

# Algorithmic Trading as a Markov Decision Problem



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# A few definitions to begin...

- Algorithmic / High-Frequency Trading:



- rapid ( $< 1s$ ) transactions
- algorithmic execution
- maintain no inventory at day's end

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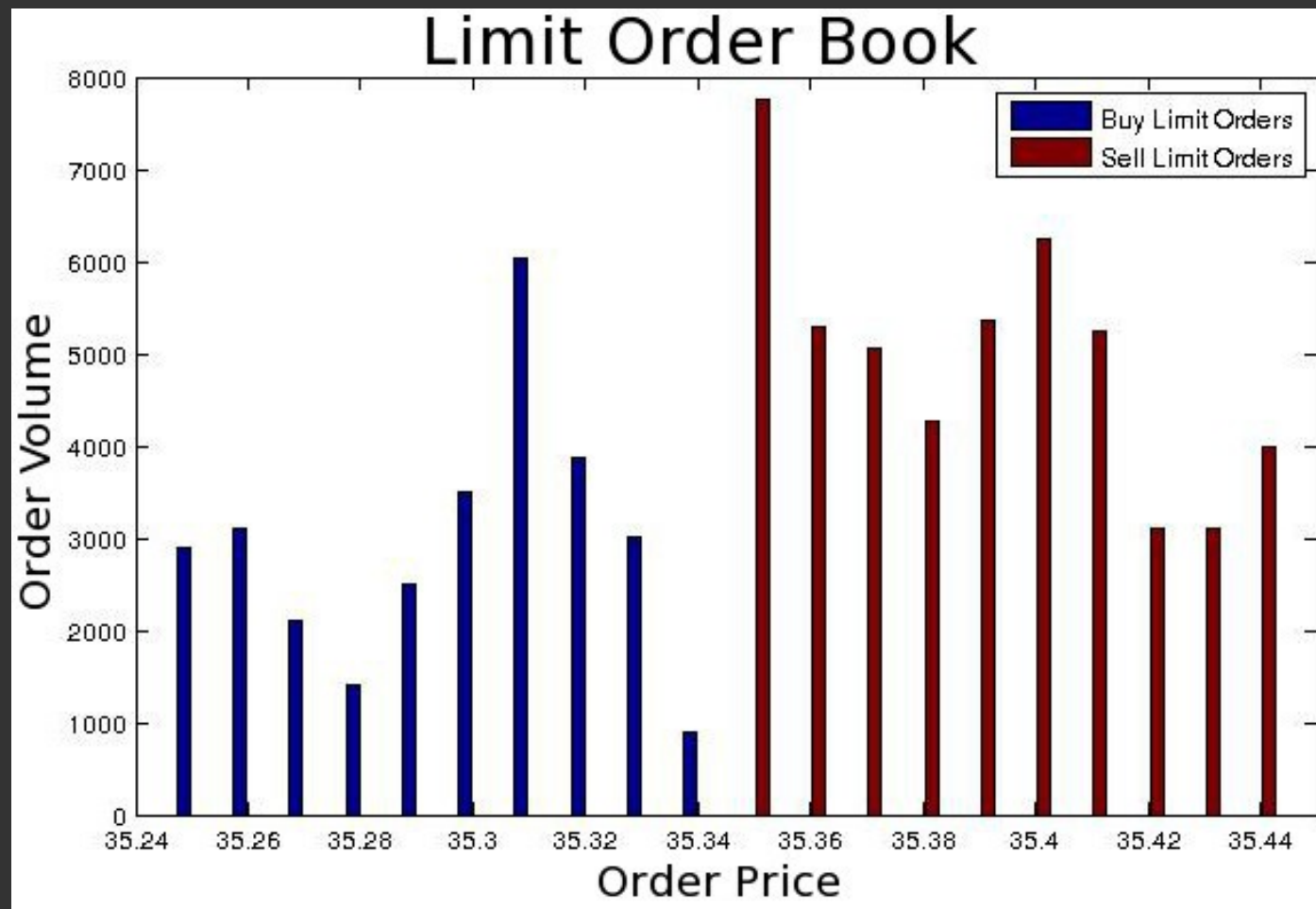
## Limit Order Book (LOB):

