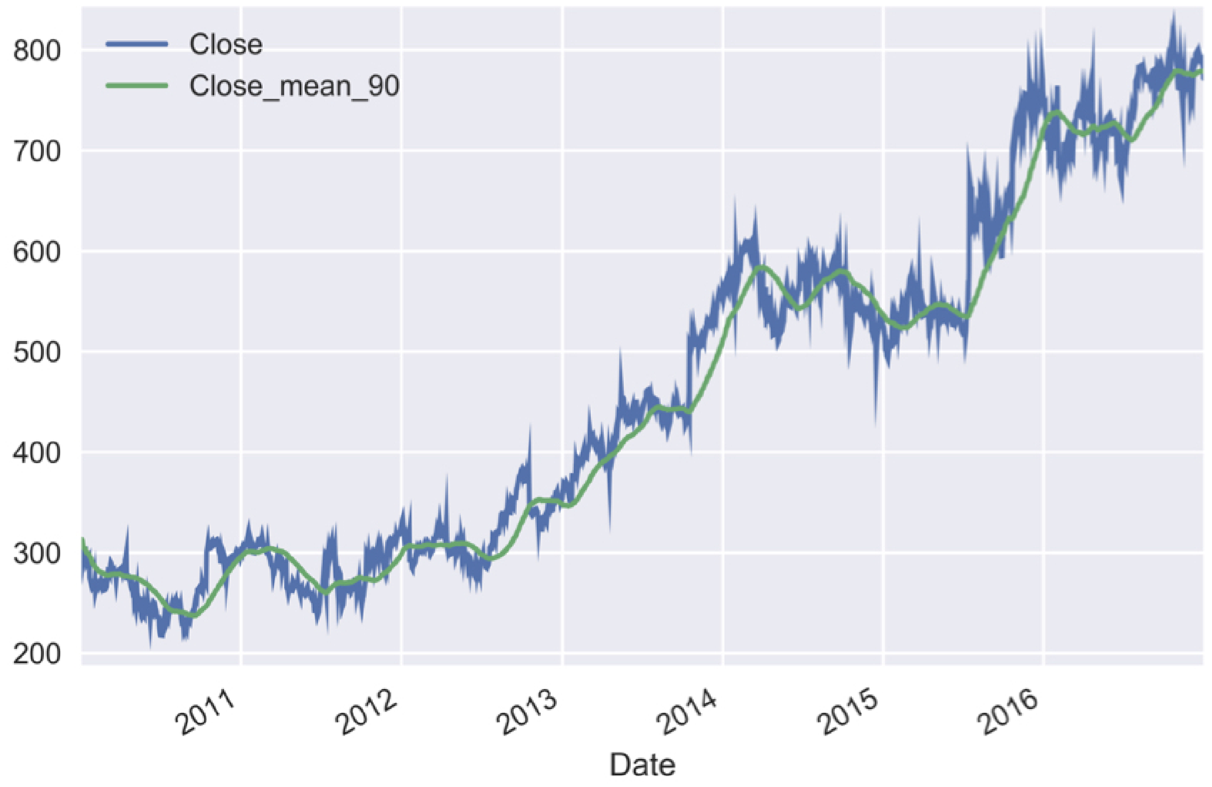
```
# Offset-based window size
data.rolling(window='30D').mean() # fixed period length
```

```
DatetimeIndex: 1761 entries, 2010-01-04 to 2017-05-24
Data columns (total 1 columns):
price    1761 non-null float64
dtypes: float64(1)
```

- `30D` : # calendar days

# 90 day rolling mean

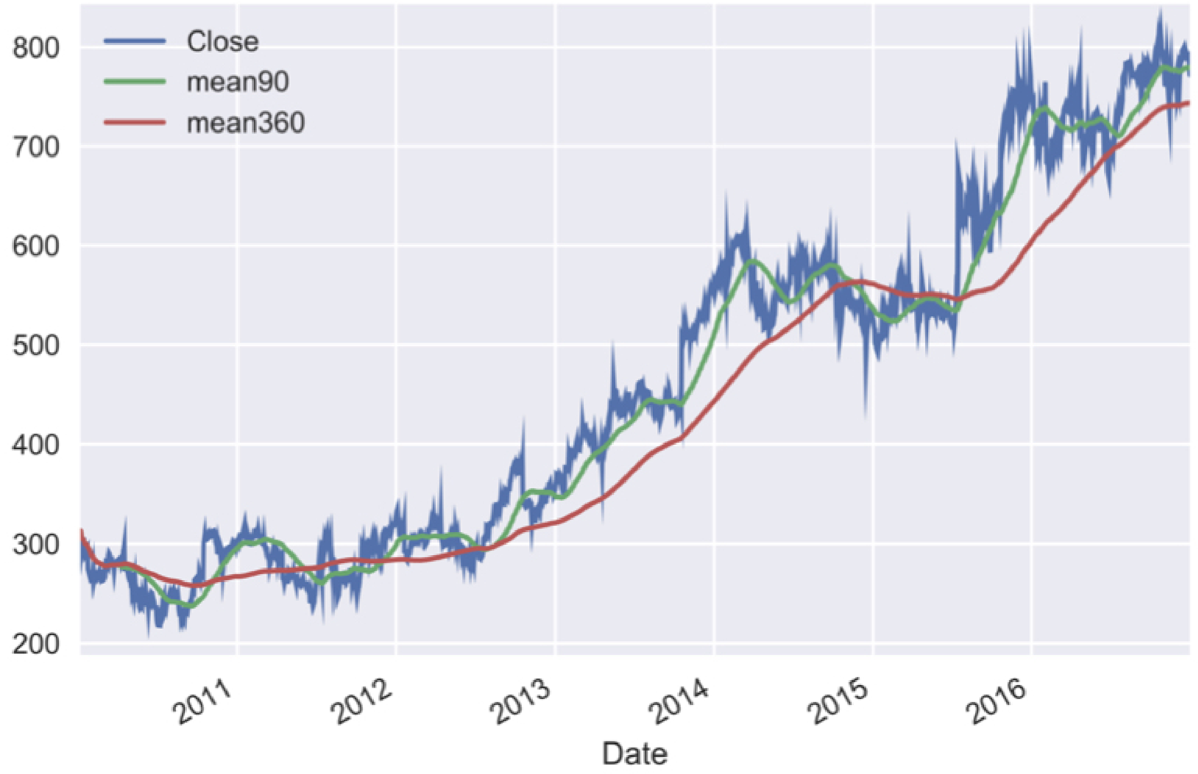
```
r90 = data.rolling(window='90D').mean()
google.join(r90.add_suffix('_mean_90')).plot()
```




