Reinforcement Learning for Finance

Ashwin Rao

Stanford University

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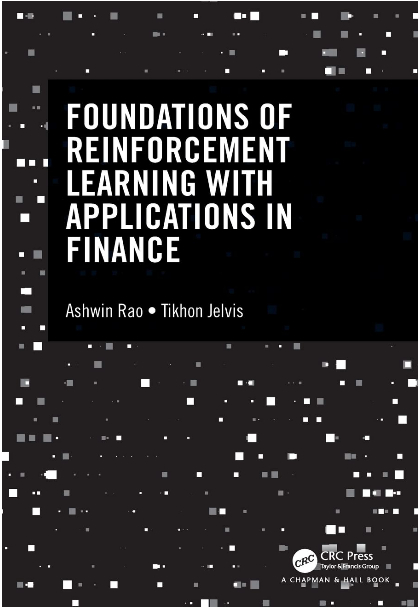
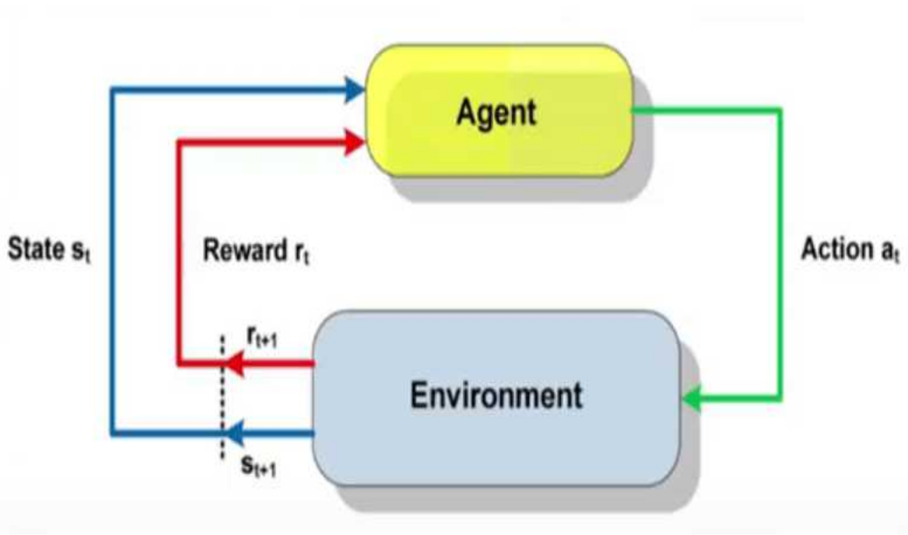
- Main job: Founder-CTO of an Enterprise AI startup cxscore.ai

RL For Finance book



The RL Framework



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- This is a dynamic (time-sequenced control) system under uncertainty

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- Strategy to win an election (highly complex)

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- To resolve both curses effectively, we need RL

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- Deep Neural Networks are typically used for function approximation

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- Possibilities in Finance are endless (I will cover 2 problems)

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- Objective: Horizon-Aggregated Expected Utility of Consumption

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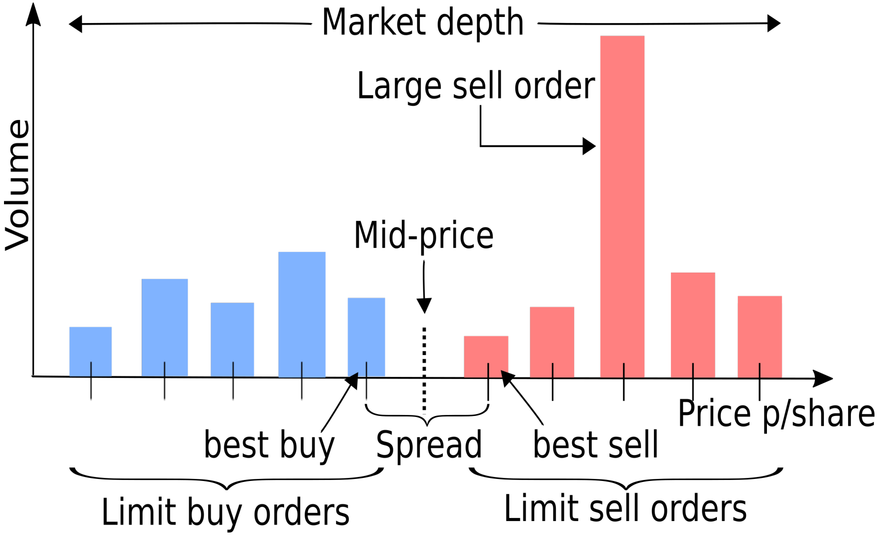
- *Model:* Career uncertainties, Asset market uncertainties