- a system (in the dynamics sense)
- tracks arrival of buy and sell orders of a given asset
- executes trades when a match is made



# A few definitions to begin...

LOB transformed into:



# Research Goal

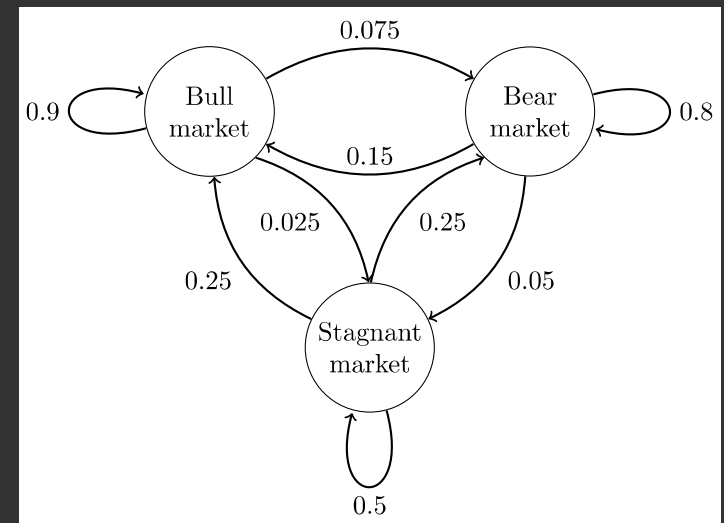
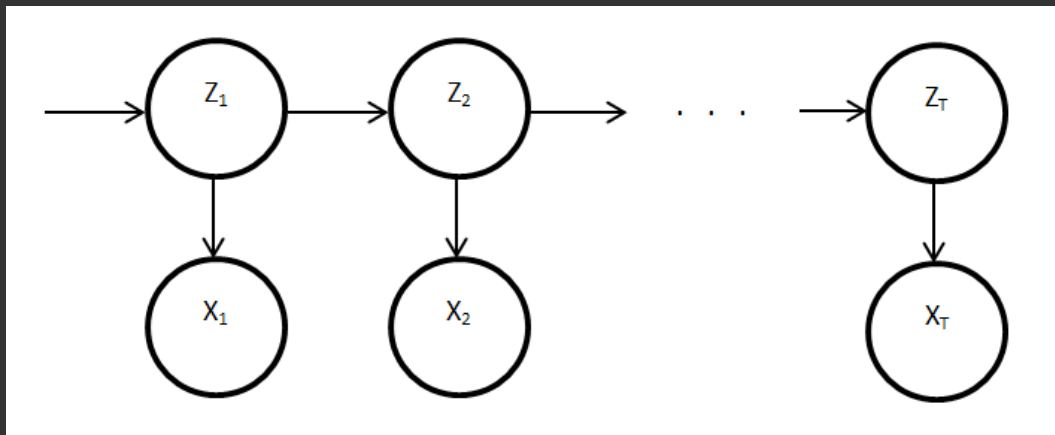
Our goal is to use the dynamics of the Limit Order Book (LOB) as an indicator for high-frequency stock price movement, thus enabling statistical arbitrage. Formally, we will study limit order book imbalance process,  $I(t)$ , and the stock price process,  $S(t)$ , and attempt to establish a stochastic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

# Research Programme

1. Modeling LOB dynamics
2. Relating order imbalance and price change
3. Exploratory data analysis
4. Deriving an optimal trading strategy

