PARAMETER OPTIMIZATION AND EMERGENT BEHAVIOUR IN DEFI

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vega.xyz

WHAT WILL WE COVER?

- What is Vega Protocol?
- Case for large-scale agent based simulations
- Vega Nullchain and Vega market simulator
    - Code: Setting up the Vega market simulator
- Scenarios, Agents and Environments
    - Code: Building a basic agent
- Reinforcement Learning
    - Code: Building a smarter agent

WH
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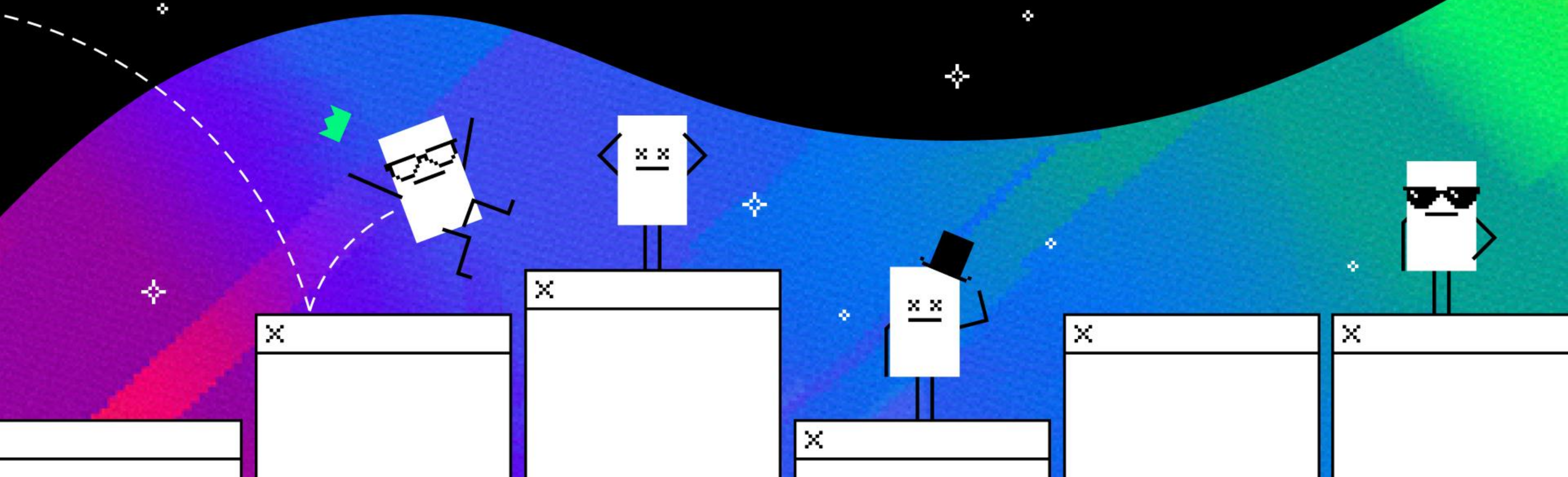
WHAT IS VEGA PROTOCOL

github.com/vegaprotocol/vega



INTRODUCTION TO VEGA PROTOCOL

- Layer 1 blockchain, PoS, Tendermint for consensus
- Optimised for trading margined products
- Price discovery is through order books (LOBs) and auctions
- Permissionless market creation
- If there is an oracle there can be a Vega market
- Bespoke liquidity mechanism for LOBs
- Assets bridged from Ethereum

WHY RUN OWN L1?

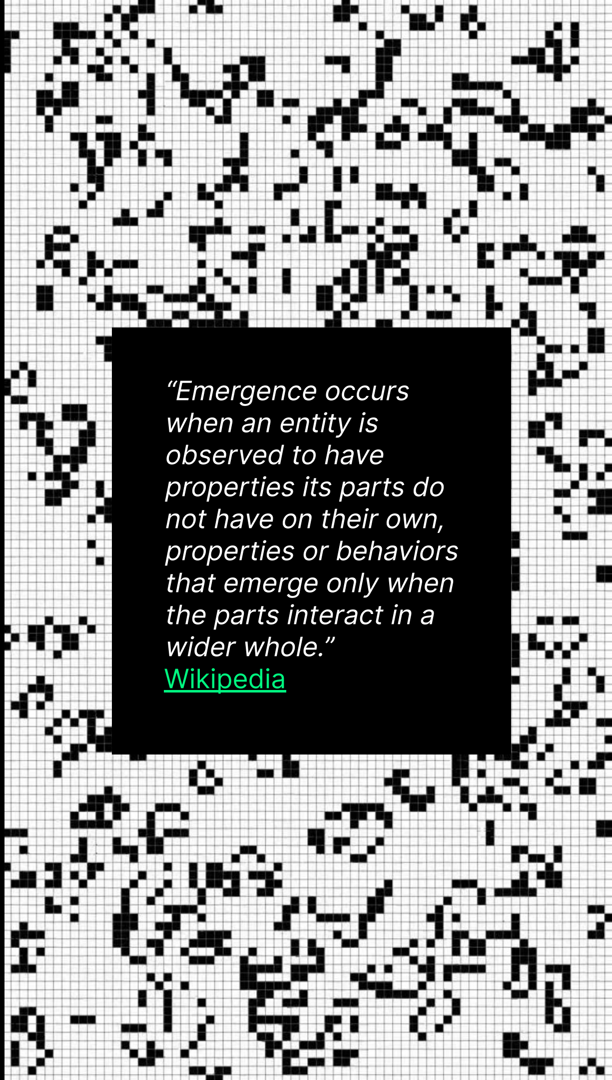
- No fees on transactions that aren’t trades
    - Limit orders are liquidity and information - why penalise?
- Atomic closeouts
- “Bare metal” for risk computations
- Fairness: Wendy
- Latency optimisation

CASE FOR LARGE-SCALE AGENT BASED SIMULATIONS

~~Economy~~ DeFi needs large agent based modelling (Nature)

CASE FOR AGENT BASED SIMULATIONS

- DeFi protocols are becoming more complex
- Simple rules can lead to complex behaviours
- With complexity, we often lose the ability to thoroughly understand how a system behaves in every possible situation
- There are many parameters set by governance which fine-tune protocol behaviours (Uniswap fees, Aave liquidation thresholds, Vega network and market parameters, risk parameters)
- DeFi is interoperable; as protocols connect and automate complexity will increase



"Emergence occurs when an entity is observed to have properties its parts do not have on their own, properties or behaviors that emerge only when the parts interact in a wider whole."
Wikipedia

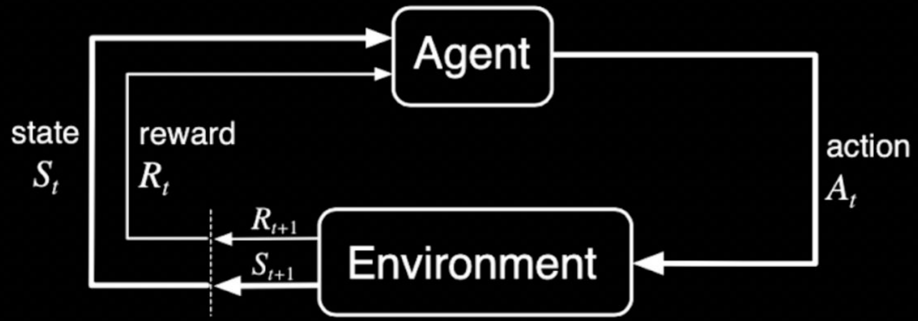
AGENT BASED MODELLING

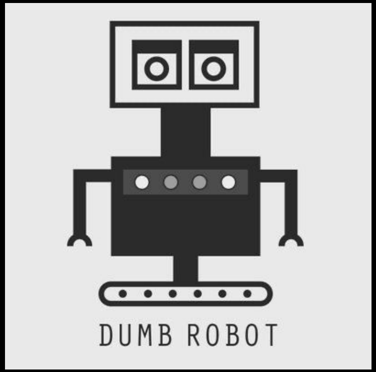
“A computational model for simulating the actions and interactions of autonomous agents (both individual or collective entities such as organizations or groups) in order to understand the behavior of a system and what governs its outcomes.“

Wikipedia

TYPES OF AGENTS

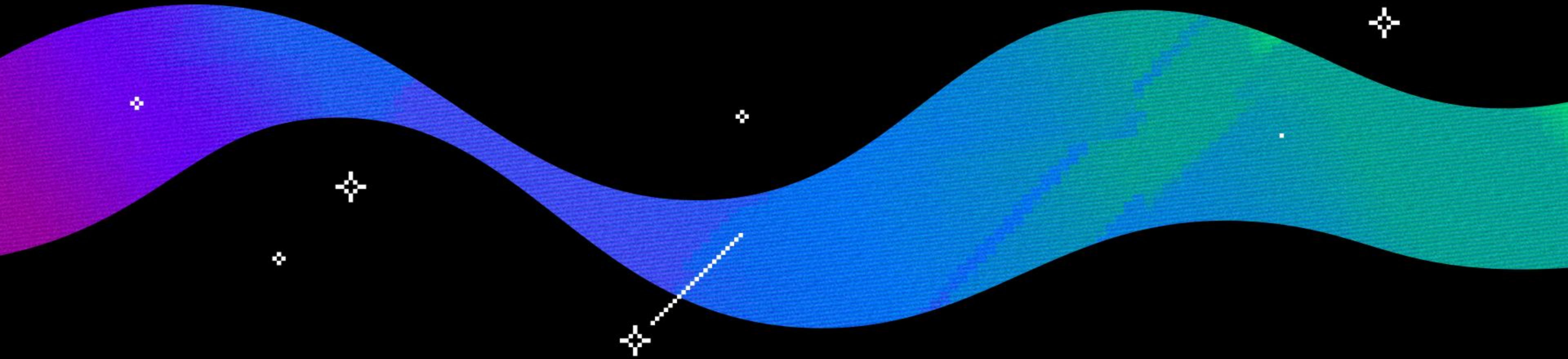
- Zero intelligence: hard coded actions based on state, no optimization, no learning
- Optimizing agents: full knowledge of how environment and others work, solving control problem / game theory problems; no learning.
- Reinforcement learning agents: State, Action, Reward, State, Action - SARSA





