Limit Order Book Dynamics

Our goal is to use the dynamics of the Limit Order Book (LOB) as an indicator for high-frequency stock price movement, thus enabling statistical arbitrage. Formally, we will the study limit order book imbalance process, I(t), and the stock price process, S(t), and attempt to establish a stochastic relationship $\dot{S} = f(S, I, t)$. We will then attempt to derive an optimal trading strategy based on the observed relationship.

Recap Next Steps

- 1. Complete in-sample backtesting of the 'naive' trading strategies.
- 2. Formulate stochastic control problem
- 3. Extra Reading: Bellman Equations, MDP, Partially Observable MDP

In-Sample Backtesting of Naive Trading Strategies

As a refresher:

We are a considering a CTMC for the joint distribution $(I(t), \Delta S(t))$ where $I(t) \in \{1, 2, \dots, \#_{bins}\}$ is the bin corresponding to imbalance averaged over the interval $[t - \Delta t_I, t]$, and $\Delta S(t) = \text{sign}(S(t + \Delta t_S) - S(t)) \in \{-1, 0, 1\}$, considered individually for the best bid and best ask prices. The pair $(I(t), \Delta S(t))$ was then reduced into one dimension with a simple encoding.

From the resulting timeseries we estimated a generator matrix G and used it to obtain a one-step transition probability matrix $P = e^{G\Delta t_I}$. The entries of P contain the conditional probabilities $\mathbb{P}\left[\rho_{curr}, \Delta S_{curr} \mid \rho_{prev}, \Delta S_{prev}\right]$, from which we can solve for the probability of now seeing a given price change (ΔS_{curr}) conditional on the current imbalance, the previous imbalance, and the previous price change.

For example, one such conditional probability matrix P_C (using 3 imbalance bins) was:

Immediately evident from P_C is that in most cases we are expecting no price change. In fact, the only cases in which the probability of a price change is > 0.5 show evidence of momentum; for example, the way to interpret the value in row 1, column 1 is: if $\rho_{prev} = \rho_{curr} = 1$ and previously we saw a downward price change, then we expect to again see a downward price change. In fact, the best way to summarize the matrix is:

$$\mathbb{P}\left[\Delta S_{curr} = \Delta S_{prev} \mid \rho_{prev} = \rho_{curr}\right] > 0.5$$

We backtested a number of naive trading strategies, outlined below, based on this observation.

Algorithm 1 Naive Trading Strategy

```
1: cash = 0
 2: asset = 0
 3: for t = 2: length(timeseries) do
         if \mathbb{P}\left[\Delta S_{curr} < 0 \mid \rho_{curr}, \rho_{prev}, \Delta S_{prev}\right] > 0.5 then
             cash += data.BuyPrice(t)
             asset = 1
 6:
         else if \mathbb{P}\left[\Delta S_{curr} > 0 \mid \rho_{curr}, \rho_{prev}, \Delta S_{prev}\right] > 0.5 then
 7:
             cash = data.SellPrice(t)
 8:
 9:
             asset += 1
         end if
10:
11: end for
12: if asset > 0 then
         cash += asset \times data.BuyPrice(t)
14: else if asset < 0 then
         cash += asset \times data.SellPrice(t)
16: end if
```

Algorithm 2 Naive+ Trading Strategy

```
1: cash = 0
 2: asset = 0
 3: for t = 2 : length(timeseries) do
         if \mathbb{P}\left[\Delta S_{curr} < 0 \mid \rho_{curr}, \rho_{prev}, \Delta S_{prev}\right] > 0.5 then
             cash += data.BuyPrice(t)
             asset = 1
 6:
 7:
         else if \mathbb{P}\left[\Delta S_{curr} > 0 \mid \rho_{curr}, \rho_{prev}, \Delta S_{prev}\right] > 0.5 \text{ then}
             cash = data.SellPrice(t)
 8:
             asset += 1
 9:
         end if
10:
11: end for
12: if asset > 0 then
         cash += asset \times data.BuyPrice(t)
14: else if asset < 0 then
         cash += asset \times data.SellPrice(t)
16: end if
```