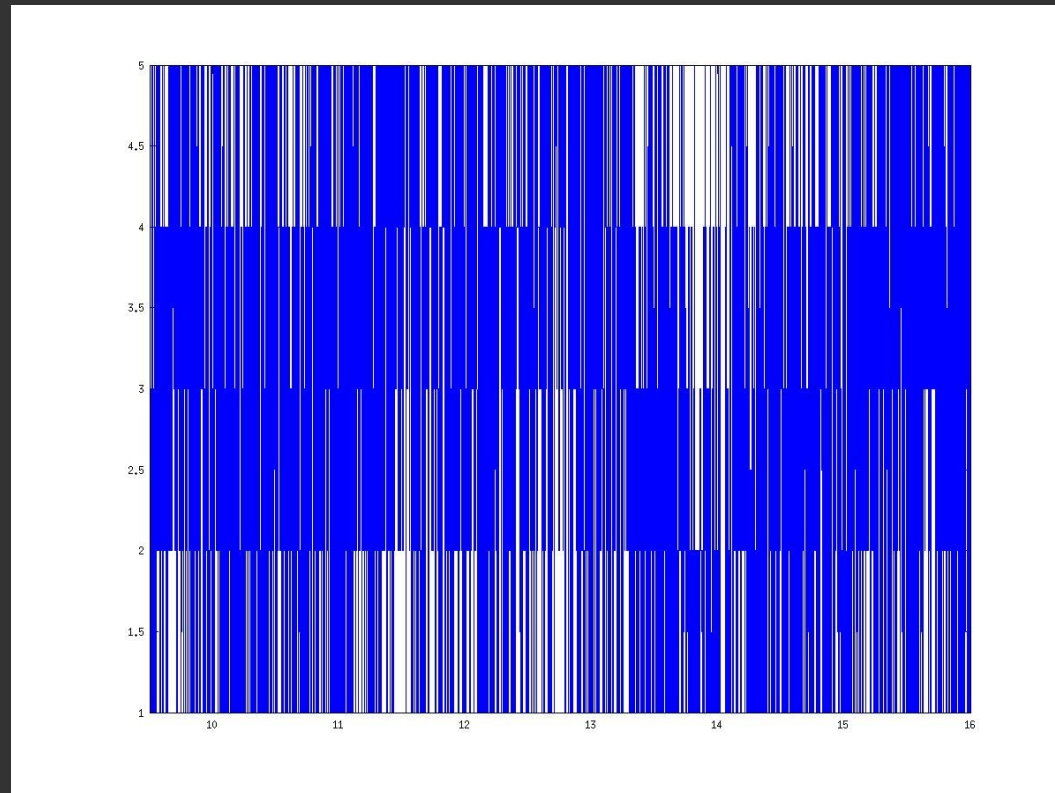
# Modeling LOB Dynamics

- To achieve goal, we need a suitable model
- Markov condition considered appropriate
- Hence, options:
  - Markov Chain, Continuous-Time Markov Chain, Hidden Markov Model, ...



# Modeling LOB Dynamics

- The imbalance process is very noisy...
  - So we average using a fixed interval...
  - And put it into bins





# Modeling LOB Dynamics

- Given the interval averaging and binning, we could use discrete-time
- But, continuous-time is more powerful
- Continuous-Time Markov Chain:
  - Contains an embedded discrete-time Markov chain
  - Therefore an obvious and simple choice

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# Imbalance and Price Change

- Consider joint distribution for  $(I(t), \Delta S(t))$
- Reduced to 1-dimension and estimated CTMC generator matrix  $G$ , satisfying:

$$\dot{P}(t) = P(t)G \Rightarrow P(t) = e^{tG}$$

- Elements of  $P$  are:

$$\begin{aligned} P_{ij} &= \mathbb{P}[Z_n \in j \mid Z_{n-1} \in i] \\ &= \mathbb{P}[(\rho_n, \Delta S_n) \in j \mid (\rho_{n-1}, \Delta S_{n-1}) \in i] \end{aligned}$$

- Rewritten:  $\mathbb{P}[\rho_n \in i, \Delta S_n \in j \mid \rho_{n-1} \in k, \Delta S_{n-1} \in m]$

# Imbalance and Price Change

- $\mathbb{P} [\rho_n \in i, \Delta S_n \in j \mid \rho_{n-1} \in k, \Delta S_{n-1} \in m]$   
 $= \mathbb{P} [\rho_n \in i, \Delta S_n \in j \mid B]$  (shorthand)

- Using Bayes' Rule, can solve:

$$\mathbb{P} [\Delta S_n \in j \mid B, \rho_n \in i] = \frac{\mathbb{P} [\rho_n \in i, \Delta S_n \in j \mid B]}{\mathbb{P} [\rho_n \in i \mid B]}$$

Probability of current price change conditional on current imbalance, previous imbalance, and previous price change

# Imbalance and Price Change

Using 3 bins, 1000ms imbalance smoothing,  
and 500ms price change, we computed:

	$\rho_n = 1$									$\rho_n = 2$									$\rho_n = 3$								
$\Delta S_n < 0 \rightarrow$	.67	.05	.04	.01	.03	.04	.00	.05	.05	.02	.50	.12	.01	.00	.02	.05	.01	.02	.00	.00	.52	.00	.01	.00	.00	.00	.00
$\Delta S_n = 0 \rightarrow$	.33	.95	.96	.99	.97	.96	.41	.93	.95	.96	.49	.87	.98	.99	.97	.91	.48	.96	.98	.95	.47	.95	.96	.93	.98	.88	.34
$\Delta S_n > 0 \rightarrow$	.00	.00	.00	.00	.00	.00	.58	.02	.00	.02	.01	.00	.01	.01	.01	.05	.51	.01	.02	.04	.01	.05	.03	.02	.02	.12	.66
	$\Delta S_{n-1} < 0$			$\Delta S_{n-1} > 0$			$\Delta S_{n-1} = 0$																				

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	$\Delta S_{n-1} < 0$			$\Delta S_{n-1} > 0$			$\Delta S_{n-1} = 0$			$\Delta S_{n-1} < 0$			$\Delta S_{n-1} > 0$			$\Delta S_{n-1} = 0$			$\Delta S_{n-1} < 0$			$\Delta S_{n-1} > 0$			$\Delta S_{n-1} = 0$		

Interpretation: there is price change momentum when staying in same imbalance bin

# Research Programme

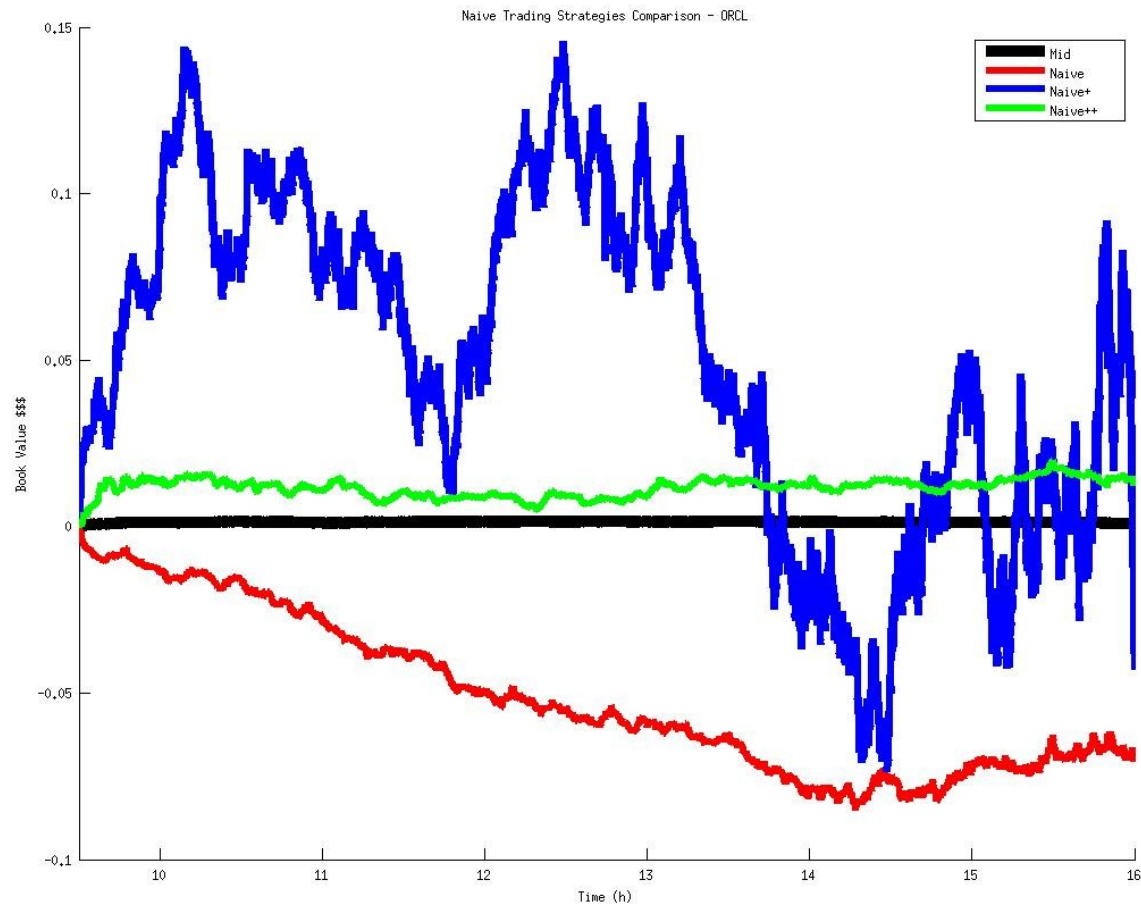
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# Exploratory Data Analysis