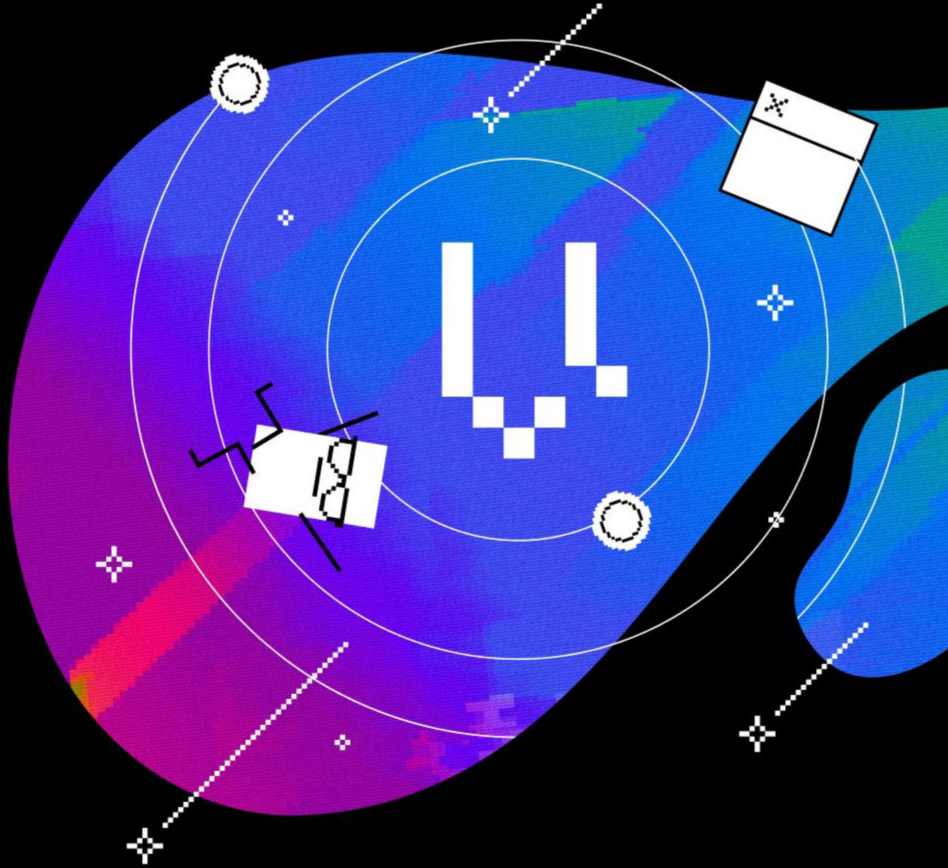
AGENT BASED SIMULATIONS WITH VEGA MARKET SIMULATOR

https://github.com/vegaprotocol/vega-market-sim/



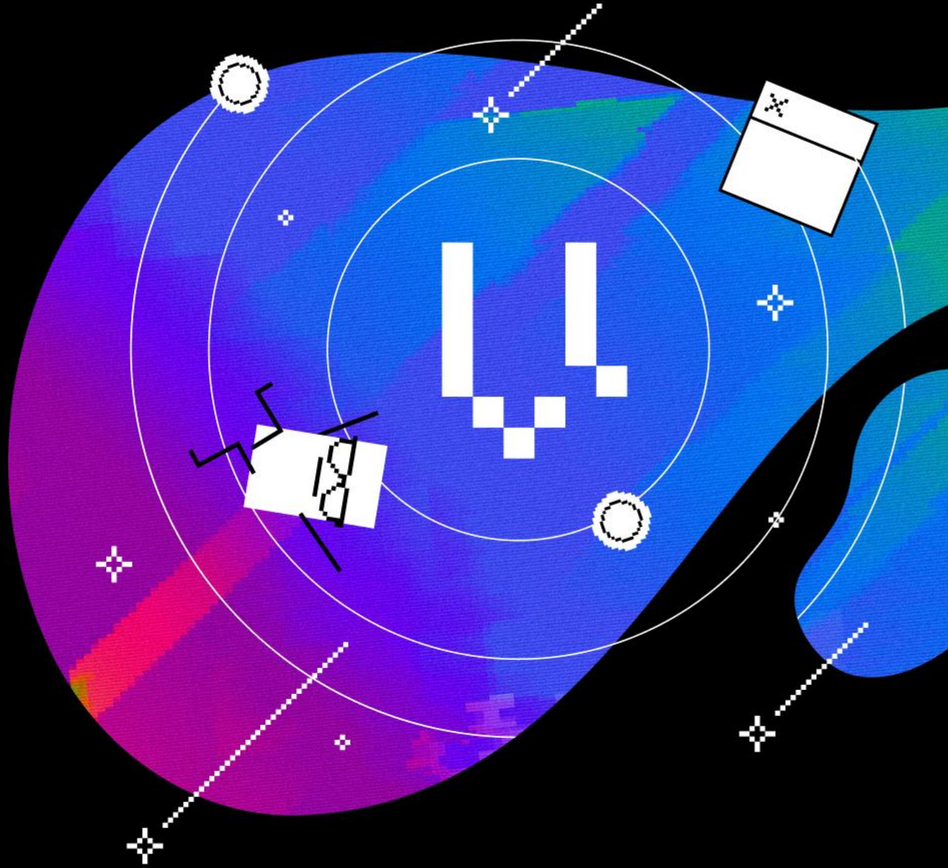
VEGA MARKET SIMULATOR

- Runs a full Vega stack, but with the Tendermint layer stripped away
- Replaced with a ‘null’ chain, a consensus layer which accepts whatever is sent and forwards time on command
- On top of this, an API layer allowing trading behaviour expression without (much) concern for the underlying blockchain



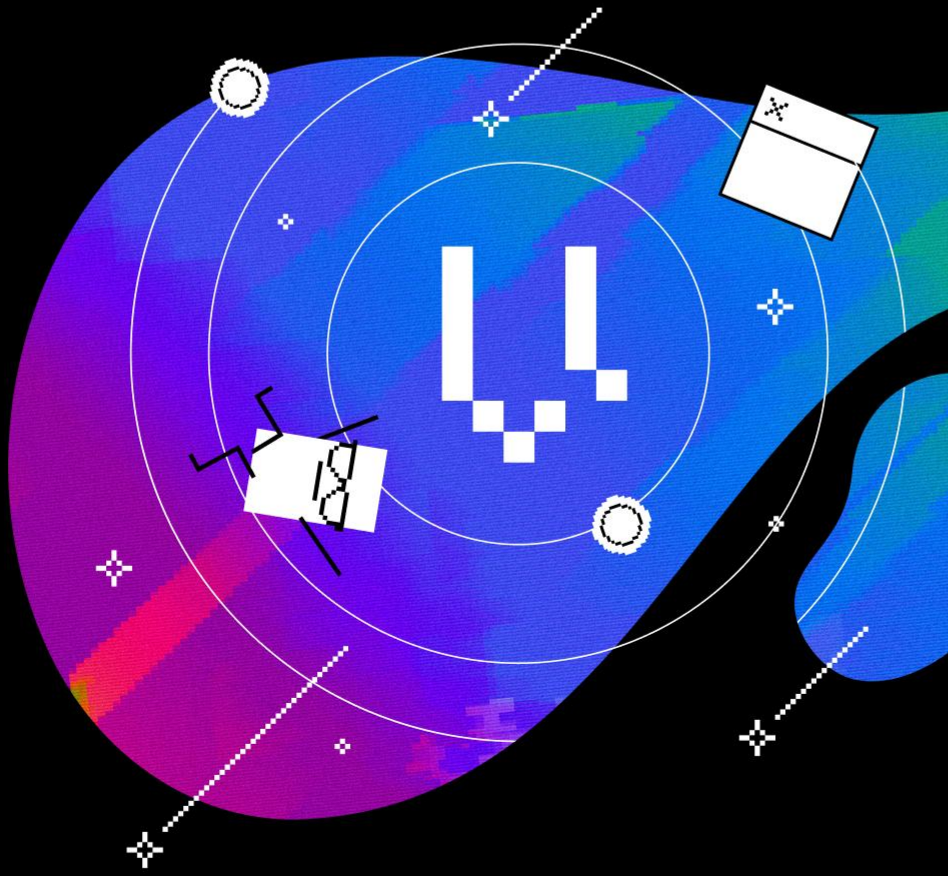
VEGA MARKET SIMULATOR

- Using this API, build:
    - Robust Scenarios covering a range of environments
    - Composable, configurable agents who can be slotted in or taken out at will



