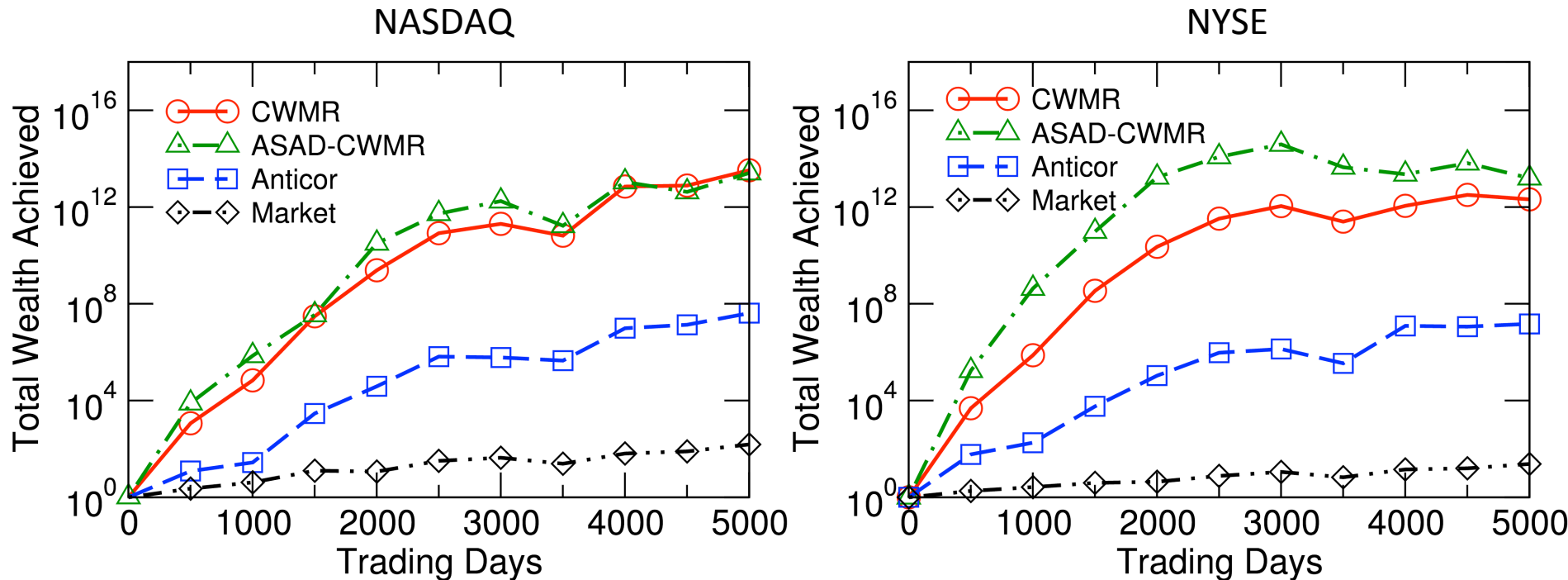


Dynamic Threshold Trading Algorithm

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Data Incubator Presentation

Motivation: My previous work on the mean reversion method



- Backtested historical data from Jan 1, 1995 to Dec 5, 2014;
- 101 most actively traded stocks (based on volume) in NASDAQ, and 334 stocks in NYSE;
- The method works better in NASDAQ, better in a bull market.

Motivation: My previous work on the mean reversion method

Stocks: {AAPL, MSFT, AMZN, ...} 101 stocks
Everyday's Price Relative: $\mathbf{x} = \{x_1, x_2, \dots, x_{101}\}$
Everyday's Portfolio: $\mathbf{b} = \{b_1, b_2, \dots, b_{101}\}$ $\mathbf{b} \cdot \mathbf{1} = 1$

The new Portfolio should be as close to yesterday's portfolio as possible in order to include the cumulative effect of poorly-performing stocks.

