Auto.gov: Optimal On-chain Governance for DeFi

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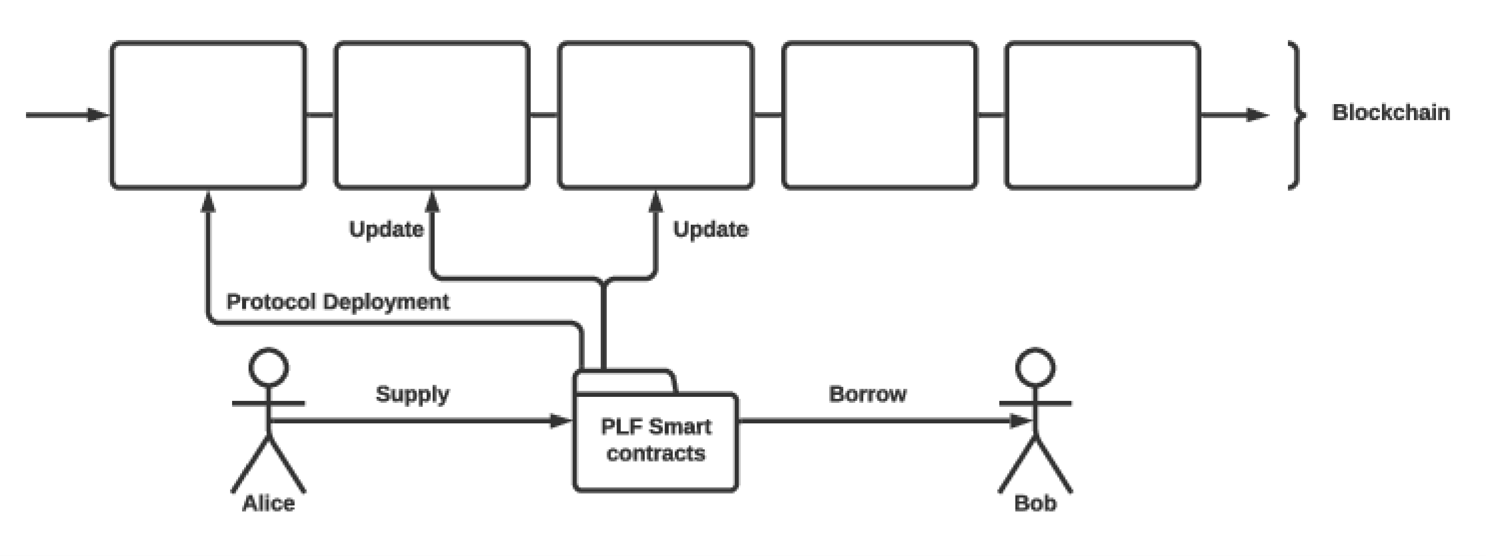
Background

Protocols for Loanable Funds (PLF)

- Protocol that intermediates funds between users
- Unlike peer-to-peer lending, funds are pooled
- Requires users to deposit collateral



PLF definitions

- ***Market*** A smart contract acting as the intermediary of loanable funds for a particular crypto-asset, where users supply and borrow funds.
- ***Supply*** Funds deposited to a market that can be loaned out to other users and used as collateral against depositors' own borrow positions.
- ***Borrow*** Funds loaned out to users of a market.
- ***Collateral*** Funds available to back a user's aggregate borrow positions.
- ***Locked funds*** Funds remaining in the PLF smart contracts, equal to the difference between supplied and borrowed funds.

Agents in the system

- ***Supplier*** A user who deposits funds to a market.
- ***Borrower*** A user who borrows funds from a market. Since a borrow position must be collateralized by deposited funds, a borrower must also be a supplier.
- ***Liquidator*** A user who purchases a borrower's supply in a market when the borrower's collateral to borrow ratio falls below some threshold.