VEGA MARKET SIMULATOR

- We interact with a Vega instance through a ‘Service’ class, entered either in a context or with a .start() method in a notebook
  - VegaServiceNull
    - A ‘Nullchain’ instance spun up locally
  - VegaServiceNetwork
    - Connect to an existing remote network



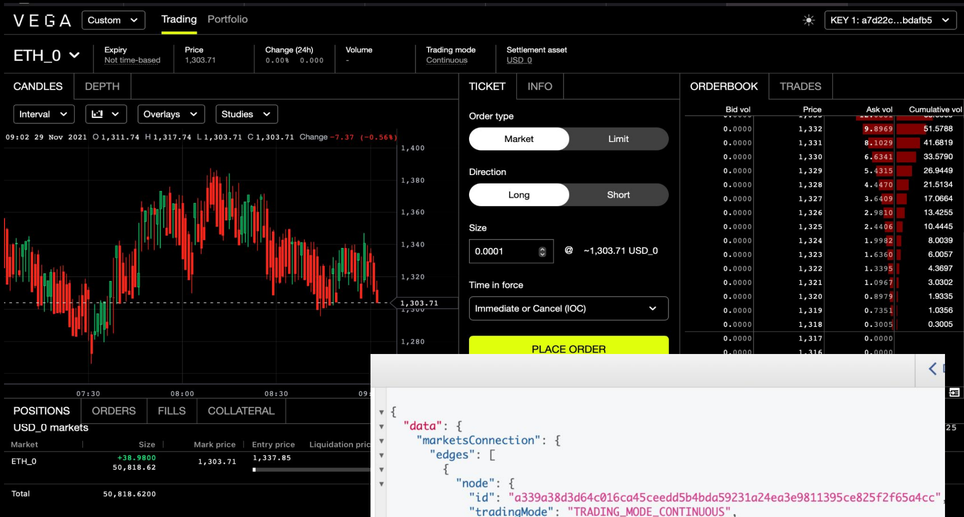
SETTING UP VEGA MARKET SIM

- Prerequisites:
  - make
  - Go 1.19
  - Python 3.10
  - Ideally poetry
- Optional:
  - For UI:
    - yarn
    - nvm
  - For learning:
    - pytorch
- Clone https://github.com/vegaprotocol/vega-market-sim/
- Follow README.md#setup
- Try at least `python -m examples.nullchain` if you skipped `make test_integration`

```
(vega-sim-py3.10) bash-5.1$ python ./examples/nullchain.py
INFO:vega_sim.null_service:Running NullChain from vegahome of /var/folders/67/mj
xp58z56yj83_1x0372gkwr0000gn/T/vega-sim-q_wn7uvo
INFO:vega_sim.null_service:Launching GraphQL node at port 63992
INFO:vega_sim.null_service:Launching Console at port 63998
WARNING:vega_sim.service:Using function with raw data from data-node VegaService
.all_markets. Be wary if prices/positions are not converted from int form
TDAI:  bf17bf3410cf85b594f6fef4030b567e273f4474cec3cd669da2b06d21f5a337
WARNING:vega_sim.service:Using function with raw data from data-node VegaService
.all_markets. Be wary if prices/positions are not converted from int form
Margin levels are: [MarginLevels(maintenance_margin=328.54405, search_level=361.
39844, initial_margin=394.25285, collateral_release_level=854.21451, party_id='0
f5f97fa23f760ba6e2c169ed2e9fe0a129f945fd4f16c9fd56c06424f5b1716', market_id='847
20861baf2c4aa3a990f62328c76c4a0a4496c64c50778420232d6ad446fd9', asset='bf17bf341
0cf85b594f6fef4030b567e273f4474cec3cd669da2b06d21f5a337', timestamp=163818546525
3066000)]
INFO:vega_sim.service:Settling market at price 100 for price.BTC.value
(vega-sim-py3.10) bash-5.1$
```

VIEWING THE MARKET

- Once the Sim is running, we have three main routes to inspect
  - API
  - GraphQL
    - Always runs, port logged on startup
    - Start VegaServiceNull with `launch_graphql=True` to automatically launch a browser
  - Console
    - `run_with_console=True` to launch console + browser

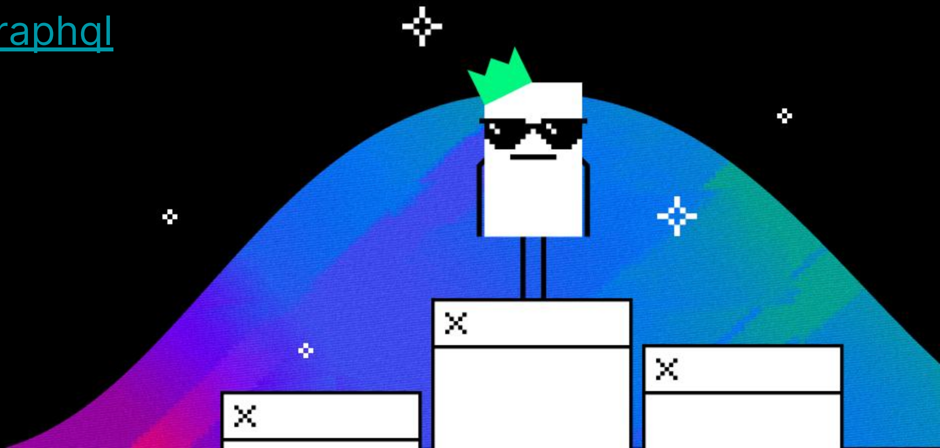



```json
{
  "data": {
    "marketsConnection": {
      "edges": [
        {
          "node": {
            "id": "a339a38d3d64c016ca45ceedd5b4bda59231a24ea3e9811395ce825f2f65a4cc",
            "tradingMode": "TRADING_MODE_CONTINUOUS",
            "data": {
              "bestBidPrice": "130371",
              "bestOfferPrice": "131774",
              "openInterest": "389801"
            }
          }
        }
      ]
    }
  }
}
```


```
INFO:vega_sim.null_service:Vega Running. Console launched at http://localhost:52647
INFO:vega_sim.null_service:Running NullChain from vegahome of /var/folders/yj/cjhtlxn90wldd1hvw5lkxnrc0000gn/T/vega-sim-ib8qcaom
INFO:vega_sim.null_service:Launching GraphQL node at port 52641
INFO:vega_sim.null_service:Launching Console at port 52647
INFO:vega_sim.environment.environment:Running wallet at: http://localhost:52638
INFO:vega_sim.environment.environment:Running graphql at: http://localhost:52641
```