- Using the observed price change momentum, we explore a few trading strategies:
  - Naive: execute a buy (resp. sell) market order if the probability of an upward (resp. downward) price change is  $> 0.5$
  - Naive+: extend the Naive strategy to additionally keep limit orders posted at-the-touch if the probability of a price change is  $< 0.5$
  - Naive++: Like the Naive strategy, but using LOs instead of MOs

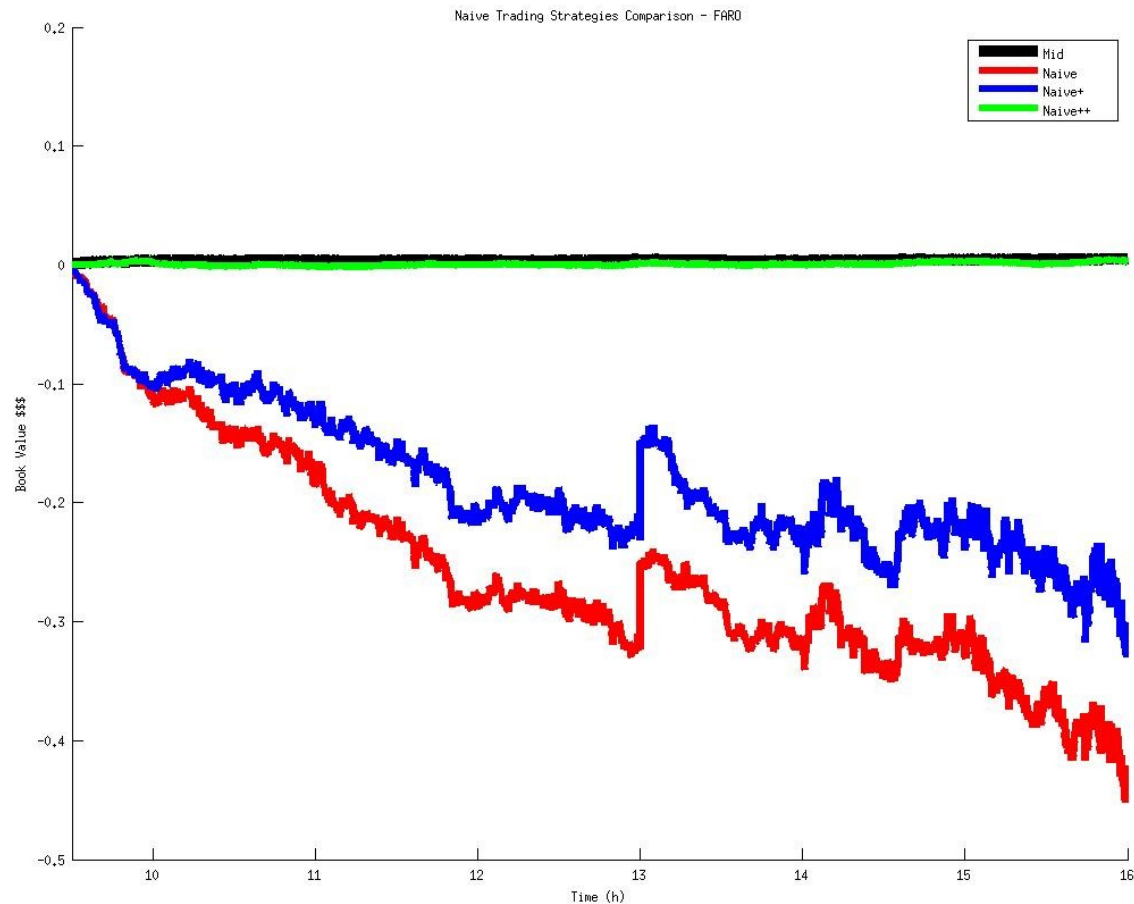


# Exploratory Data Analysis



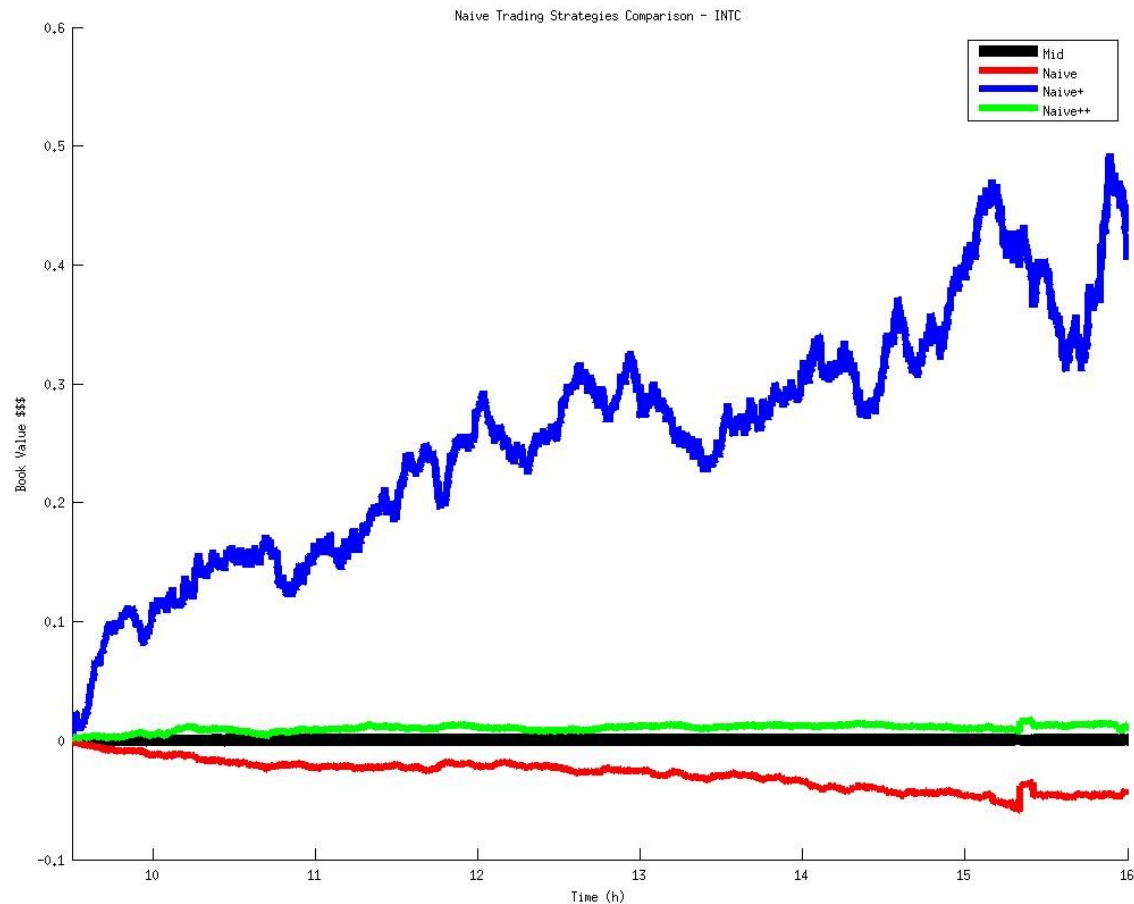
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# Exploratory Data Analysis