$$\mathbf{b}_{t+1} = \operatorname{argmin} \|\mathbf{b} - \mathbf{b}_t\|^2$$

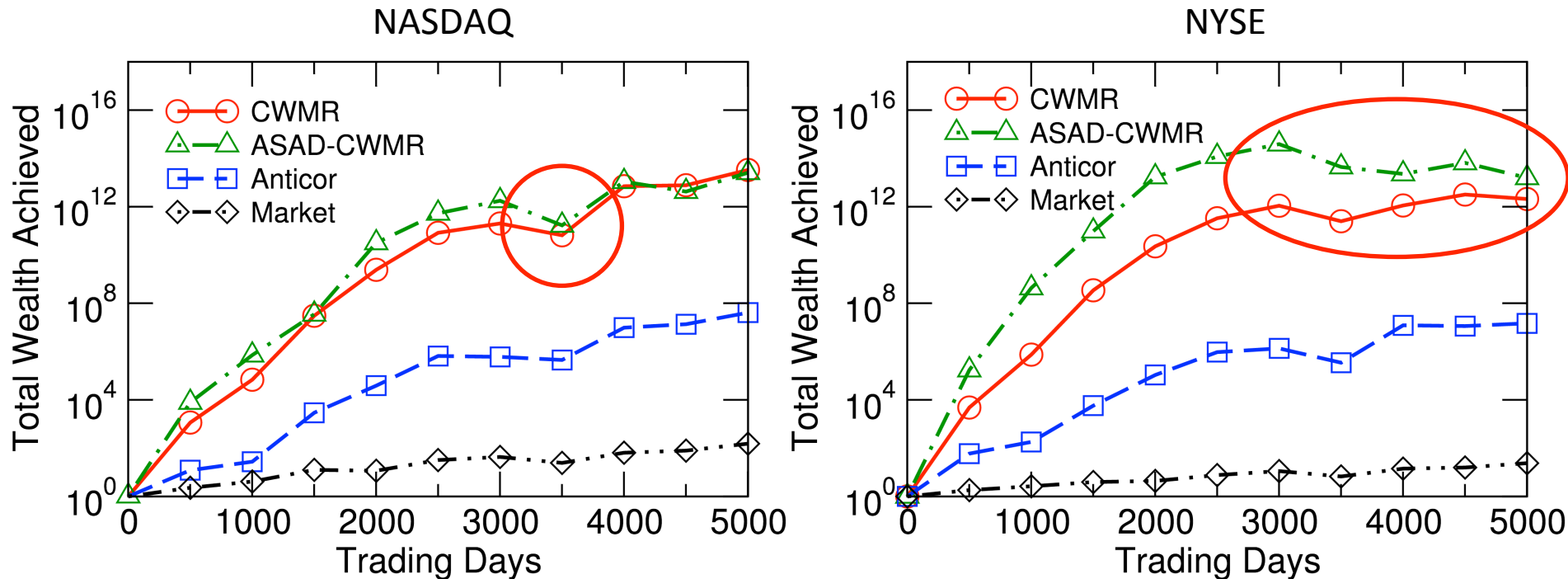
subject to

$$\mathbf{b} \cdot \mathbf{x}_t \leq \epsilon$$
$$\mathbf{b} \cdot \mathbf{1} = 1$$

If we apply the new portfolio to yesterday's market, the performance should be below a threshold.

Optimization problem subject to 2 constraints:
Solve it with Lagrangian with 2 Lagrange multipliers

Motivation: My previous work on the mean reversion method



- The method works better in NASDAQ, better in a bull market.
- It did not perform well in a bear market, especially in financial crisis, and recent years in NYSE.

Improvement: Dynamic threshold with reinforcement learning

Stocks: {AAPL, MSFT, AMZN, ...} 101 stocks
Everyday's Price Relative: $\mathbf{x} = \{x_1, x_2, \dots, x_{101}\}$
Everyday's Portfolio: $\mathbf{b} = \{b_1, b_2, \dots, b_{101}\}$ $\mathbf{b} \cdot \mathbf{1} = 1$

This part is still the same! Less portfolio fluctuation takes into account the cumulative effect.