PLF building blocks

- ***Interest rate models*** Some function(s) taking liquidity as an argument and returning an interest rate
- ***Interest disbursement mechanism*** Interest typically accrued per second and paid out per block. Often an interest bearing derivative token used.
- ***Collateral*** Deposit that can be sold off to recover debt of defaulted position
- ***Liquidations*** The process of selling a borrower's collateral to recover the debt value upon default
- ***Governance mechanism*** Decentralized governance typically achieved through an ERC-20 governance token, where token holders' votes are in proportion to their stake

Deep reinforcement learning overview

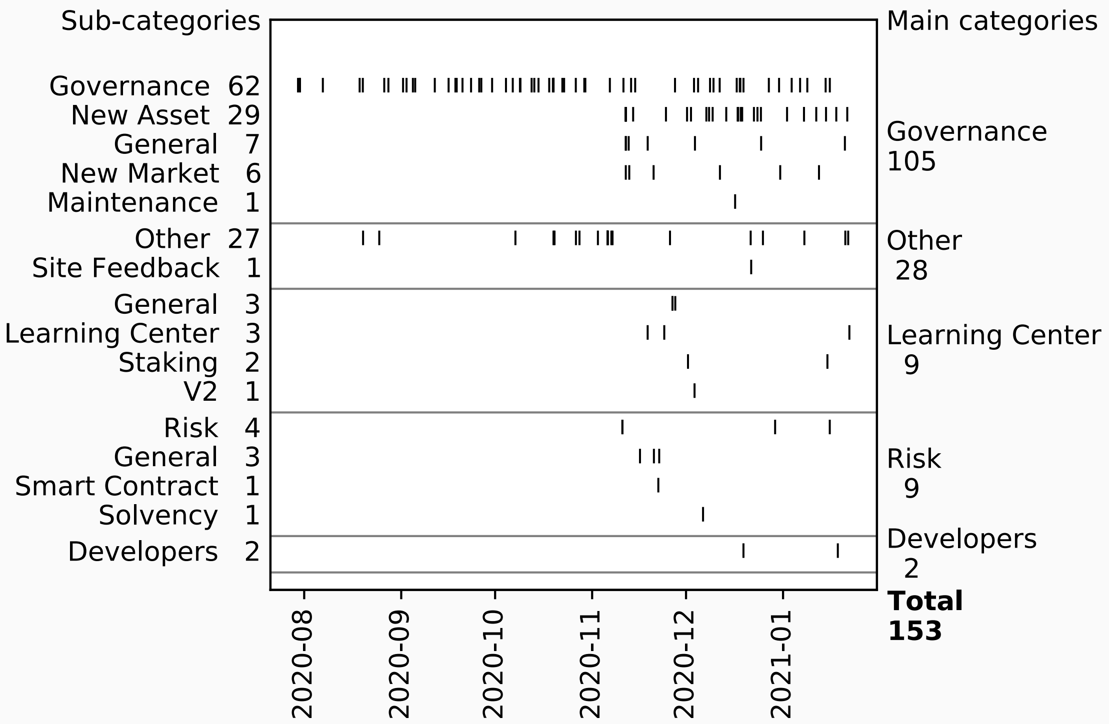
- A type of machine learning where an agent learns to make decisions by performing actions in an environment and receiving feedback in the form of rewards.
- Combines the concepts of Reinforcement Learning with deep learning techniques.
- Uses deep neural networks as function approximators to represent the policy, value function, or model of the environment.

