# Computational Finance

### 18 Feb 2020

#### Returns

We can evaluate returns based on a time series of prices, denoted as . For instance,

We can consider returns as . It is important to note the asymmetry here, as if we were to take an example, with , then consequently if we were to flip the values for .

#### Multiperiod Returns

Returns over multiple time steps are a product rather than a sum, and this could be demonstrated with an example over 4 time steps, where . The returns would yield . This does not sum to 0.6, but in fact the product still yields the correct values.

#### Return on a Portfolio

Assuming assets (google, gold, USD, etc...) with an allocation of where , and

Presuming as capital, your set up is , which evaluates to

#### Annualizing Returns

This creates a standard to compare return rates. You can consider monthly vs yearly.

Where , where

Or you can do . Note here that instead of 365, 300 is used. This is a variation within the field, having values such as 250, 275, 300, 365, etc... (My best guess to why this is the case is because we are going off the presumption that we are not trading every day)

Notice that we use exponential to take into account the notion of compounding.

#### Value of Money

To answer the question of “how much is one dollar today worth tomorrow?” We need to look at the frequency of returns.

Consider:

, the future value, denoted

, the future value, denoted

, the future value, denoted

Generalized as , where is the current value.

There is a theoretical consideration here where we consider the returns to be continuous, allowing us to use limits, which results in our calculations to come to:

(We can kind of remember vaguely something similar to this when we originally calculated compounding interest)

It is not considered realistic in practice however.

Note that this formula also allows for a symmetry (whereas the multiperiod returns before do not).

Multiperiod Continuous returns are additive.

#### Book-keeping

It is done in the format , for instance, or . The indicates the BUY, and the indicates the SELL.

Note that in the market, there is not a singular price for any given item, but rather a ASK and a BID price. Meaning that BUY and SELL prices are marked differently. The difference between the ASK and BID price is called the spread.

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There’s a website that simulates a market that could be interesting to play with some of the concepts: oanda

#### Modeling in Time Series analysis (and it’s not what you think)

When taking a look at a time series, we might want to consider values of interest of points of analysis such as mean (expected value), variance, standard deviation, and even things like monthly return, etc... These factors are what are taken into account when we talk about “modeling”.

It is important to separate the terminology of “modeling” with “prediction” since in the finance world, we are not talking about the same thing. The difference here is that the model speaks to nothing about the future or attempts to make a “prediction” like we think about in regular machine learning, but rather, we are talking about a descriptor or an explanation of the current data that we have.

#### Stationary is a pre-requisite in Modeling

When looking at time series analysis and modeling, it might be counter intuitive to consider the fact that we make some assumptions or even manipulate what we take into account in our analysis in order to “fix” or make stationary the data. We are not looking at trends (upwards increase that is somewhat linear) nor are we looking at the seasonalities of the data (some sort of up and down with regards to time). That is not to say that we don’t care about patterns, but rather more importantly,

#### We are looking beyond at patterns which are a function of time

This means that we fix properties about the time series. The two conditions for our stationary property is:

1. Meaning that the average is the same along the time series.

2. Meaning that the variance is the same with regards to any points.

One of the very good examples that highlight this type of “fixing” or stationary property is to look at a time series with a upwards trend:

//see the paper notes

and see that when we take the monthly returns and look at the data that originally had an upwards trend, to notice that we sort of “removed” this upwards trend when we take the monthly returns. Essentially, we are attempting to find a pattern in the data, or descriptor in the data that is not a function of time (intuition might be to understand that obviously things will increase or decrease, but perhaps we are more worried about HOW they increase or decrease, or even maybe WHY they could increase decrease).

#### Autocorrelation of a Model in order to find (hidden) patterns

The autoregressive model gives us the concept of an autocorrelation, which when we formalize into the autocorrelation function, gives us a tool to analyze the (hidden) patterns of our data. We can take a time series, and view its autocorrelation function. It is useful to see the paper notes images regarding this part.