Trading Order Book (abbrev. OB)



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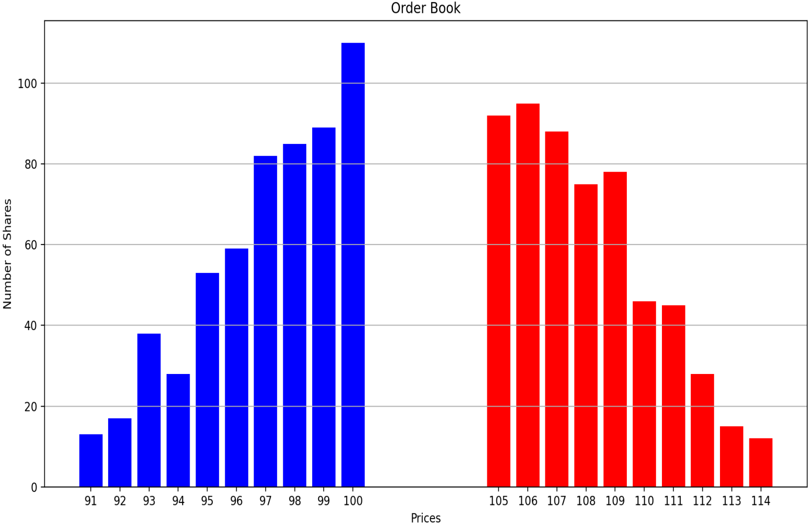
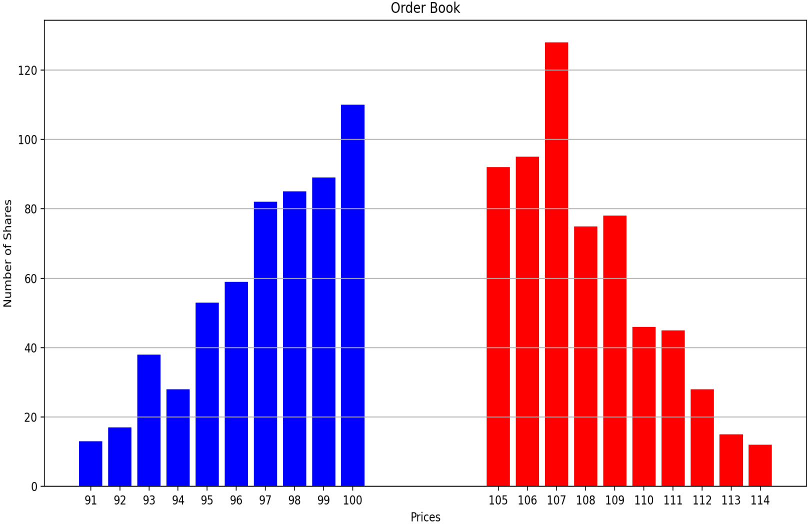
- Price Impact Models with OB Dynamics can be quite complex