.join:
**concatenate** Series **or** DataFrame **along** axis=1

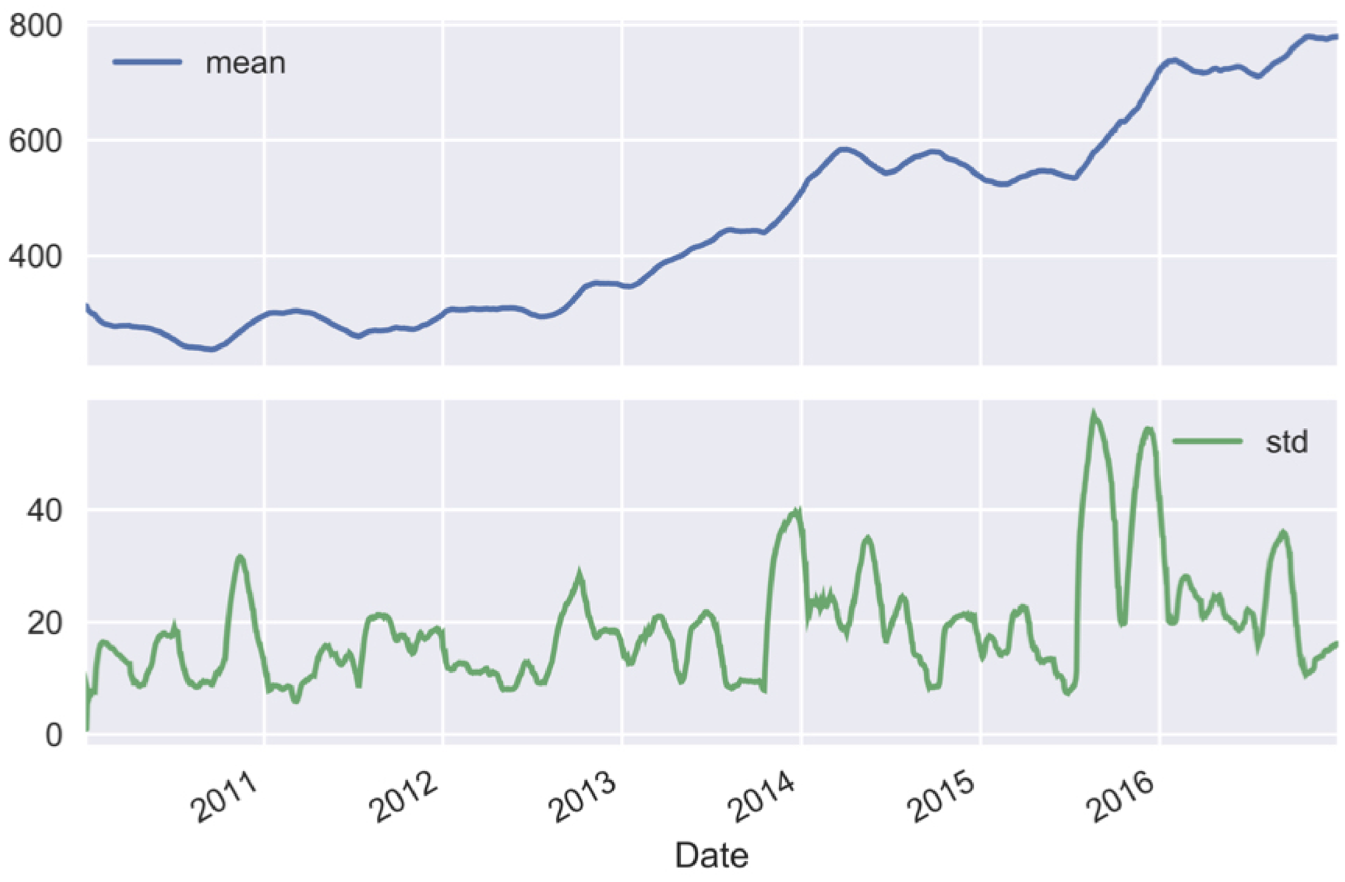
# 90 & 360 day rolling means

```
data['mean90'] = r90
r360 = data['price'].rolling(window='360D'.mean()
data['mean360'] = r360; data.plot()
```



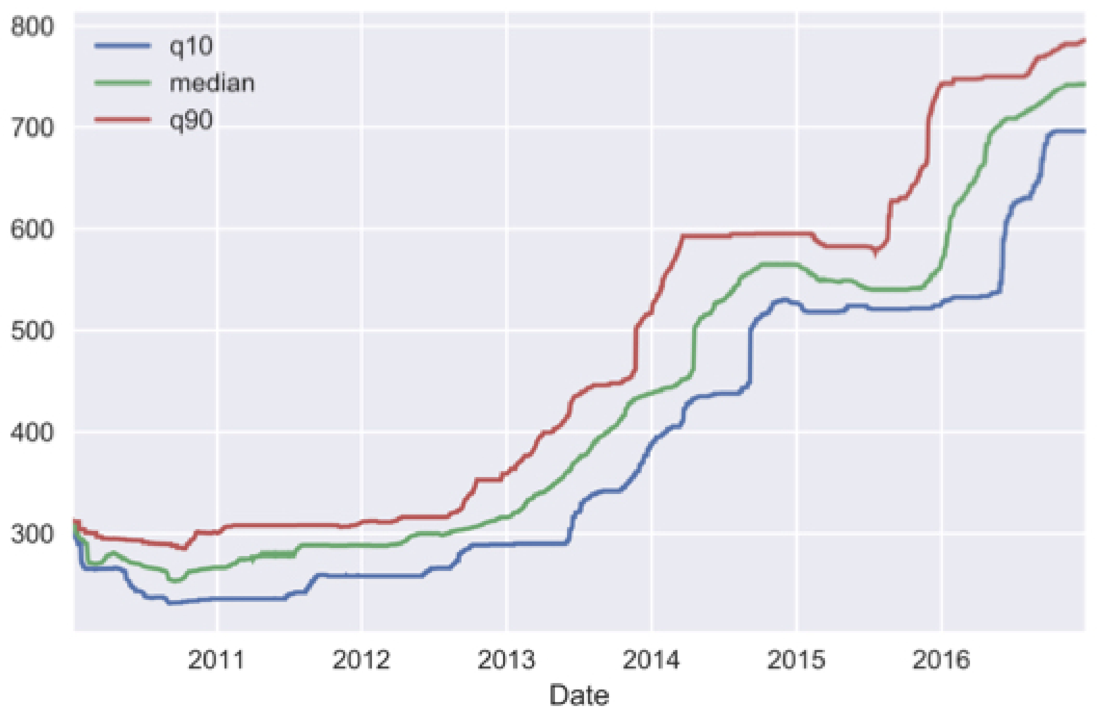
# Multiple rolling metrics (1)

```
r = data.price.rolling('90D').agg(['mean', 'std'])
r.plot(subplots = True)
```



# Multiple rolling metrics (2)

```
rolling = data.google.rolling('360D')
q10 = rolling.quantile(0.1).to_frame('q10')
median = rolling.median().to_frame('median')
q90 = rolling.quantile(0.9).to_frame('q90')
pd.concat([q10, median, q90], axis=1).plot()
```



# Let's practice!

# Expanding window functions with pandas

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# Expanding windows in pandas