$$\mathbf{b}_{t+1} = \operatorname{argmin} \|\mathbf{b} - \mathbf{b}_t\|^2$$

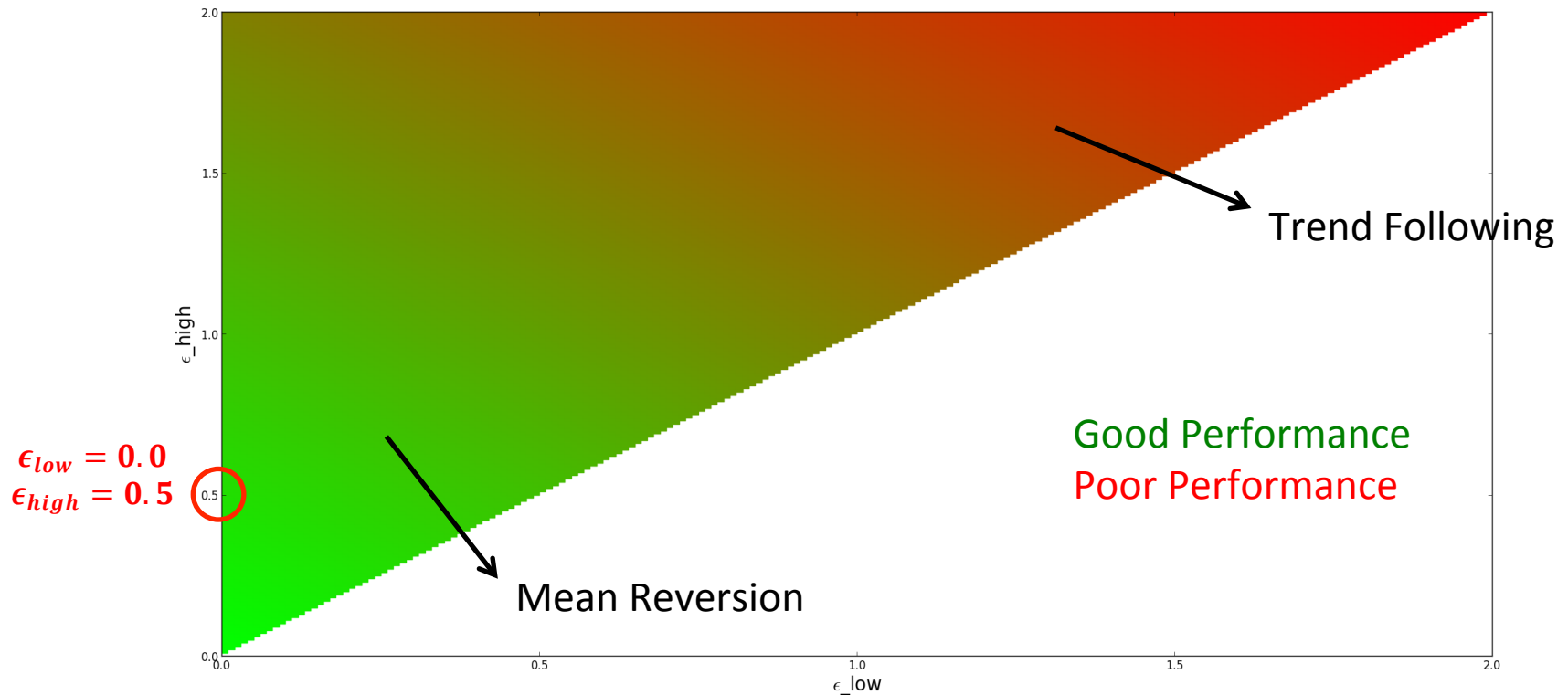
subject to $\epsilon_{low} \leq \mathbf{b} \cdot \mathbf{x}_t \leq \epsilon_{high}$

$$\mathbf{b} \cdot \mathbf{1} = 1$$

The new constraint hybrids mean reversion and trend following as it suggests that stocks in a specific performance range will have good performance. We have two thresholds now.

The two thresholds determine the correlations hidden in the market. It could fluctuate sometime, but in much less magnitude than stock prices! That's where reinforcement learning can come in!