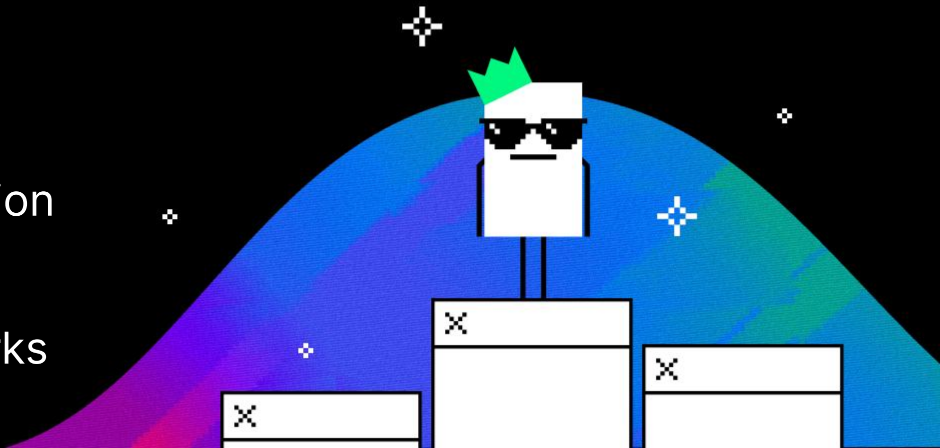
VIEWING THE MARKET

- For a more interesting scenario run:
  - ```
    python -m vega_sim.scenario.adhoc \
        -s historic_shaped_market_maker \
        --console \
        --graphql \
        --pause
    ```
- GraphQL Docs:
  - https://docs.vega.xyz/docs/testnet/graphql

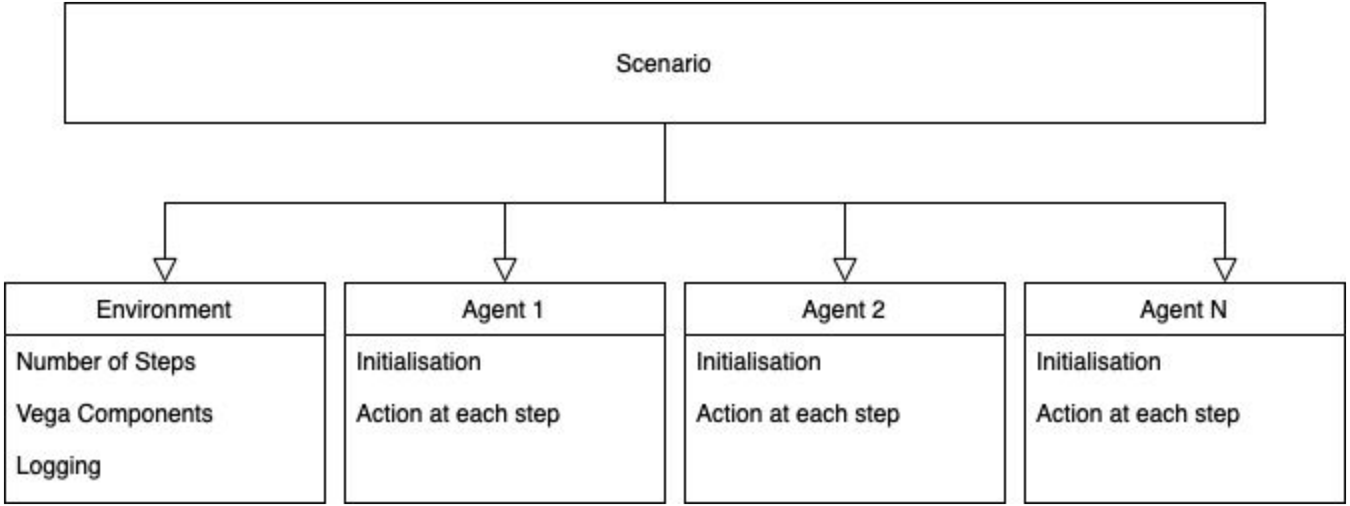

    ```

VEGA MARKET SIMULATOR - VEGASERVICENULL

- Core
  - Process transactions, maintains state, produces events
- Datanode
  - A storage layer allowing query of historic data from a Vega instance, consumes events
- Vegawallet (Optional)
  - Signs transactions and web interaction
- Console (Optional)
  - A frontend web GUI for Vega networks

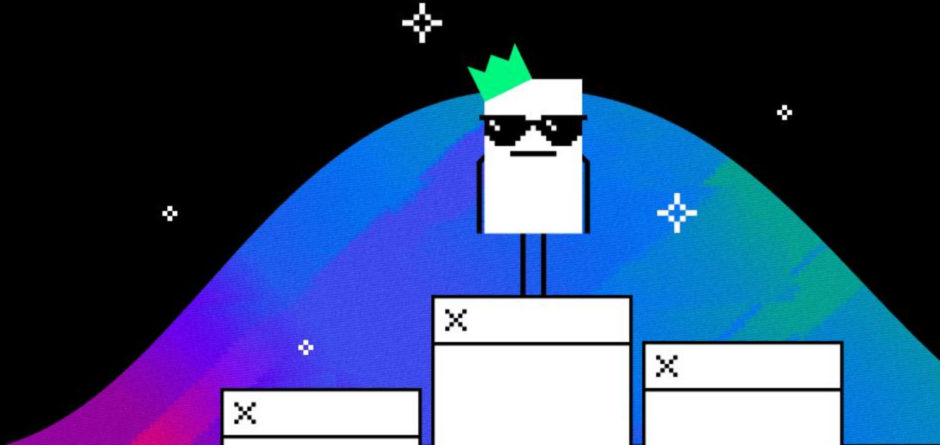


ENVIRONMENTS, AGENT STATE, ACTION → STATE STEP



VEGA SIM - AGENTS & SCENARIOS

- What is a Scenario?
  - Agents
    - Take actions at each
  - Environment
    - Number of steps
    - Vega instance config
    - Logging

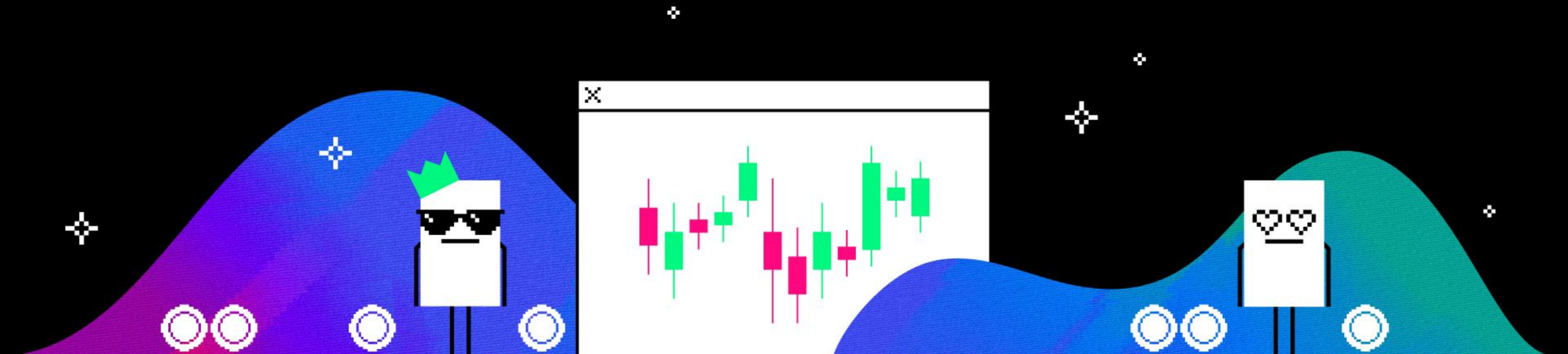


VEGA SIM - AGENTS & SCENARIOS

- What is an agent?
- Class with three interfaces:
  - `initialise`
    - Called at start of a scenario
  - `step`
    - Called once each scenario step
  - `finalise`
    - Called at end of a scenario
- `wait_for_total_catchup`
  - Keeps things in sync

SIMPLE AGENT: A WALKTHROUGH

Starting from a skeleton, we'll build a basic agent

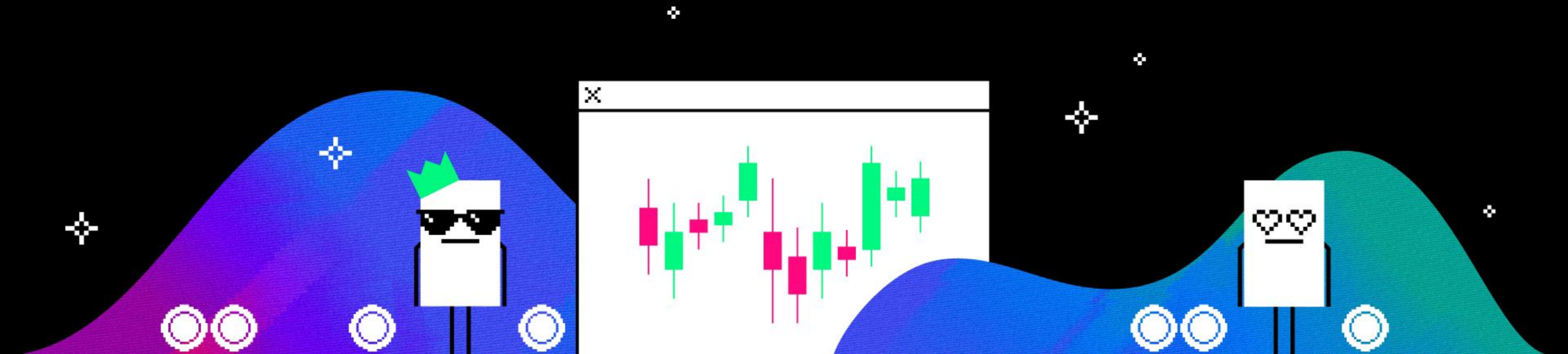


```python
class Agent(ABC):
    def step(self, vega: VegaService):
        pass

    def initialise(self, vega: VegaService):
        self.vega = vega

    def finalise(self):
        pass
```

```python
########################################################################
A simple agent framework which you can extend with some custom logic.

As-is, this agent will faucet itself some tokens in the setup phase
and then do nothing for the rest of the trading session.

Fill in your own logic into the `step` function to make them trade
however you'd like.

Below, we have a range of building blocks,
copy and paste these into your code to get started

########################################################################

### Pull best bid/ask prices
best_bid, best_ask = self.vega.best_prices(self.market_id)

### Pull market depth (up to a specified number of levels)
market_depth = self.vega.market_depth(self.market_id, num_levels=5)
```

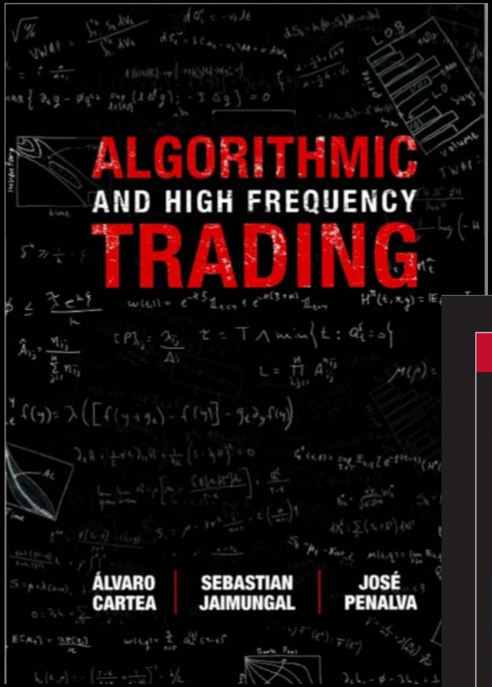
```python
class AgentWithWallet(Agent):
    def __init__(
        self,
        wallet_name: str,
        wallet_pass: str,
        key_name: Optional[str] = None,
    ):
        """Agent for use in environments as specified in environment.py.
        To extend, the crucial function to implement is the step function which will
        be called on each timestep in the simulation.