Components of Deep Reinforcement Learning

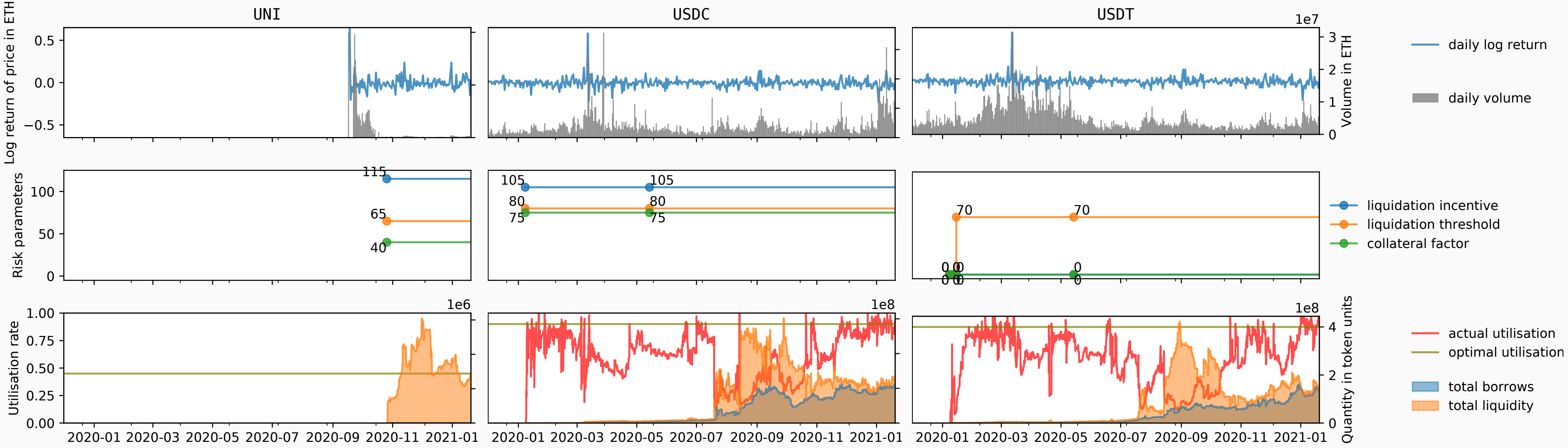
- ***Agent*** The agent takes actions in the environment.
- ***Environment*** The environment is the world in which the agent operates and receives rewards for its actions.
- ***State*** The state represents the current condition of the environment.
- ***Action*** The action is taken by the agent in response to the state.
- ***Reward*** The reward is feedback received by the agent in response to its actions.