- From rolling to expanding windows
- Calculate metrics for periods up to current date
- New time series reflects all historical values
- Useful for running rate of return, running min/max
- Two options with pandas:
  - `.expanding()` - just like `.rolling()`
  - `.cumsum()` , `.cumprod()` , `cummin()` / `max()`

# The basic idea

```
df = pd.DataFrame({'data': range(5)})
df['expanding sum'] = df.data.expanding().sum()
df['cumulative sum'] = df.data.cumsum()
df
```

```
   data  expanding sum  cumulative sum
0     0            0.0               0
1     1            1.0               1
2     2            3.0               3
3     3            6.0               6
4     4           10.0              10
```

# Get data for the S&P 500

```python
data = pd.read_csv('sp500.csv', parse_dates=['date'], index_col='date')
```

```
DatetimeIndex: 2519 entries, 2007-05-24 to 2017-05-24
Data columns (total 1 columns):
SP500    2519 non-null float64
```

# How to calculate a running return

- Single period return $r_t$: current price over last price minus 1:

$$r_t = \frac{P_t}{P_{t-1}} - 1$$

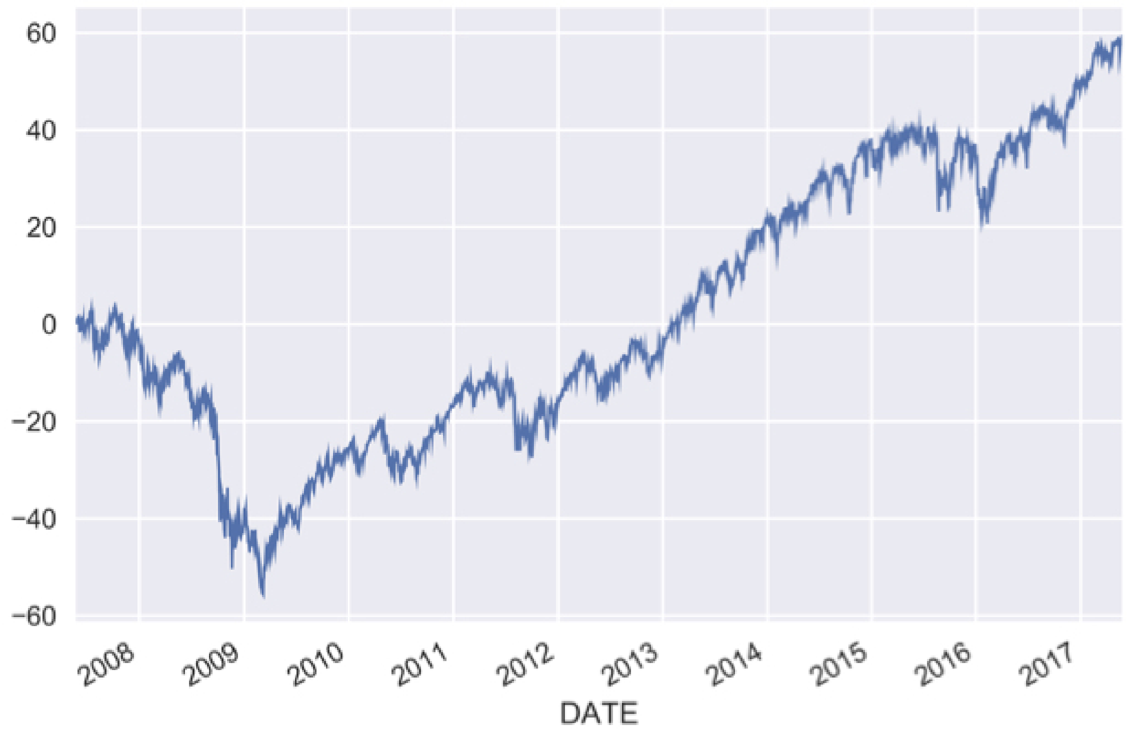
  - Multi-period return: product of $(1 + r_t)$ for all periods, minus 1:

$$R_T = (1 + r_1)(1 + r_2)...(1 + r_T) - 1$$

  - For the period return: `.pct_change()`
  - For basic math `.add()`, `.sub()`, `.mul()`, `.div()`
  - For cumulative product: `.cumprod()`

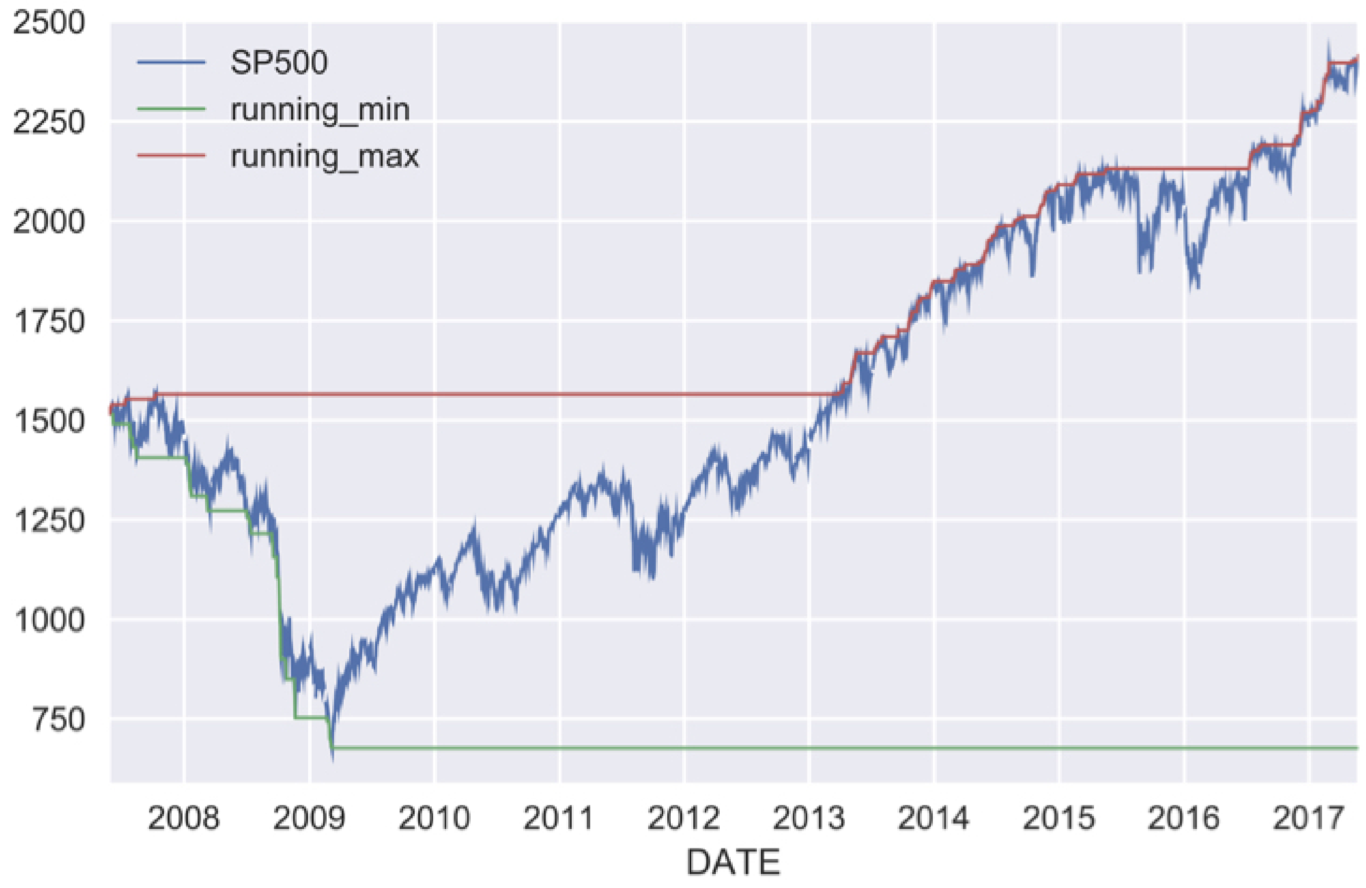
# Running rate of return in practice

```
pr = data.SP500.pct_change() # period return
pr_plus_one = pr.add(1)
cumulative_return = pr_plus_one.cumprod().sub(1)
cumulative_return.mul(100).plot()
```



