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Financial Regime Modeling using Markov Chains

In the world of quantitative finance, a financial regime is a period of time during which a market or security exhibits consistent conditions. For example, a regime can be bullish, meaning it's on an uptrend, bearish, meaning it's on a downtrend, or sideways, meaning it's neutral. Knowing which regime a market and/or a security is in can be invaluable when determining investment strategies, and as a result, the ability to model them is extremely useful. This led us to our project idea of using the concept of Markov Chains to try and model the long-term steady state market distribution of a market/security using a Markov Process, and see along the way the types of insights we can gain based on our analysis.

Firstly, why the Markov Model in particular? In finance, there is a hypothesis called the Efficient Market Hypothesis which states that "share prices reflect all available information" (Downey). This in essence suggests that the current price of an asset already reflects all past pricing information. Based on this assumption, it can be concluded that the current state of the asset/market holds enough information to make predictions of the future market, without taking into account the path to get there. This makes it the perfect candidate for Markovian analysis as the Markovian property states that future outcomes solely depend on the present and not the past. This property enabled our strategy of assigning movement patterns to different states so that we could construct a transition probability matrix and calculate the long term steady state market distribution.

Before applying the model to specific securities, we constructed the methodology using the S&P 500, which is the index that tracks the top 500 largest companies, as the base case. To apply the Markov process, we split the process into a sequence of steps. Firstly, we had to establish variables: $P(t)$: The closing price of the S&P 500 at time t. $R(t)$: the daily return calculated as $P(t)-P(t-1)/P(t-1)$. $\boldsymbol{\sigma}$: the standard deviation (volatility) of the daily returns over the historical period. δ: the state classification, which for this case was determined using the threshold $0.1\boldsymbol{\sigma}$. After determining the variables, we were able to begin to model the price as a stochastic process. To begin, we started with three base states: increasing, decreasing, and stable. To determine the states, we calculated the daily return percentage, and then used the standard deviation to establish thresholds for what was considered an increasing state, decreasing state, or stable state. The conventions for assigning the states were: decreasing if $R(t) < -\delta$, increasing if $R(t) > \delta$ and stable if $R(t)$ was between those two values. After assigning each market day a state based on its previous day, it was possible to create a probability transition matrix. Once we had the probability transition matrix established, we were able to use the formula $\pi P = \pi$ to calculate the steady state distribution.