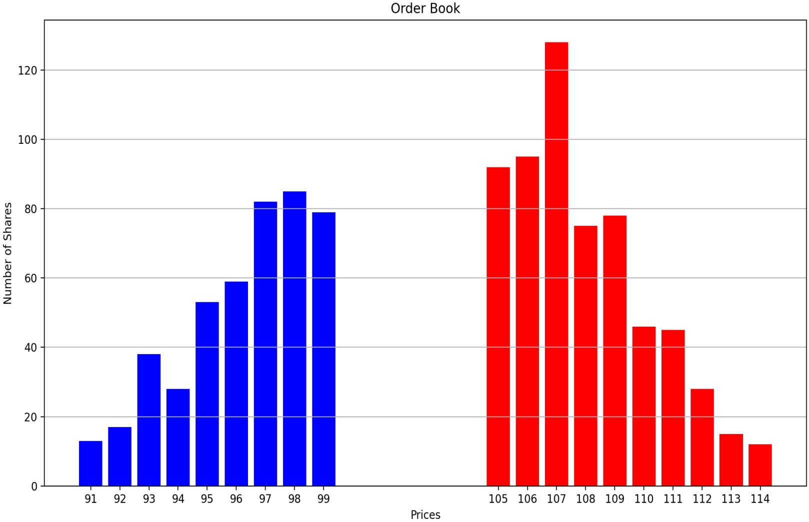
Stylized Example of an Order Book



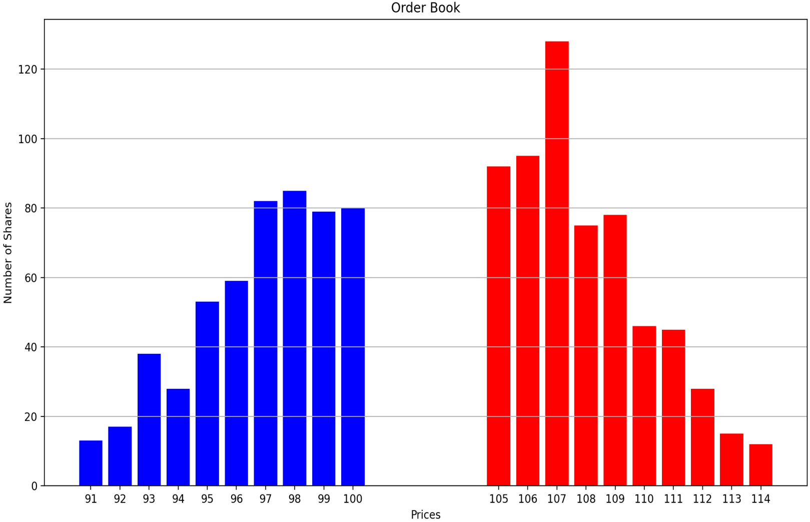
Sell Limit Order: 40 Shares @ 107 Price



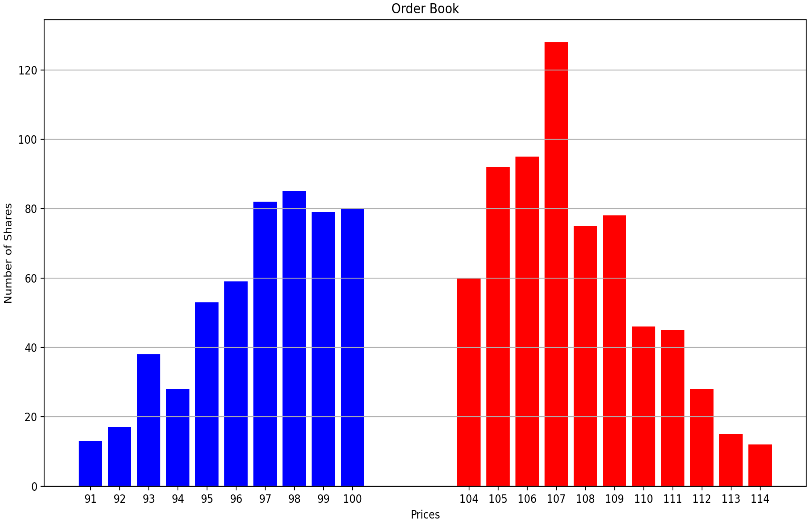
Sell Market Order: 120 Shares



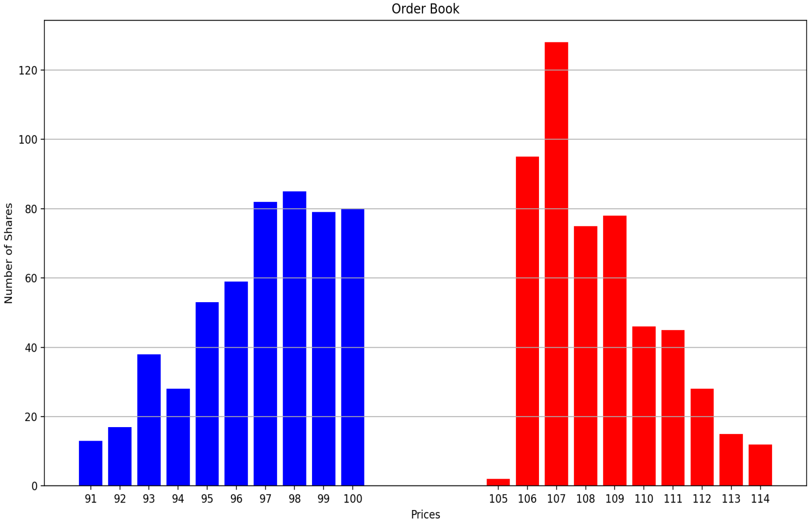
Buy Limit Order: 80 shares @ 100 Price



Sell Limit Order: 60 shares @ 104 Price



Buy Market Order: 150 shares



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