# Getting the running min & max

```
data['running_min'] = data.SP500.expanding().min()
data['running_max'] = data.SP500.expanding().max()
data.plot()
```

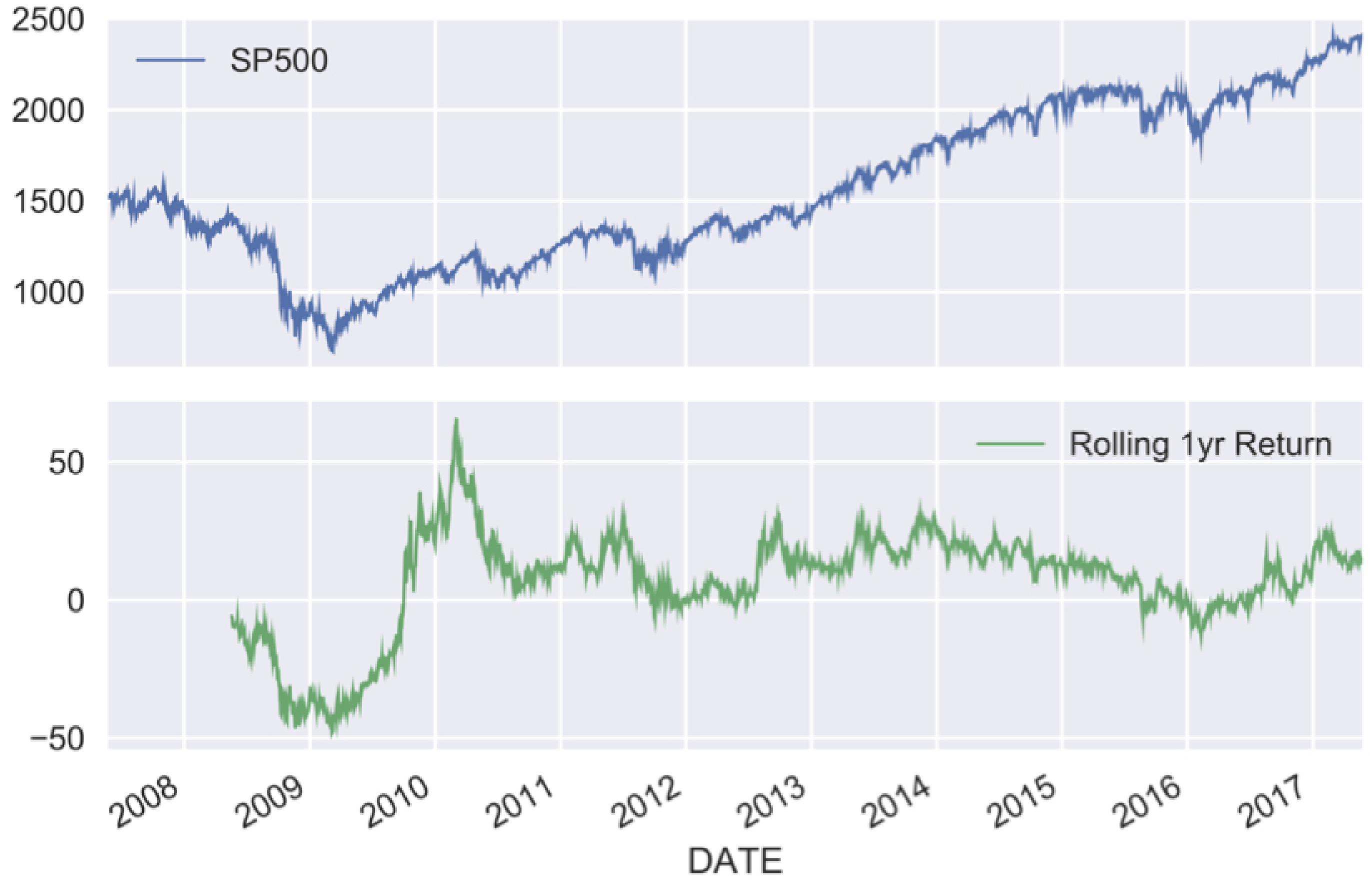


# Rolling annual rate of return

```
def multi_period_return(period_returns):
    return np.prod(period_returns + 1) - 1
pr = data.SP500.pct_change() # period return
r = pr.rolling('360D').apply(multi_period_return)
data['Rolling 1yr Return'] = r.mul(100)
data.plot(subplots=True)
```

# Rolling annual rate of return

```
data['Rolling 1yr Return'] = r.mul(100)
data.plot(subplots=True)
```



# Let's practice!

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# Case study: S&P500 price simulation

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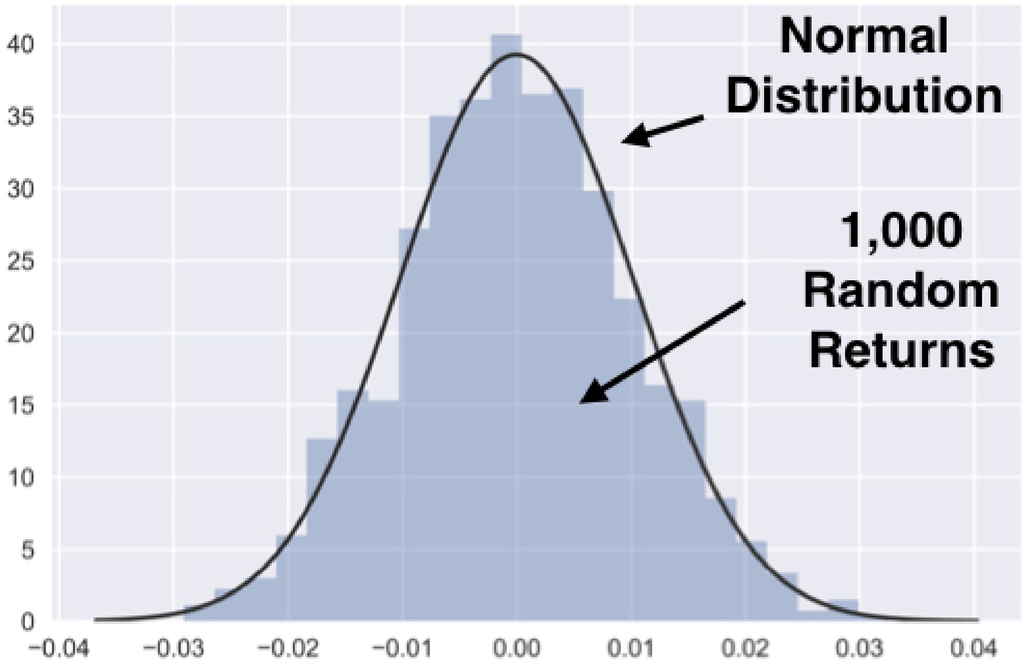
# Random walks & simulations

