Dynamic Fee Mechanism Simulation with Reinforcement Learning

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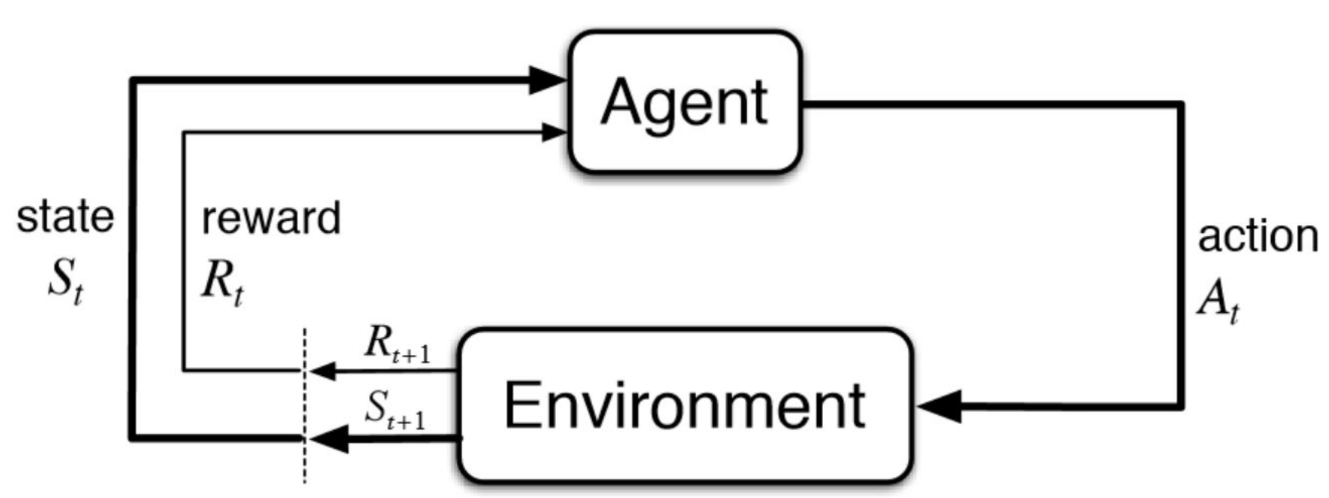
INTRODUCTION

- Exchange fees have a significant impact on a traders' decisions
  - Low exchange fees → traders buy/sell more
  - Binance, a leading cryptocurrency exchange, charges a flat 0.1% exchange fee rate on all transactions
- The exchange fee rate can be manipulated to...
  - Encourage transactions when they happen less often
  - Stabilize transactions when they happen often
- The goal is to gain more insight into how users will react to the network when applying different fee-setting mechanisms
- Used various machine learning agents
  - Each wants to maximize their profits using reinforcement learning methodology
- We worked to identify the ideal fee mechanism based on how each agents optimal policy for each fee mechanism

APPROACHES

- In this observation, the total commission and volume levels are observed to see how they differ after a Reinforcement Learning (RL) agent has learned to maximize its profits after being exposed to various trading environments.
- Simulation Steps:
  - (1) RL agent learns in basic fee environment
  - (2) Transfer learning in different fee environment
  - (3) Observe behavior of agent in each environment

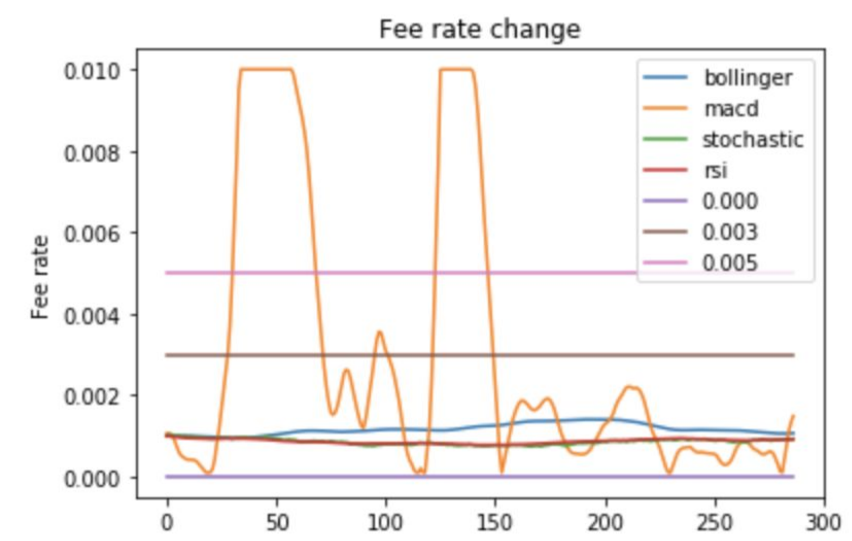
APPROACHES & RESULTS: RL Agent in Basic Fee Environment