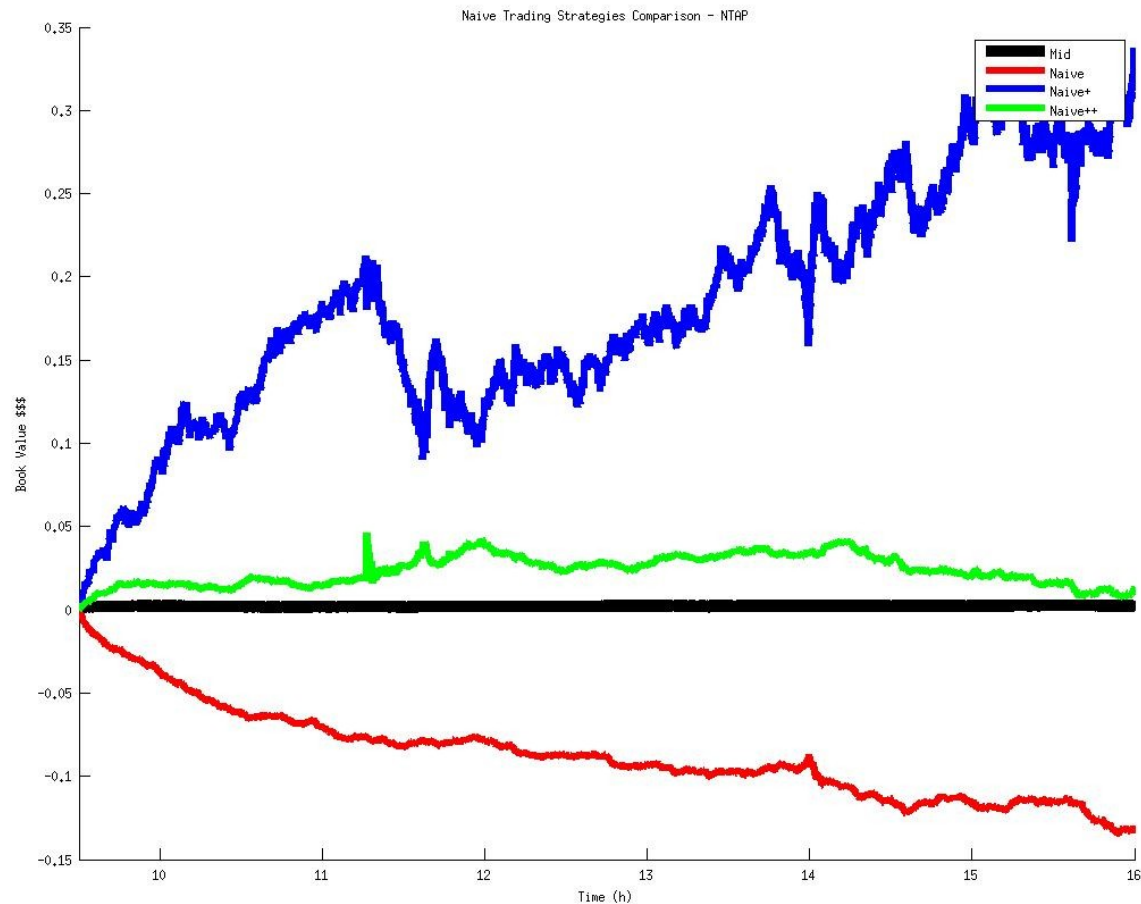
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# Exploratory Data Analysis