- Daily stock returns are hard to predict
- Models often assume they are random in nature
- Numpy allows you to generate random numbers
- From random returns to prices: use `.cumprod()`
- Two examples:
  - Generate random returns
  - Randomly selected actual SP500 returns

# Generate random numbers

```
from numpy.random import normal, seed
from scipy.stats import norm
seed(42)
random_returns = normal(loc=0, scale=0.01, size=1000)
sns.distplot(random_returns, fit=norm, kde=False)
```

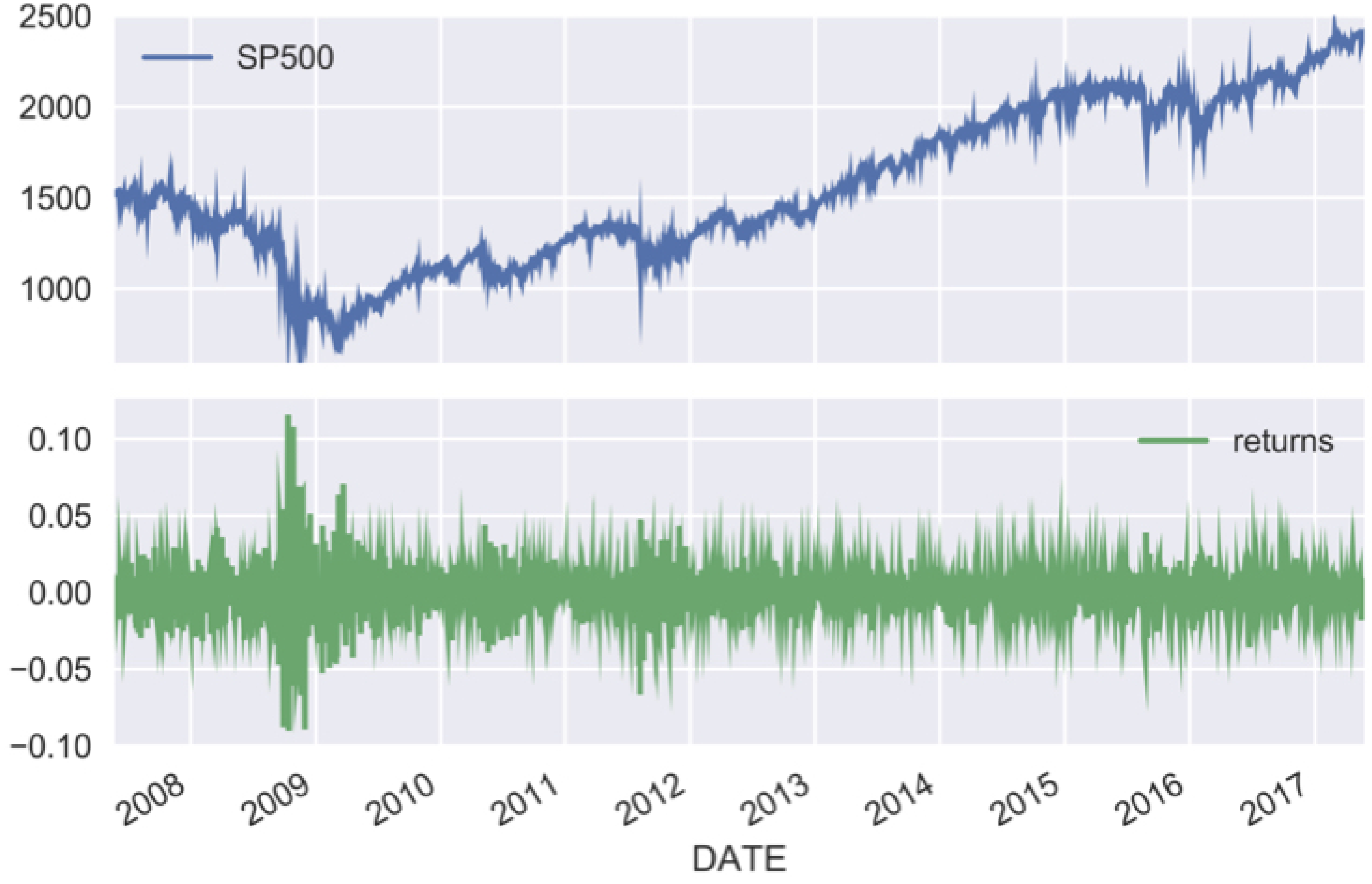


# Create a random price path

```
return_series = pd.Series(random_returns)
random_prices = return_series.add(1).cumprod().sub(1)
random_prices.mul(100).plot()
```