RL agent learns what action is best rewarded in environment

APPROACHES & RESULTS: RL Agent in Different Fee Environment

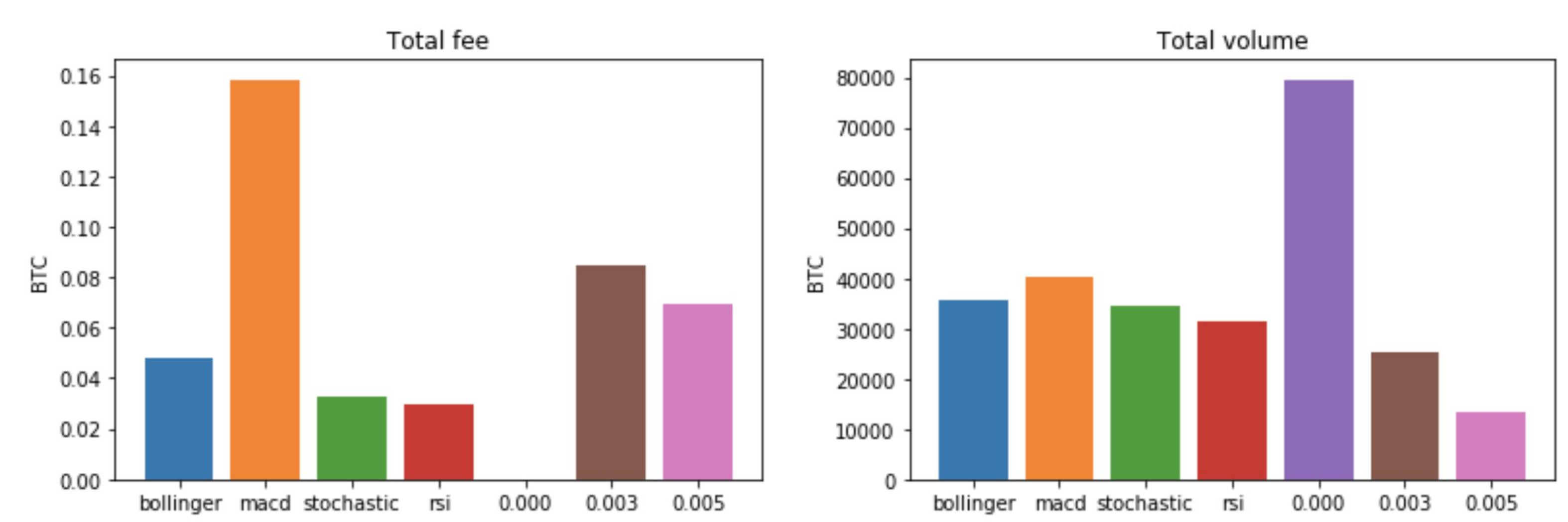
- RL agents trained in basic fee environment trained again in different fee-rate policy environment



Fees would change depending on the environment

- Last 3 environments have static fees and first 4 have fees that change based on derivative index
- 30 agents trained for 1000 episodes in default fee environment
- Same agents trained for 500 episodes in dynamic fee environment
- Expected that the optimal behavior of agents will vary since the commission policy is different from the initial environment
  - Leads to different total fees and total transaction volume

OBSERVATIONS



Total Fee and Volume Per Trading Environment

- More transactions occur in a dynamic fee environment than in a static one (0.000, 0.003, 0.005).
- Suggests possibility that a dynamic fee policy could further stimulate the market and create a favorable situation for exchange
- Trend strongest with MACD environment since fee change is steepest.

ANALYSIS

- Just increasing or decreasing the fee rate does not significantly affect the behavior of the RL agent
  - For example, the differences in total transaction volume for fees 0.003 and 0.005 were negligible
- A dynamic fee does significantly impact the RL agent's policy
  - The total transaction volume and the total fee income increased
  - A dynamic fee would be beneficial to trading platforms, as it increases transactions and their profit
- This implementation changed the fee using the derivative index, so using a more complex dynamic pricing methodology we could optimize further for either the exchanges or users

CHALLENGES & LIMITATIONS

- Challenges
  - Understanding and manipulating the different training environments
- Limitations
  - We simulated only one agent dealing with the market at a time (unlike in reality)
  - Each individual has a negligible effect on the market, so we assume the results will be similar to a multi-agent simulation

REFERENCES

- Bhardwaj, Kartikeya. "Integrated Gradients for Deep Neural Networks." Medium, Medium, 5 Sept. 2019, medium.com/@kartikeyabhardwaj98/integrated-gradients-for-deep-neural-networks-c114e3968eae.
- Lim, Jeffrey. "Dynamic Fee Mechanism Simulation with Reinforcement Learning." Medium, DECON Simulation, 20 Sept. 2019, medium.com/decon-simulation/dynamic-fee-mechanism-simulation-with-reinforcement-learning-97c847aa5c.
- Vaswani, Ashish, et al. "The Annotated Transformer." The Annotated Transformer, 3 Apr. 2018, nlp.seas.harvard.edu/2018/04/03/attention.html.