        Additionally, the initialise function can be added to. This function is call
        once before the main simulation and can be used to creat assets, set up mark
        faucet assets to the agent etc.

        Args:
            wallet_name:
                str, The name to use for this agent's wallet
            wallet_pass:
                str, The password which this agent uses to log in to the wallet
            key_name:
                str, optional, Name of key in wallet for agent to use. Defaults
                to value in the environment variable "VEGA_DEFAULT_KEY_NAME".
        """
        super().__init__()
        self.wallet_name = wallet_name
        self.wallet_pass = wallet_pass
        self.key_name = key_name

    def step(self, vega: VegaService):
        pass

    def initialise(self, vega: VegaService, create_wallet: bool = True):
        super().initialise(vega=vega)
        if create_wallet:
            self.vega.create_wallet(
                name=self.wallet_name,
                passphrase=self.wallet_pass,
                key_name=self.key_name,
            )
        else:
            self.vega.login(name=self.wallet_name, passphrase=self.wallet_pass)
```

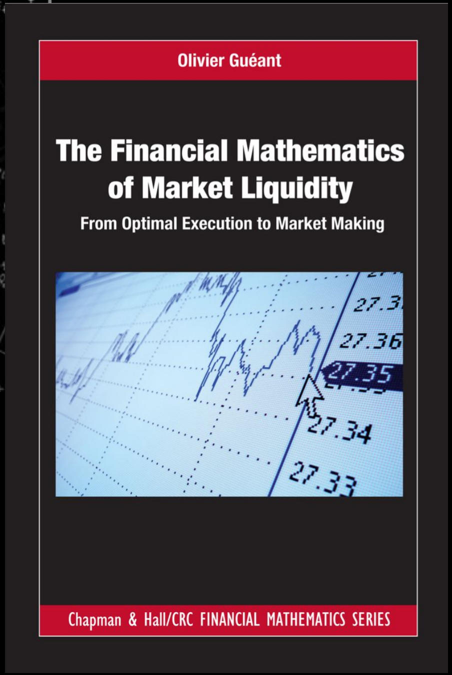
- The agent itself:
  - `vega_sim.reinforcement.agents.simple_agent`
- To run the Scenario
  - `python -m vega_sim.reinforcement.run_simple_agent`



EXISTING AGENTS

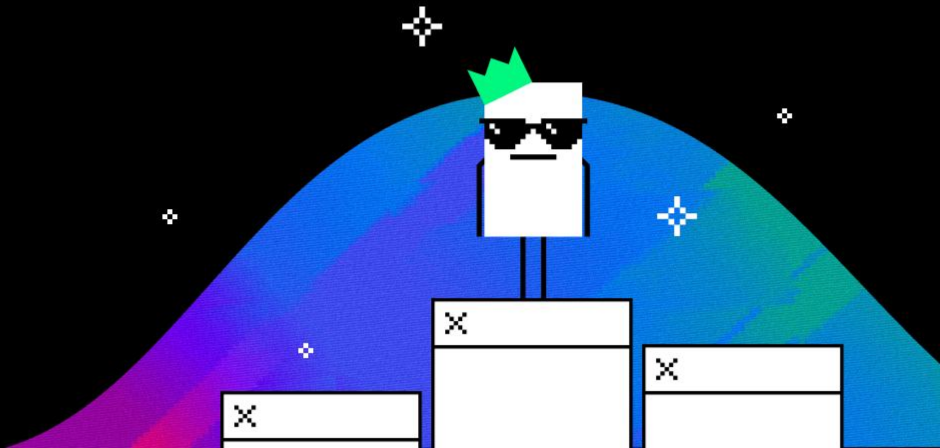
- Market makers: Ideal MM v1 and v2, Curve market maker (optimising)
- Liquidity taker (no int)
- Informed trader (no int)
- Momentum traders (no int)





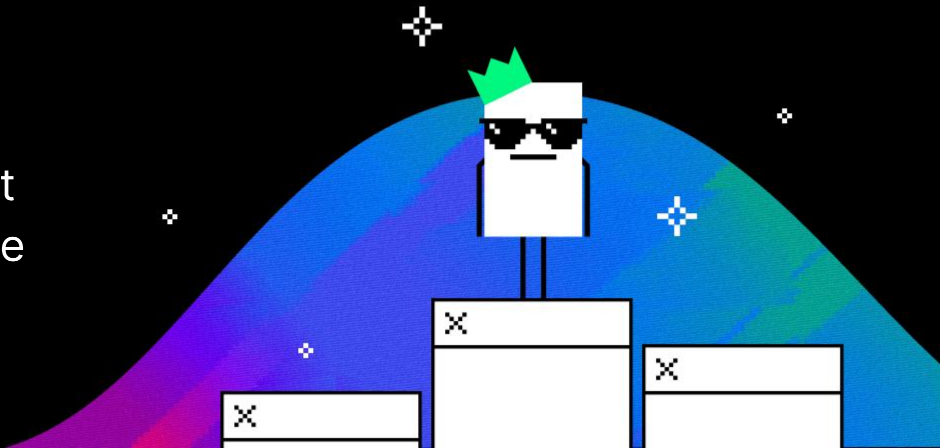
PARAMETER SETTING

- Simulations, with agents performing (mostly) logical, real world actions
- With a stable of agents, and some initial parameters, investigate the metrics you care about as the system evolves
- Note: The agents don't have to actually make money!

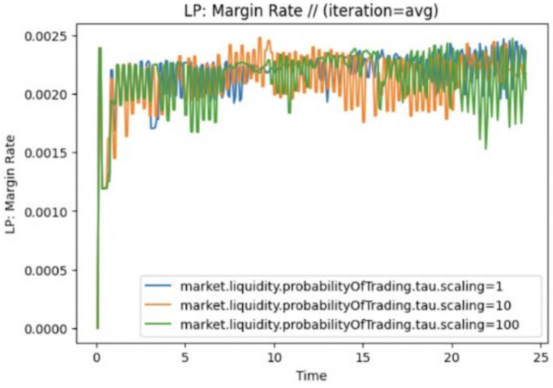


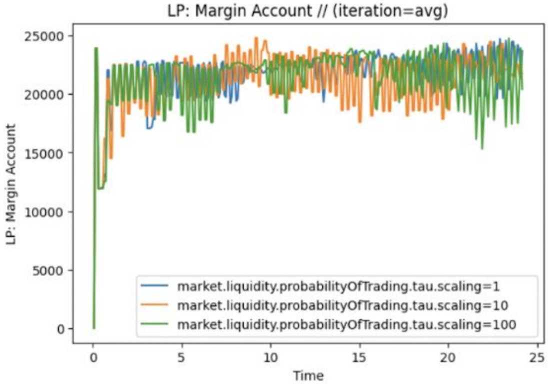
PARAMETER SETTING

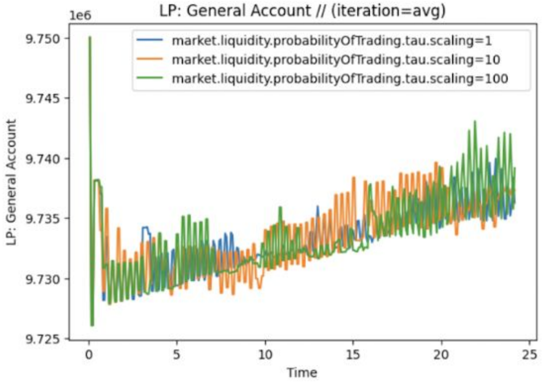
- Agent testing allows the system to be evaluated far more thoroughly than can ever be done manually
- But we still have limitations:
  - What initial conditions do we start from?
    - Test a range
    - Look at the real world
  - What agents do we use?
    - Agents with set logic are a great starting point, but limit the range of states we investigate

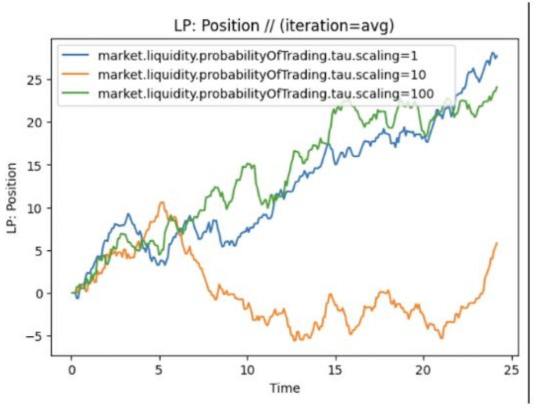


EFFECT OF RISK METRICS ON MM PROFITABILITY

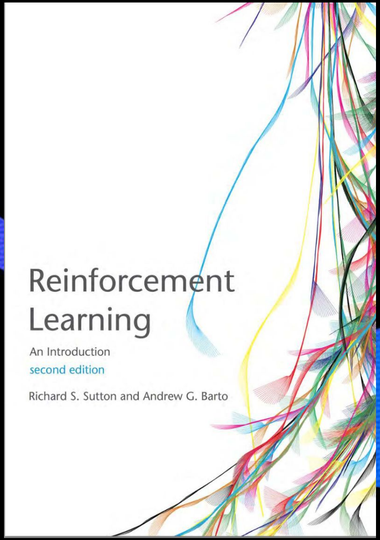


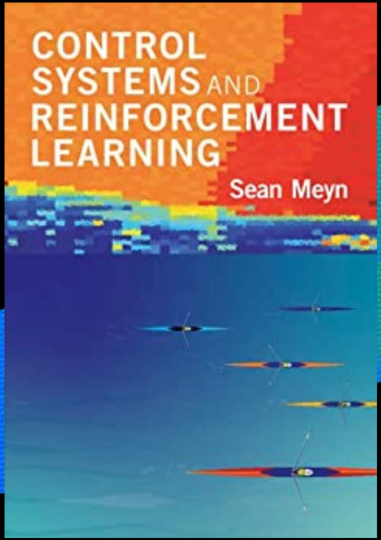






BUILDING RL AGENTS

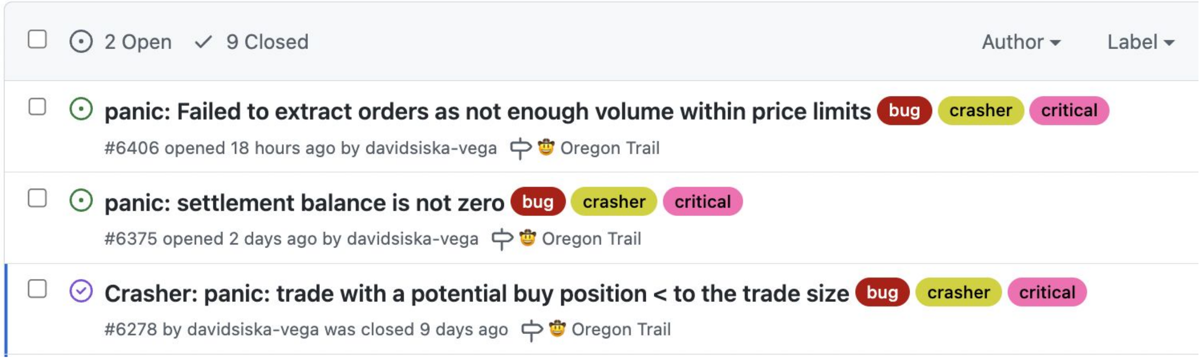




WHY DO WE WANT RL AGENTS?

- Zero intelligence and optimizing agents are "statistically" very similar even if each run is different
- Once you've run an environment 10-100 times you've seen it all

RL agents explore and learn, stressing the system in new ways



Outline

Markov Decision Process (MDP)

Reinforcement Learning
- Q-learning
- Policy Gradient

Environment Dynamics

Finite MDP consits of:

- Finite sets of states $\mathcal{S}$, actions A.
- Environment dynamics. Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space. For $a \in A, y, y' \in \mathcal{S}$ **we are given** $p^a(y, y')$ of a discrete time Markov chain $(X_n^\alpha)_{n=0,1,\dots}$ so that

$$\mathbb{P}(X_{n+1}^\alpha = y' | X_n^\alpha = y) = p^{\alpha_n}(y, y')$$

- α is the control process. α is measurable with respect to $\sigma(X_k^\alpha, k \leq n)$. In other words, α **can't look into the future**.

Value Function

- Let $\gamma \in (0, 1)$ be a fixed discount factor
- Let $f : \mathcal{S} \times A \to \mathbb{R}$ be a running reward.
- Our aim is to maximize the expected return

$$J^\alpha(x) = \mathbb{E}^x \left[\sum_{n=0}^{\infty} \gamma^n f(\alpha_n, X_n^\alpha) \right]$$

over all controlled processes, where $\mathbb{E}^x := \mathbb{E}[\cdot | X_0^\alpha = x]$

- For all $x \in \mathcal{S}$, we define the value function and the optimal value function as

$$v^\alpha(x) = J^\alpha(x), \quad v^*(x) := \max_{\alpha \in \mathcal{A}} J^\alpha(x)$$

Dynamic Programming for controlled Markov Processes

Theorem (DPP)

Let f be bounded. Then for all $x \in S$ we have

$$v^*(x) = \max_{a \in A} \mathbb{E}^x \left[f^a(x) + \gamma v^*(X_1^a) \right]$$

Corollary

Among all admissible control processes, it is enough to consider the ones that depend only on the current state.

Policy Iteration

Start with initial guess of $\alpha^0(x_i)$ for $i = 1, \ldots, |\mathcal{S}|$. Let $V^k(x_i), \alpha^k(x_i)$ be defined through the iterative procedure

1. **Evaluate** the current policy

$$V^{k+1}(x_i) = f(x_i, \alpha^k(x_i)) + \gamma \underbrace{\mathbb{E}\left[V^k(X_1^{\alpha_k})|X_0^{\alpha_k} = x_i\right]}_{p^{\alpha^k(x_i)}(y,y') \text{ needed!}}$$

2. **Improve** the policy

$$\alpha^{k+1}(x_i) \in \arg\max_{a \in A} f(x_i, a) + \gamma \overbrace{\mathbb{E}\left[V^{k+1}(X_1^a)|X_0^a = x_i\right]}^{p^a(y,y') \text{ needed!}}$$

Outline

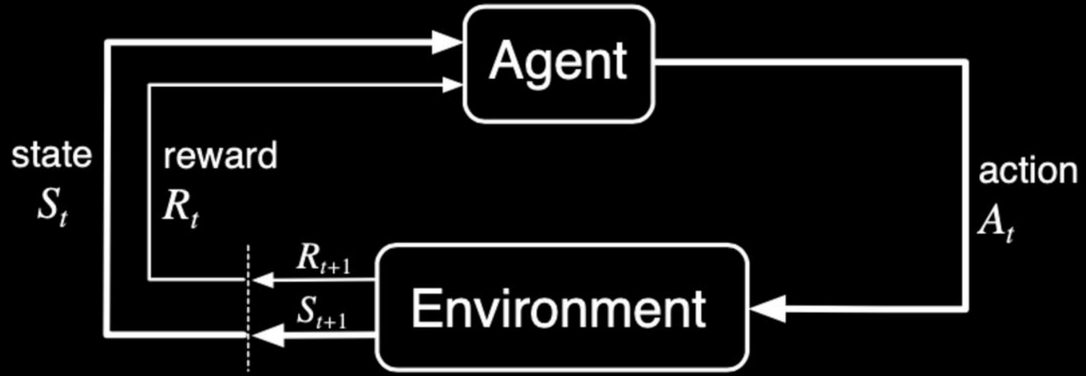
Markov Decision Process (MDP)

Reinforcement Learning
- Q-learning
- Policy Gradient

RL

Remark

In policy iteration, we need to know the transition probabilities $p^a(y, y'))$, f and g! This is not the usual case. The alternative is to learn the policy from data, collected from interacting with the environment.



Q-learning

Definition (Q-function)

$$Q^{\alpha}(x,a) := r(x,a) + \gamma \mathbb{E}[v^{\alpha}(X_1^a)]$$
$$Q^{*}(x,a) := r(x,a) + \gamma \mathbb{E}[v^{*}(X_1^a)]$$

From DPP, we know that, $\max_a Q^*(x,a) = v^*(x)$, therefore

$$Q^*(x,a) = r(x,a) + \gamma \mathbb{E}^x[\max_{b\in A} Q^*(X_1^a, b)].$$

Re-arranging,

$$0 = r(x,a) + \gamma \mathbb{E}^x[\max_{b\in A} Q^*(X_1^a, b)] - Q^*(x,a)$$

Q-learning Algorithm - Stochastic Approximation

Stochastic approximation arises when one wants to find the root θ^* of the following expression

$$0 = C(\theta) := \mathbb{E}_{X\sim\mu}(c(X,\theta))$$