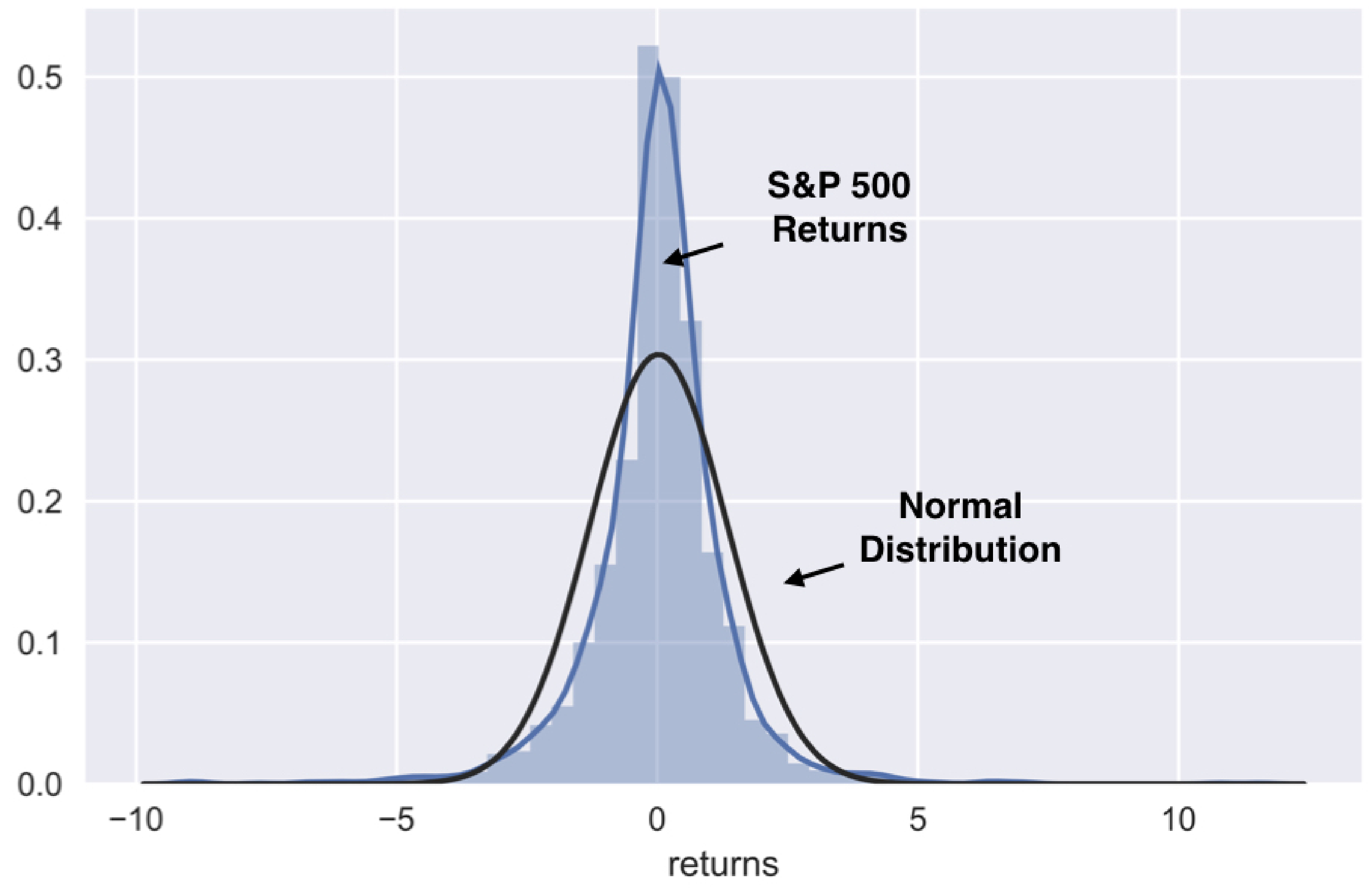
# S&P 500 prices & returns

```
data = pd.read_csv('sp500.csv', parse_dates=['date'], index_col='date')
data['returns'] = data.SP500.pct_change()
data.plot(subplots=True)
```



# S&P return distribution

```
sns.distplot(data.returns.dropna().mul(100), fit=norm)
```



# Generate random S&P 500 returns

```python
from numpy.random import choice
sample = data.returns.dropna()
n_obs = data.returns.count()
random_walk = choice(sample, size=n_obs)
random_walk = pd.Series(random_walk, index=sample.index)
random_walk.head()
```

```
DATE
2007-05-29   -0.008357
2007-05-30    0.003702
2007-05-31   -0.013990
2007-06-01    0.008096
2007-06-04    0.013120
```

# Random S&P 500 prices (1)

```
start = data.SP500.first('D')
```

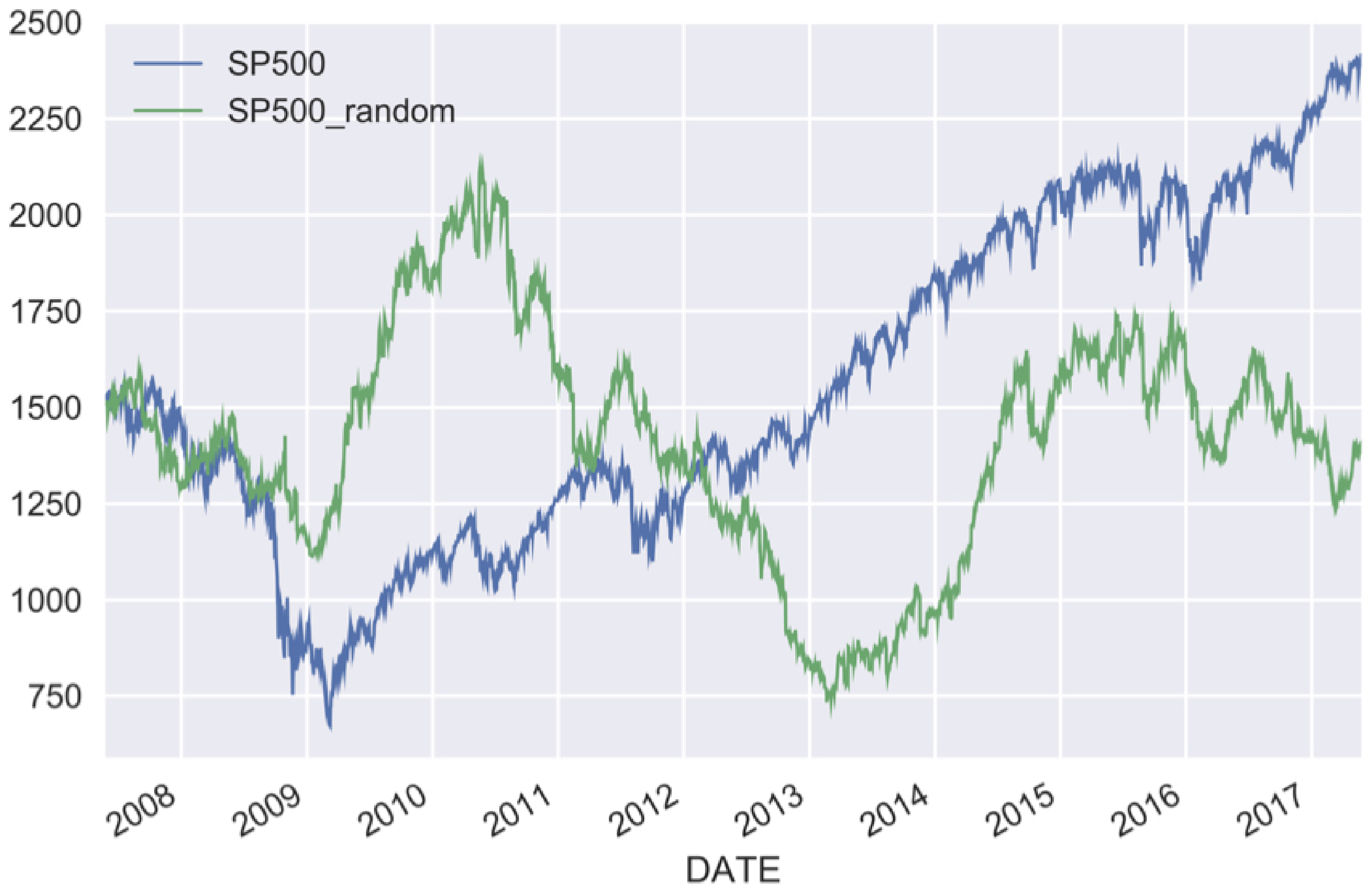
```
DATE
2007-05-25    1515.73
Name: SP500, dtype: float64
```

```
sp500_random = start.append(random_walk.add(1))
sp500_random.head())
```

```
DATE
2007-05-25    1515.730000
2007-05-29       0.998290
2007-05-30       0.995190
2007-05-31       0.997787
2007-06-01       0.983853
dtype: float64
```