Empirical results

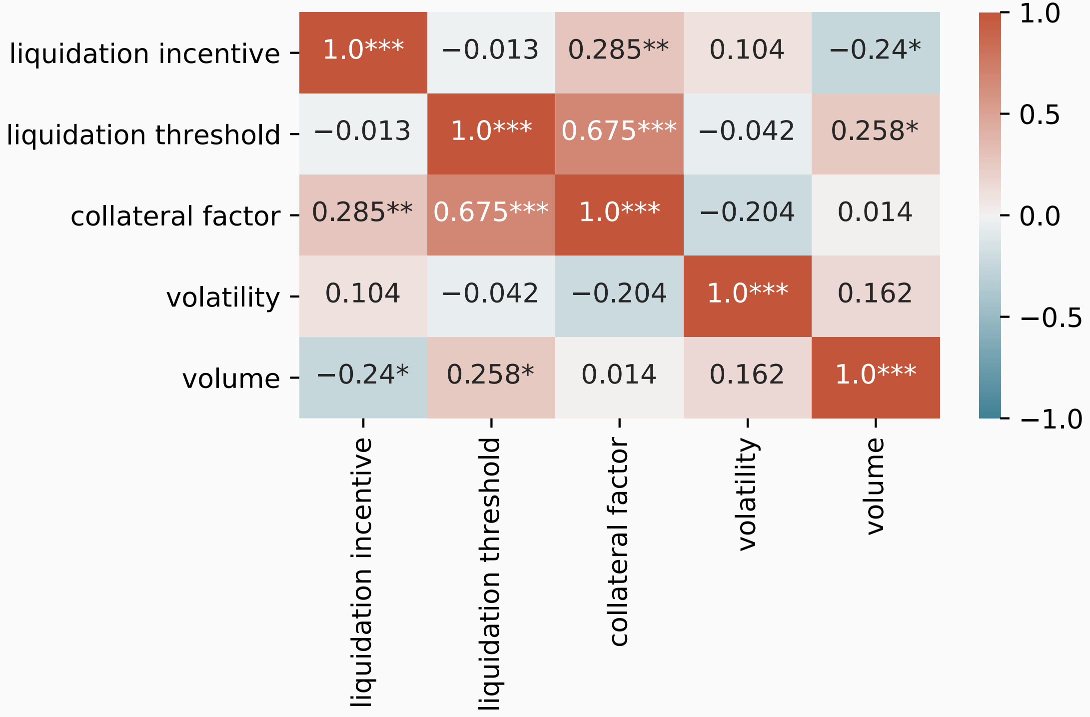
AAVE governance forum discussion



Empirical states of AAVE

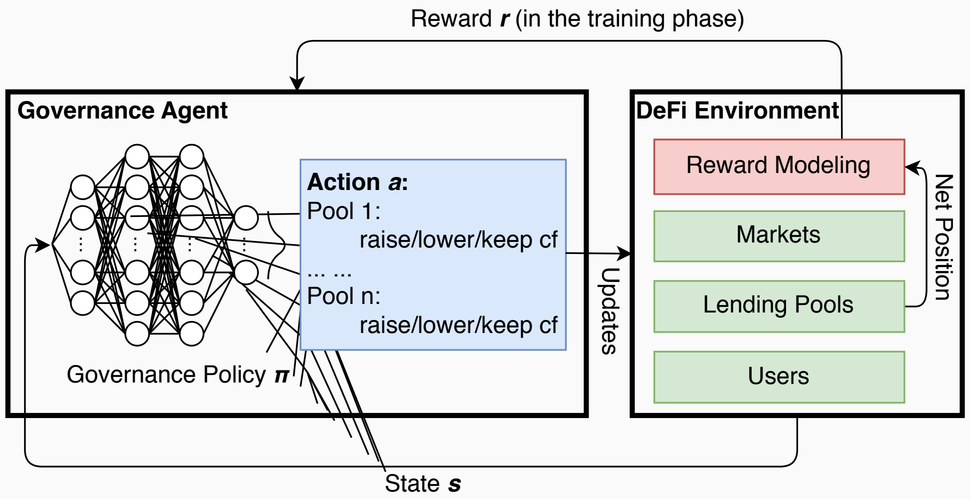


Empirical correlation of state variables

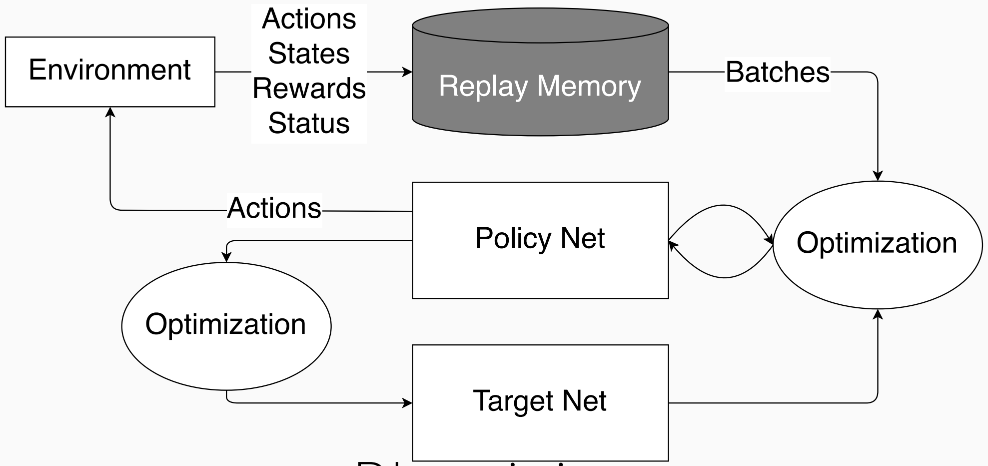


Modelling framework

Deep reinforcement q-learning architecture



RL architecture applied to DeFi environment



RL training

A simplified DeFi environment for training (1/2)