If we have access to unbiased approximations of $C(\theta)$, namely $\tilde{C}(\theta)$, then the following updates

$$\theta \leftarrow \theta - \delta_n \tilde{C}(\theta)$$

with $\delta_n \in (0,1)$ satisfying

$$\sum_n \delta_n = +\infty, \quad \sum_n \delta_n^2 < +\infty$$

will converge to θ^*

Going back to Q-learning, we want to find an unbiased approximation of

$$r(x,a) + \gamma \mathbb{E}^x[\max_{b\in A} Q^*(X_1^a, b)] - Q^*(x,a)$$

Q-learning Algorithm

Recall $\mathcal{S}, A$ are finite (they can be big). Transition probabilities, running cost and final cost are unknown, but we can observe tuples (x_n, a_n, r_n, x_{n+1}) from interacting with the environment.

1. Make initial guess, for $Q^*(x, a)$ denoted by $Q(x, a)$ for all x, a.
2. We select and perform an action a (either by following the current policy, or by doing some sort of exploration).
3. We select the state we landed in, denoting it by y. If it is not terminal, adjust

$$Q(x,a) \leftarrow Q(x,a) + \delta_n \left(r(x,a) + \gamma \max_{b \in A} Q(y,b) - Q(x,a) \right)$$

   Note: we are doing Stochastic Approximation using $max_{b \in A} Q(y,b)$ as an unbiased approximation of $\mathbb{E}^x[\max_{b \in A} Q(X_1^a, b)]$.
4. Go back to (2)

Q-learning Algorithm - Function approximation

In practice, the state space might be very large (or continuous). It is then infeasible to sample (x_n, a, r, x_{n+1}) to explore all the space.
Alternatively, Q can be approximated with a Neural Network with parameters θ.
The optimal policy will be defined as $\alpha(x) = \max_{b \in A} Q_{\theta^*}(x, a)$ for some optimal parameters θ^*.

1. Initialise network's parameters θ.
2. Sample tuples $(x_n, a_n, r_n, x_{n+1})_{n=1,\dots,M}$ from the environment, using some exploration-exploitation heuristics.
3. Find θ^* that minimise the L_2-error

$$J(\theta) = \frac{1}{2} \mathbb{E}_{x,a\sim\mu} \left(Q_\theta(x, a) - (r(x, a) + \gamma \mathbb{E}^x \max_{b \in A} Q_{\bar{\theta}}(X, b)) \right)^2$$

where μ is the empirical measure of the visited action-states, using gradient ascent. We use the following approximation of the gradient

$$\nabla_\theta J = \mathbb{E}_{x,a\sim\mu} \left(Q_\theta(x, a) - (r(x, a) + \gamma \mathbb{E}^x \max_{b \in A} Q_{\bar{\theta}}(X, b)) \right) \nabla_\theta Q_\theta(x, a)$$

Soft Policies

From DPP it follows that the optimal policy is a deterministic function of the state. In practice, since the environment and the running cost/reward function are unkown, we will use **soft policies**,

$$\pi : \mathcal{S} \to \mathcal{P}(A)$$

where $\mathcal{P}(A)$ is the space of probability meaures on A.
I will abuse the notation, and I will indistinctively use $\pi(\cdot|x)$ for the distribution, the probability mass function (or the density) of $\pi(x)$.

Remark (Relationship between the value function and the Q-function)

$$v^{\pi}(x) = \mathbb{E}_{A \sim \pi(\cdot|x)} Q(x, A)$$

Policy Gradient for Soft Policies I

Consider a soft (random) policy with probability mass function $\pi_\theta(\cdot|x)$ parametrised by some parameters θ. Let ρ be some initial state distribution.
Instead of finding the optimal policy through the Q-function, we directly maximise the expected return for all $x \in S$.

$$J^{\pi_\theta}(\theta) = \mathbb{E}_{A_n \sim \pi(\cdot|X_n)}\left[\sum_{n=0}^{\infty} \gamma^n r(A_n, X_n^\alpha) \middle| X_0 \sim \rho\right]$$

Assume we know an expression for $\nabla_\theta J^{\pi_\theta}$ (next slide). Then $\arg\max_\theta J^{\pi_\theta}(\theta)$ is found using gradient ascent using a learning rate τ

$$\theta \leftarrow \theta + \tau \cdot \nabla_\theta J^{\pi_\theta}$$

Policy Gradient for Soft Policies II

We need to find an expression for $\nabla_\theta J^{\pi_\theta}$. This is given by The Policy Gradient Thm, Section 13.2 in [Sutton and Barto, 2018]

Theorem (Policy Gradient Theorem)

$$\begin{aligned}\nabla_\theta J^{\pi_\theta}(\theta) &\propto \sum_{x\in\mathcal{S}} \mu(x) \sum_{a\in A} \nabla_\theta \pi_\theta(a|x) Q_{\pi_\theta}(x,a) \\ &\propto \mathbb{E}_{X_n\sim\mu}\left[\mathbb{E}_{A_n\sim\pi_\theta(\cdot|X_n)} \nabla_\theta \log(\pi_\theta(A_n|X_n)) Q_{\pi_\theta}(X_n, A_n)\right]\end{aligned}$$

where μ is the visitation measure.

We need to approximate Q_{π_θ}!

Policy Gradient for Deterministic Policies

If we have a deterministic policy with continuous actions $\alpha_\alpha : \mathcal{S} \to A$, then the Deterministic Policy Gradient for Reinforcement Learning with continuous actions is given by Theorem 1 in [Silver et al., 2014]

Theorem

$$\nabla_\theta J^{\alpha_\theta}(\theta) = \mathbb{E}_{X_n \sim \mu}\left[\nabla_\theta \alpha_\theta(x) \nabla_a Q_{\alpha_\theta}(X_n, \alpha_\theta(s))\right]$$

We need to approximate Q_{α_θ}

Actor-Critic type Algorithms

Policy Gradient theorems include the Q-function. In practice, one can either

- approximate it using Monte Carlo (i.e. by simulating several games starting from (x, a) and approximate it with the average). This is expensive and might have a high variance.
- Using a function approximation $Q_\psi(x, a)$ with parameters ψ. This motivates **actor-critic** algorithms:
  1. **Policy evaluation**: approximate the Q-function (the critic) using for example the Bellman equation.

     $$\psi^* = \arg\max_{\psi} \frac{1}{2} \mathbb{E}_{x,a\sim\mu} \left(Q_\psi(x, a) - (r(x, a) + \gamma \mathbb{E}^x v_{\bar{\psi}}(X)) \right)^2$$

     where we recall that $v_{\bar{\psi}}(X) = \mathbb{E}_{a\sim\pi_\theta(\cdot|X)}[Q_\psi(X, a)]$
  2. **Policy improvement** improve the policy (the actor) with gradient ascent using the Policy Gradient theorems.

References I

- Silver, D., Lever, G., Heess, N., Degris, T., Wierstra, D., and Riedmiller, M. (2014).
  Deterministic policy gradient algorithms.
  In *International conference on machine learning*, pages 387–395. PMLR.
- Sutton, R. S. and Barto, A. G. (2018).
  Reinforcement learning: An introduction.
  MIT press.

Simple RL Agent - A walkthrough

- Start in ./vega_sim/reinforcement
- run_rl_agent.py --rl-max-it 100
- run_rl_agent.py --evaluate 10

