Fill Probability Based Mid-Frequency Market Making

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1 Introduction and Background

Market-making refers to the activity of providing liquidity to the market by continuously quoting buy and sell prices for a financial instrument. Market-makers are individuals or entities that engage in market-making on electronic exchanges. A market-maker primarily profits from the bid-ask spread, which is the difference between the price at which they are willing to buy (bid) and the price at which they are willing to sell (ask). However, market-making also involves significant risks, namely liquidity risk, inventory risk, and adverse selection risk. Adverse selection risk occurs when market-makers are more likely to be on the losing side of trades due to information asymmetry. For example, if a market-maker quotes a buy price that is too high, they may end up buying an asset that is worth less than the price they paid for it. Conversely, if they quote a sell price that is too low, they may end up selling an asset that is worth more than the price they received for it. Inventory risk arises when a market-maker holds a large position in a particular asset, which can lead to significant losses if the price of that asset moves against them. Liquidity risk arises when a market-maker is unable to execute trades at the desired price due to a lack of liquidity in the market. Market-makers must carefully manage these risks in order to be successful in their trading activities. To minimise these risks, the market maker must carefully manage their inventory and adjust their quotes based on market conditions.

The task of identifying the correct pricing for quotes is a challenging time-series forecasting problem, which has been extensively studied in the literature. This boils down to estimating signals known as alphas, which predict the future price movements based on the current Limit Order Book (LOB), the past movements, and signals from other data sources. But once a good signal is identified, the next step is to properly place the quotes in the LOB to reach the desired inventory. Market makers can only place limit orders, and for these to be executed would require a market order to hit them. Hence, the placement of the quotes is crucial, and this is where the fill probability comes into play. The fill probability is the probability that a limit order will be executed within a given time horizon. By estimating the fill probability, market-makers can determine the optimal placement of their quotes in the LOB to maximize their chances of execution while minimizing their risks. Initially, it might seem that placing the quotes as close as possible to the mid-price would maximize the fill probability. Though this is true, it also increases the risk of adverse selection. On the other hand, placing the quotes too far from the mid-price might reduce the fill probability and hence reduce the chances of execution. Therefore, market-makers must find the optimal balance between these two factors when placing their quotes in the LOB.

2 Proposal

In this paper, we attempt to model the fill probability in a given time horizon as a function of the state of the LOB. Along with this, we also attempt to model the adverse selection risk at each price level. This information together will help us develop a framework for optimal quoting in the limit order book.

We choose to focus on crypto markets for this study, precisely for the reason that the crypto data is relatively easily accessible free of cost and also crypto markets are more challenging in that, they have very low tick-sizes and hence levels are very closely populated and dense order-books. This makes the task of estimating the fill probability and adverse selection risk even more crucial for market-makers in crypto markets. Also, crypto markets are more challenging because they are decentralized, open 24/7, and react to market events from all over the world, unlike traditional localized exchanges. This makes the task of modeling the fill probability and adverse selection risk even more complex and interesting. In this project, we will do a detailed review of existing literature, identify the techniques that work, try to replicate them and will try to improve them for crypto markets. Towards the end of this project, we aim to develop a mathematical or machine learning based model for fill-probability and possibly for adverse selection, which when combined with the standard signals will help improve the strategy profitability compared to the case when fill-probability and adverse selection risk are not taken into account.

3 Related Work

The following papers are relevant to our understanding of the problem and to our proposed approach. This list will be expanded as our literature review progresses.
Avellaneda and Stoikov [2008] is one of the standard papers for market-making. Discusses how market-makers' pricing should change based on inventory and risk aversion. Assumes fill-probability is a Poisson process, that only depends on the distance from the mid-price. Assumes adverse-selection risk, by assuming that the mid-price as the true future price.
Maglaras et al. [2022] - Models the time-to-fill as a function of the state of the LOB using RNNs/LSTMs. Works with simulated NASDAQ data and only models the time-to-fill for top-bid and top-ask.

References

Marco Avellaneda and Sasha Stoikov. High-frequency trading in a limit order book. *Quantitative Finance*, 8(3):217–224, 2008. doi: 10.1080/14697680701381228.

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