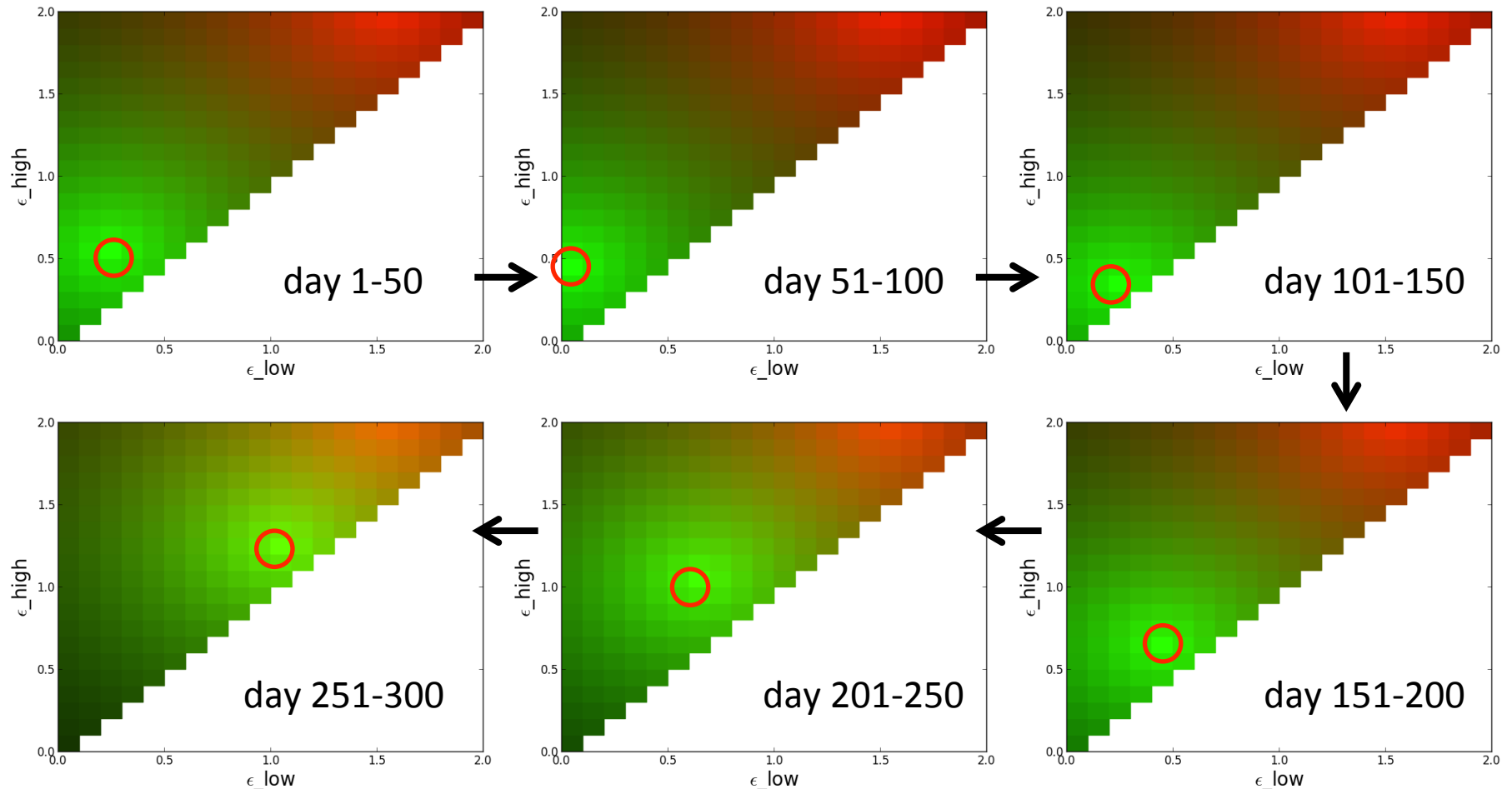
Improvement: Thresholds sensitivity of cumulative return (a hypothetical plot here)



- I used (0.0, 0.5) for my previous work. I plan to try the other $200 \times 200 / 2$ grid points as well. **Parallel computing is needed here.**
- I plan to make a plot of thresholds sensitivity of cumulative return for every 50 days. Then we will see how this plot evolves with time!

Improvement: Follow the green!

(hypothetical plots here)



Why is this project important?

- A hybrid method on mean reversion and trend following has never been studied before.
- It could potentially be a good method that outperforms both mean reversion and trend following, and thus produce very high return!
- By investigating how thresholds sensitivity of cumulative return evolves with time, we will better understand how the market behavior and psychology of investors change with time.

Assumptions

- No transaction cost. The calculation of transaction cost for personal investment and for financial companies is very different.
- One can always buy and sell required quantities of stocks at closing price.
- The strategy has not impact on the market behavior.