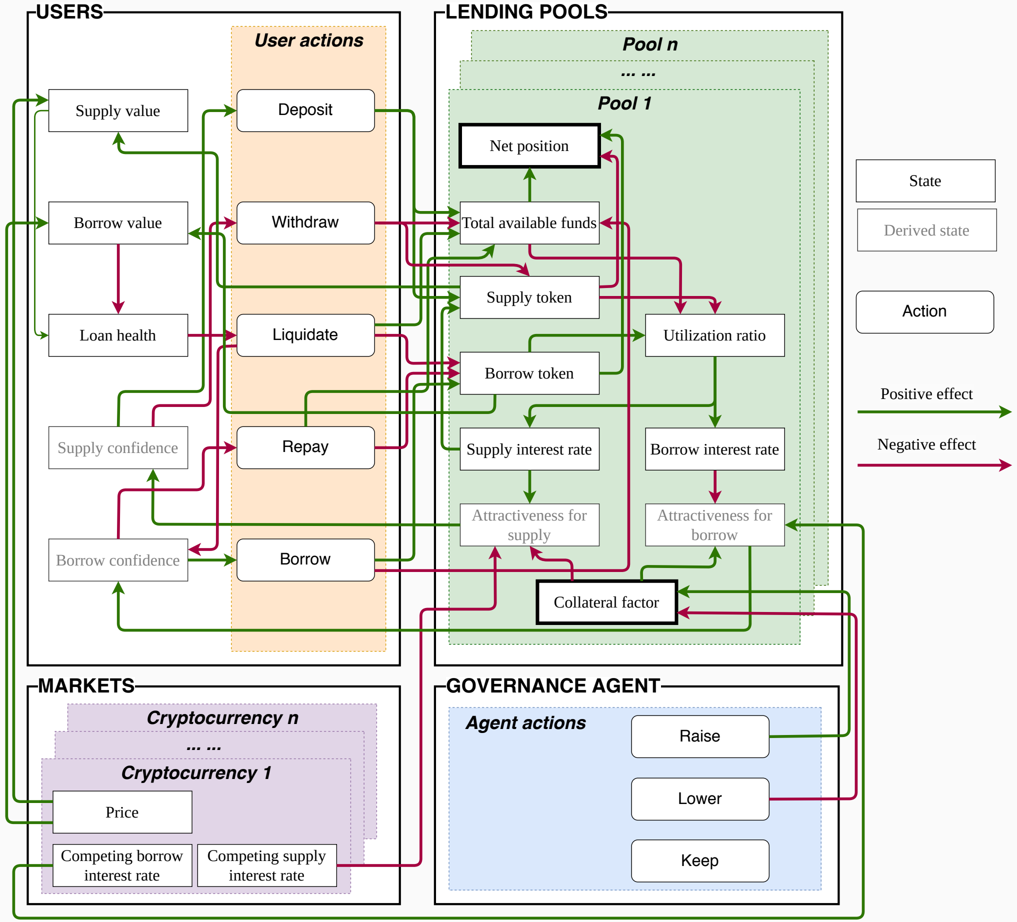
- Three PLF pools
  - WETH – the numeraire for the protocol
  - USDC – a USD-pegged stablecoin
  - TKN – an arbitrary token
- One adjustable risk parameter: collateral factor
- One aggregate market user

A simplified DeFi environment for training (2/2)

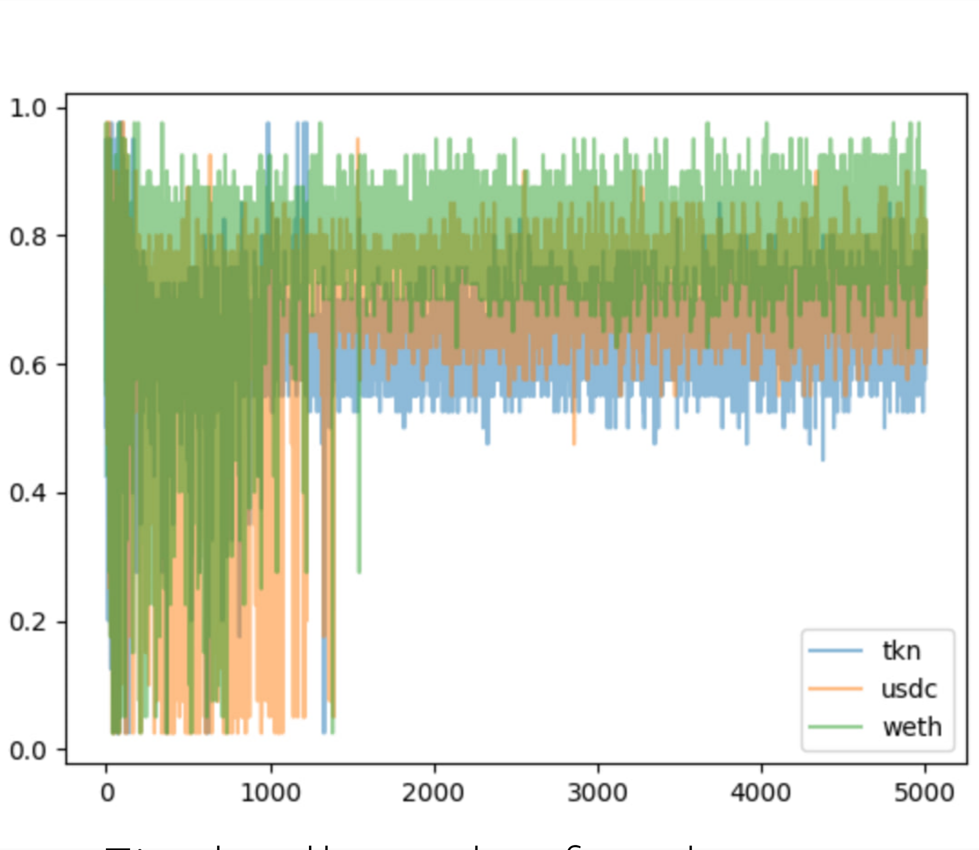
Pre-programmed user behavior reactive to market condition