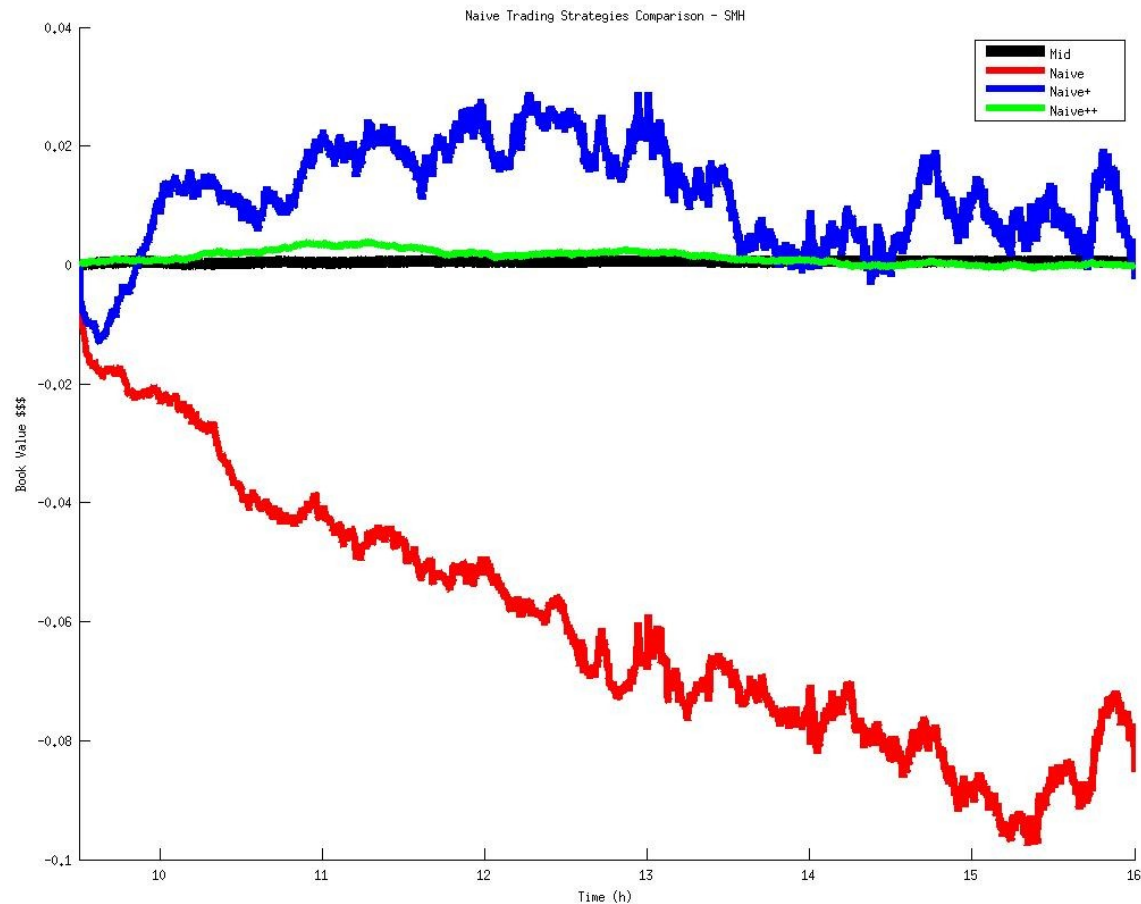
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# Exploratory Data Analysis



NTAP

# Exploratory Data Analysis



SMH

# Exploratory Data Analysis

- Conclusion: posting at-the-touch LOs on average produces positive returns
- Other considerations still being investigated:
  - How do we calibrate parameters?
  - How do we compute imbalance?

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# Optimal Trading Strategy

$m$  - market orders strategy

$X_t^m$  - cash at time  $t$  given orders  $m$

$S_t$  - stock price at time  $t$

$\Delta_t$  - bid/ask spread at time  $t$

$m_t^+$  - buy MO at time  $t$

$m_t^-$  - sell MO at time  $t$

$q_t^m = m_t^+ - m_t^-$  - # shares held at time  $t$

Cash stream:

$$dX_t^m = -(S_t + \Delta_t)dm_t^+ + (S_t - \Delta_t)dm_t^-$$



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# Optimal Trading Strategy

Terminal (end of day) wealth:

$$W_T^m = X_T + q_T^m (S_T - \text{sign}(q_T^m) \Delta_T)$$

How do we measure performance or constrain possible strategies  $m$ ?

# Optimal Trading Strategy

1.  $\max \mathbb{E}[W_T]$  Maximize profit
2.  $\max \mathbb{E}[W_T | W_T < 0]$  Minimize loss
3.  $\max \mathbb{E}[W_T - \gamma \cdot \mathbf{1}_{W_T < 0} \cdot W_T]$  Risk aversion
4.  $\max \frac{\mathbb{E}[W_T]}{\text{var}(W_T)}$  Maximize Sharpe ratio
5.  $\max \frac{\mathbb{E}[W_T]}{\text{var}[W_T | W_T < 0]}$  Maximize Sortino ratio

# Next Steps

- Include limit orders into stochastic framework
- Derive optimal trading strategy based on Markov Decision Processes
  - dynamic programming