```
INFO:vega_sim.environment.environment:Running wallet at: http://localhost:49978
INFO:vega_sim.environment.environment:Running graphql at: http://localhost:49981
INFO:vega_sim.service:Settling market at price 999.281 for price.tDAI_49.value
INFO:vega_sim.environment.environment:Run took 8s
100%|██████████████████████████████████████████| 10/10 [00:06<00:00,  1.54it/s]
100%|██████████████████████████████████████████| 10/10 [00:02<00:00,  3.90it/s]
```

Do:
1. Collect SARSA from policy
2. Update q-function approximation (critic)
3. Update policy (actor)

While: error > threshold

Collect SARSA data from fixed policy

Policy is fixed (initially random neural network weights)

```python
learning_agent.move_to_cpu()
_ = run_iteration(
    learning_agent=learning_agent,
    step_tag=it,
    vega=vega,
    market_name=market_name,
    run_with_console=False,
    pause_at_completion=False,
)
```

```python
def step(self, vega_state: VegaState):
    learning_state = self.state(self.vega)
    self.step_num += 1
    self.latest_action = self._step(learning_state)
    self.latest_state = learning_state

    if learning_state.full_balance <= 0:
        return
    if learning_state.market_in_auction:
        return

    if self.latest_action.buy or self.latest_action.sell:
        try:
            self.vega.submit_market_order(
                trading_wallet=self.wallet_name,
                market_id=self.market_id,
                side="SIDE_BUY" if self.latest_action.buy else "SIDE_SELL",
                volume=self.volume,
                wait=False,
                fill_or_kill=False,
            )
        except Exception as e:
            print(e)
```

Collect SARSA data from fixed policy

```python
def _step(self, vega_state: LAMarketState) -> Action:
    # learned policy
    state = vega_state.to_array().reshape(1, -1)  # addi
    state = torch.from_numpy(state).float()  # .to(self.

    with torch.no_grad():
        c = self.sample_action(state=state, sim=True)
    choice = int(c.item())

    return Action(buy=choice == 0, sell=choice == 1)
```

```python
def state(self, vega: VegaServiceNull) -> LAMarketState:
    position = self.vega.positions_by_market(self.wallet_name, self.market_id)

    position = position[0].open_volume if position else 0
    account = self.vega.party_account(
        wallet_name=self.wallet_name,
        asset_id=self.tdai_id,
        market_id=self.market_id,
    )
    book_state = self.vega.market_depth(
        self.market_id, num_levels=self.num_levels
```

```python
def states_to_sarsa(
    states: List[Tuple[LAMarketState, AbstractAction]],
    inventory_penalty: float = 0.0,
) -> List[Tuple[LAMarketState, AbstractAction, float, LAMarketState, AbstractAction]]:
    res = []
    for i in range(len(states) - 1):
        pres_state = states[i]
        next_state = states[i + 1]

        if next_state[0].full_balance <= 0:
            reward = -1e12
            res.append(
                (
                    pres_state[0],
                    pres_state[1],
                    reward,
                    next_state[0] if next_state is not np.nan else np.nan,
                    next_state[1] if next_state is not np.nan else np.nan,
                )
            )
            break
```

Improve Q-function estimate