- Motivated to deposit when collateral factor is low (safer market) and supply interest rate is high compared to competing rate; withdraw when the opposite is true
- Motivated to borrow when collateral factor is high, liquidation and collateral factor change do not occur often, and borrow interest rate is low compared to competing rate; repay when the opposite is true
- Other action constraints apply (e.g. must have sufficient collateral to borrow, must have sufficient balance to withdraw, etc.)

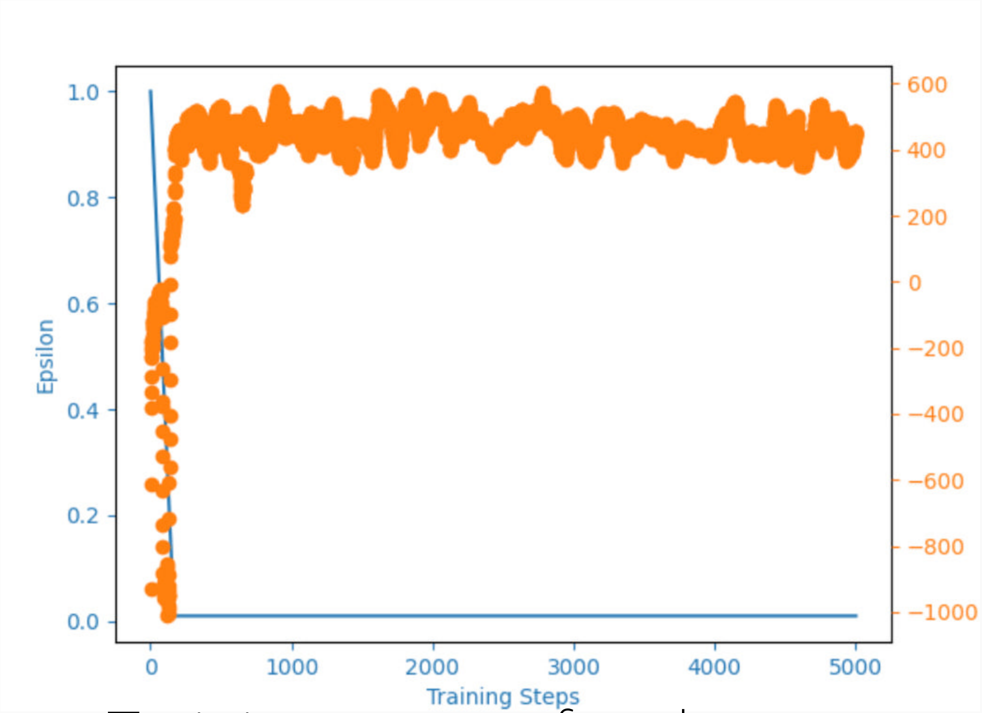
DeFi environment for training



Preliminary training results



Final collaterals of each game



Training scores of each game

Future direction

- Add more training dimensions, e.g. more users with different risk preferences, more assets, more risk parameters
- Add more training scenarios, e.g. different market conditions (varying price volatility and competing interest rates etc.), different user behaviors
- Applying more sophisticated ML techniques, e.g. multi-agent RL by allowing users to also be reinforcement learning agents

Conclusion

- We developed a deep reinforcement q-learning framework for modelling the dynamics of a PLF market
- Framework can learn the optimal policy for a simplified DeFi environment, and adjust collateral factor automatically to optimize the protocol
- We are working on extending the framework to a more realistic DeFi environment
- Learning result suggests that the optimal policy is to have the collateral factor highest for least volatile asset, and lowest for most volatile asset
- Aligns with the current AAVE governance mechanism; but able to learn the optimal policy in a more efficient and automated way

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