# Random S&P 500 prices (2)

```
data['SP500_random'] = sp500_random.cumprod()
data[['SP500', 'SP500_random']].plot()
```



# Let's practice!

# Relationships between time series: correlation

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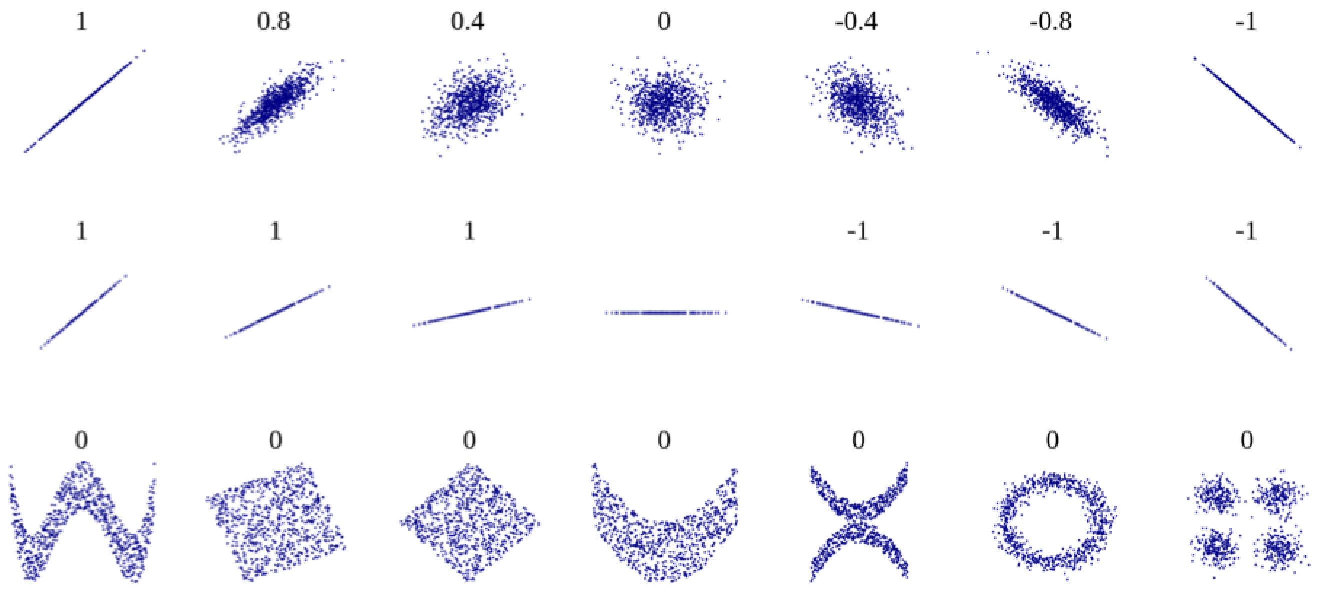
# Correlation & relations between series

- So far, focus on characteristics of individual variables
- Now: characteristic of relations between variables
- Correlation: measures linear relationships
- Financial markets: important for prediction and risk management
- `pandas` & `seaborn` have tools to compute & visualize

# Correlation & linear relationships

- Correlation coefficient: how similar is the pairwise movement of two variables around their averages?
- Varies between `-1` and `+1`