```python
def policy_eval(
    self,
    batch_size: int,
    n_epochs: int,
):
    toggle(self.policy_discr, to=False)
    toggle(self.q_func, to=True)

    dataloader = self.create_dataloader(batch_size=batch_size)

    pbar = tqdm(total=n_epochs)
    for epoch in range(n_epochs):
        for (
            i,
            (
                batch_state,
                batch_action_discrete,
                batch_reward,
                batch_next_state,
            ),
        ) in enumerate(dataloader):
            next_state_terminal = torch.isnan(
                batch_next_state
            ).float()  # shape (batch_size, dim_state)
            batch_next_state[next_state_terminal.eq(True)] = batch_state[
                next_state_terminal.eq(True)
            ]
            self.optimizer_q.zero_grad()
```

```python
            pred = torch.gather(
                self.q_func(batch_state),
                dim=1,
                index=batch_action_discrete,
            )

            with torch.no_grad():
                v = self.v_func(batch_next_state)
                target = (
                    batch_reward
                    + (1 - next_state_terminal.float().mean(1, keepdim=True))
                    * self.discount_factor
                    * v
                )
            loss = torch.pow(pred - target, 2).mean()
            loss.backward()
            self.optimizer_q.step()
        self.losses["q"].append(loss.item())
        # logging loss
        with open(self.logfile_pol_eval, "a") as f:
            f.write(
                "{},{:.2e},{:.2e},{:.2e}\n".format(
                    epoch + self.lerningIteration * n_epochs,
                    loss.item(),
                    self.coefH_discr,
                    self.coefH_cont,
                )
            )
        pbar.update(1)
    return 0
```

Improve policy

```python
def policy_improvement(self, batch_size: int, n_epochs: int):
    toggle(self.policy_discr, to=True)
    toggle(self.q_func, to=False)

    dataloader = self.create_dataloader(batch_size=batch_size)

    pbar = tqdm(total=n_epochs)
    for epoch in range(n_epochs):
        for i, (batch_state, _, _, _) in enumerate(dataloader):
            self.optimizer_pol.zero_grad()
            d_kl = self.D_KL(batch_state).mean()
            d_kl.backward()
            # nn.utils.clip_grad_norm_(self.policy_volume.
            self.optimizer_pol.step()
        self.losses["d_kl"].append(d_kl.item())
        with open(self.logfile_pol_imp, "a") as f:
            f.write(
                "{},{:.4f}\n".format(
                    epoch + n_epochs * self.lerningIteration, d_kl.item()
                )
            )
        pbar.update(1)
```

$$\pi^*_{\mathrm{MaxEnt}}(\mathbf{a}_t|\mathbf{s}_t) = \exp\left(\frac{1}{\alpha}\left(Q^*_{\mathrm{soft}}(\mathbf{s}_t,\mathbf{a}_t) - V^*_{\mathrm{soft}}(\mathbf{s}_t)\right)\right).$$

Reinforcement Learning with Deep Energy-Based Policies

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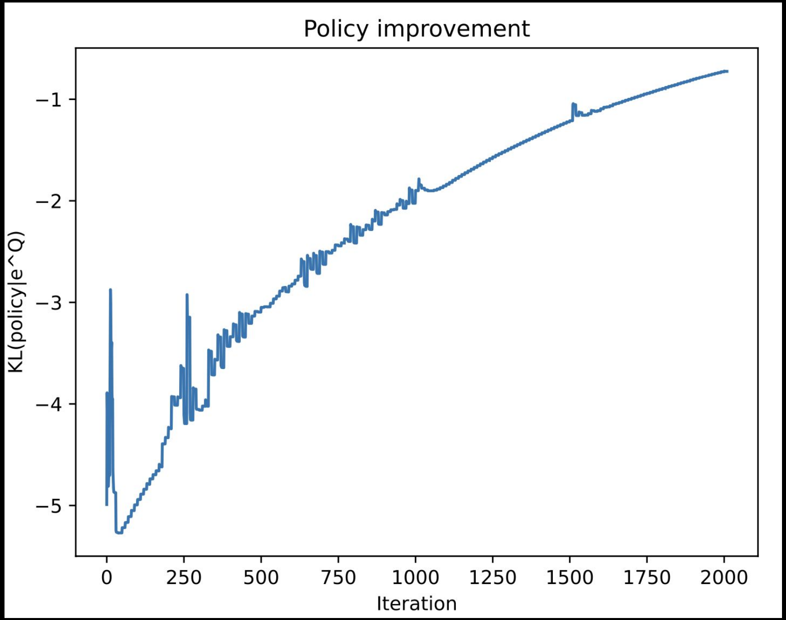
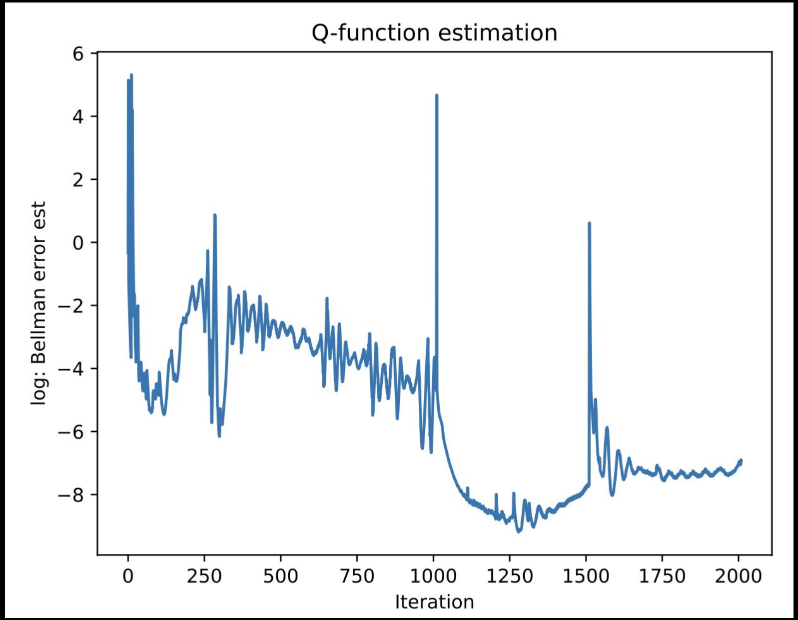
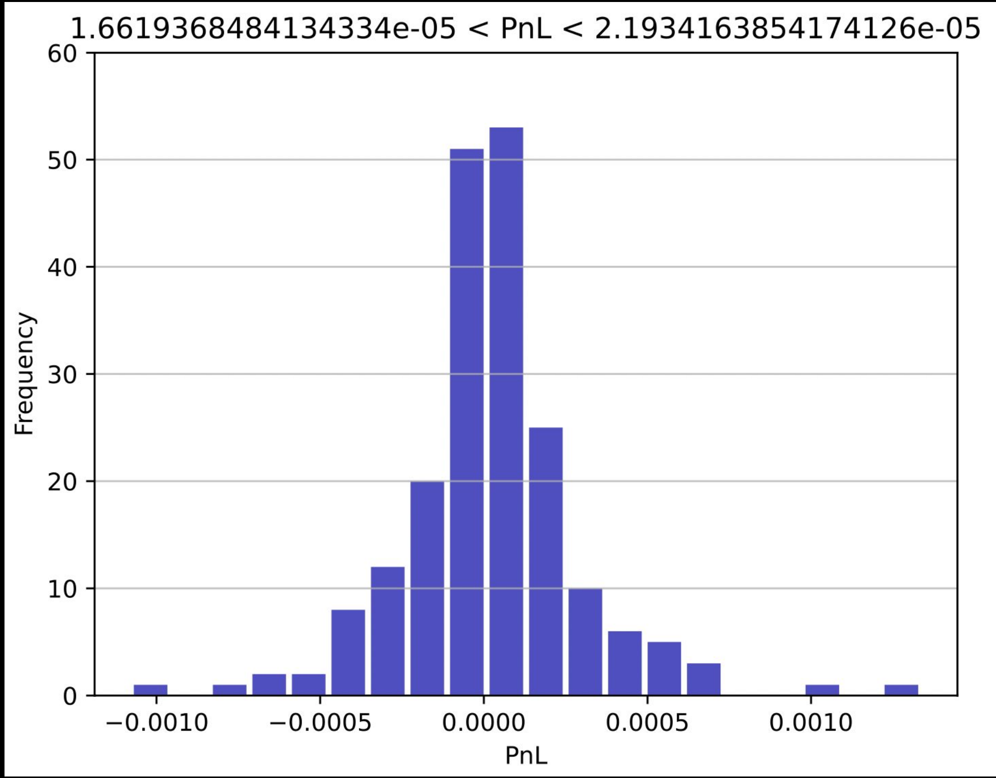
What to expect?





Evaluation



1.6619368484134334e-05 < PnL < 2.1934163854174126e-05
60
50
40
30
20
10
0
Frequency
−0.0010
−0.0005
0.0000
0.0005
0.0010
PnL

THANK YOU!

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