$$r = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{s_x s_y}$$




**Strength of linear relationship**

**Positive or negative**

**Not: non-linear relationships**

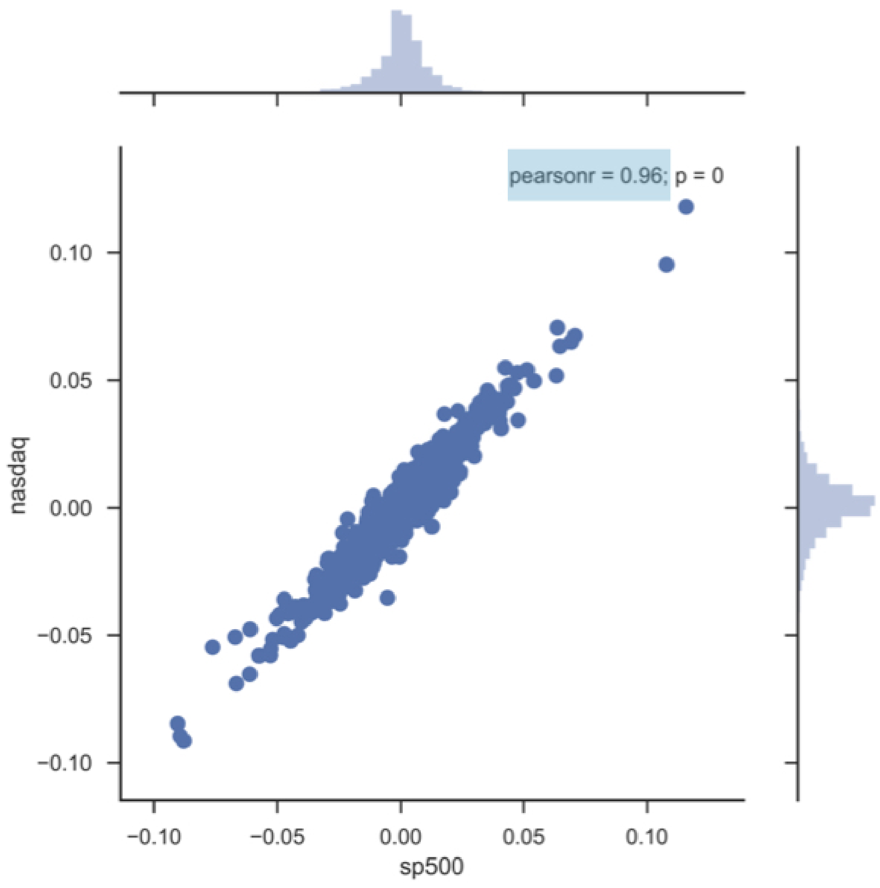
# Importing five price time series

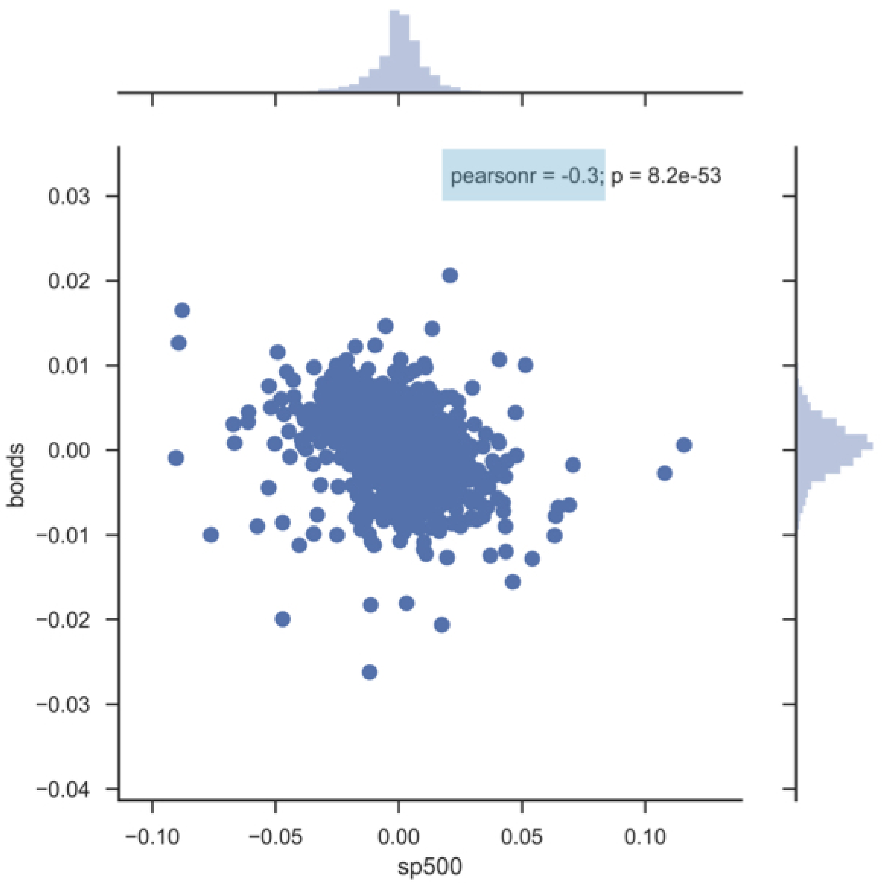
```
data = pd.read_csv('assets.csv', parse_dates=['date'],
                   index_col='date')
data = data.dropna().info()
```

```
DatetimeIndex: 2469 entries, 2007-05-25 to 2017-05-22
Data columns (total 5 columns):
sp500     2469 non-null float64
nasdaq    2469 non-null float64
bonds     2469 non-null float64
gold      2469 non-null float64
oil       2469 non-null float64
```

# Visualize pairwise linear relationships

```
daily_returns = data.pct_change()
sns.jointplot(x='sp500', y='nasdaq', data=data_returns);
```



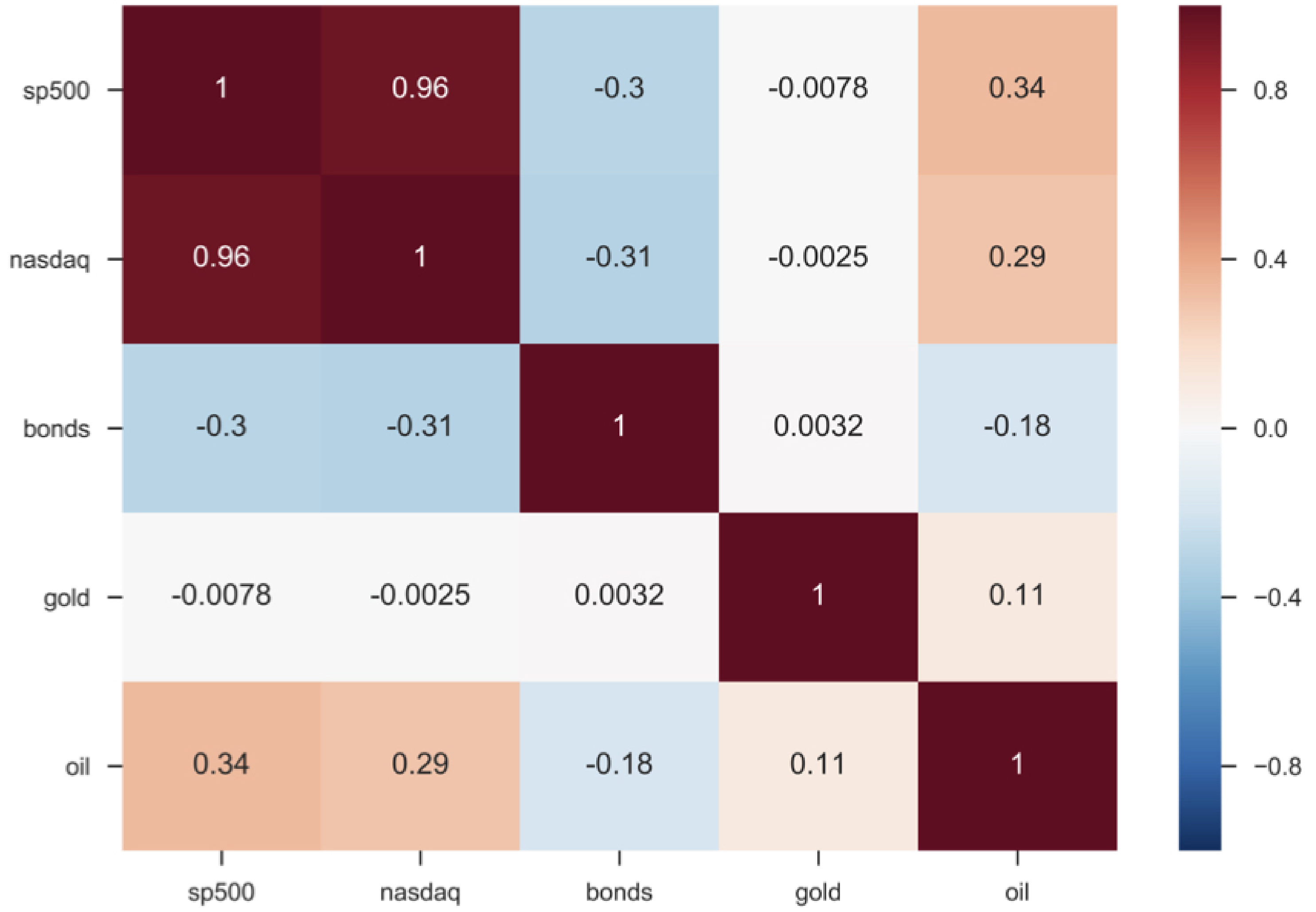
# Calculate all correlations

```
correlations = returns.corr()
correlations
```

```
bonds        oil      gold     sp500    nasdaq
bonds   1.000000 -0.183755  0.003167 -0.300877 -0.306437
oil    -0.183755  1.000000  0.105930  0.335578  0.289590
gold    0.003167  0.105930  1.000000 -0.007786 -0.002544
sp500  -0.300877  0.335578 -0.007786  1.000000  0.959990
nasdaq -0.306437  0.289590 -0.002544  0.959990  1.000000
```

# Visualize all correlations

```python
sns.heatmap(correlations, annot=True)
```



# Let's practice!