

Optimized Kalman Filter

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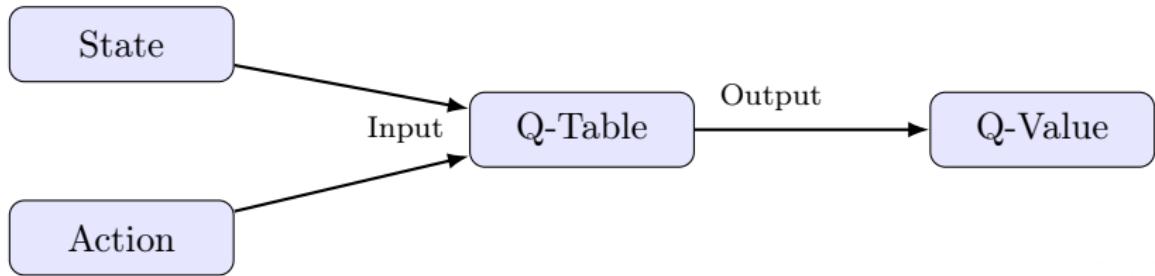
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Epsilon-Greedy Policy

- **Q-table:** Internally, Q-Learning uses a Q-table storing values for each state-action pair. Initially, all values are zero, and the table is updated iteratively during training.

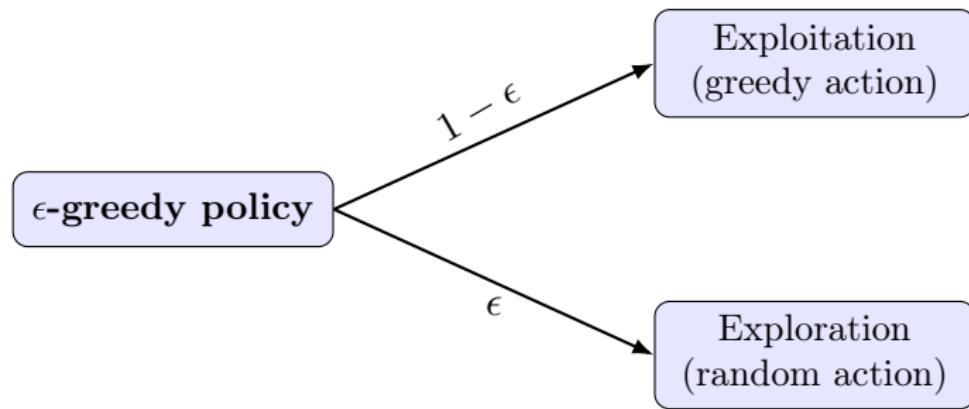
$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_{t+1} + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t) \right]$$



Epsilon-Greedy Policy

- **Epsilon-Greedy Strategy :** To balance exploration and exploitation, actions are chosen using an epsilon-greedy policy

$$\pi^*(s) = \arg \max_a Q^*(s, a)$$



Environement Implementation

TradingEnv

- df : DataFrame
 - n_steps : int
 - current_step : int
 - initial_balance : float
 - balance : float
 - position : int
 - last_action : int
 - observation_space : Box
 - action_space : Discrete
-
- + __init__(df)
 - + _get_obs()
 - + sample_valid_action()
 - + get_valid_actions()
 - + step(action)
 - + set_data(df)
 - + reset()

Algorithm 1: Trading Environment Behavior

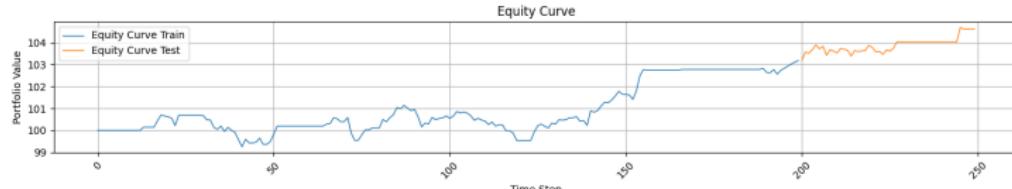
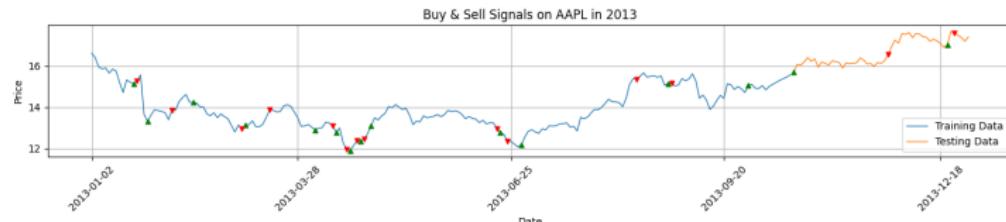
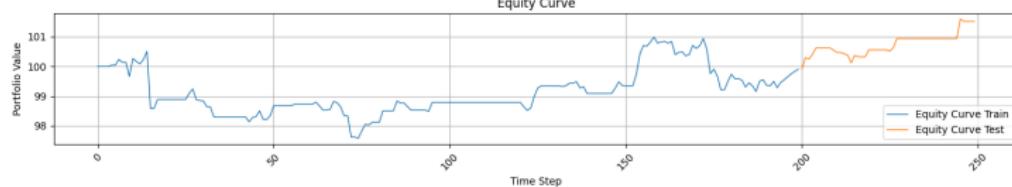
Input: Environment env , number of episodes N , exploration rate ϵ

Output: Episode value and rewards

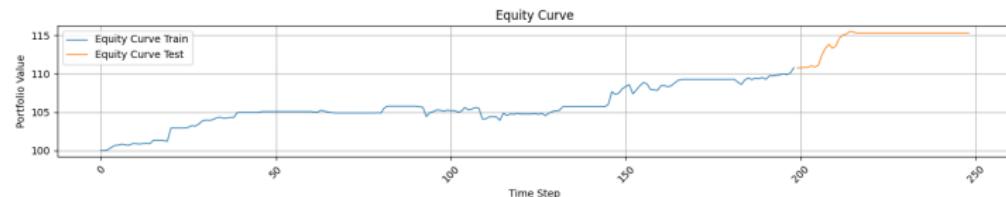
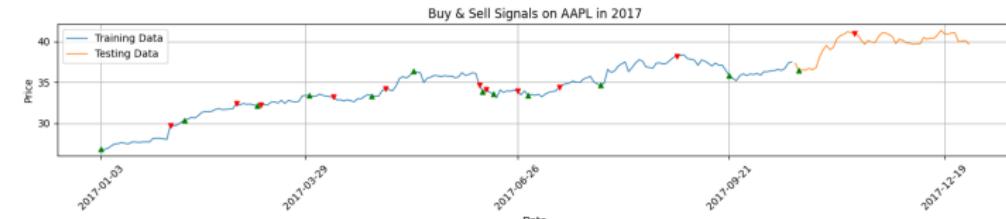
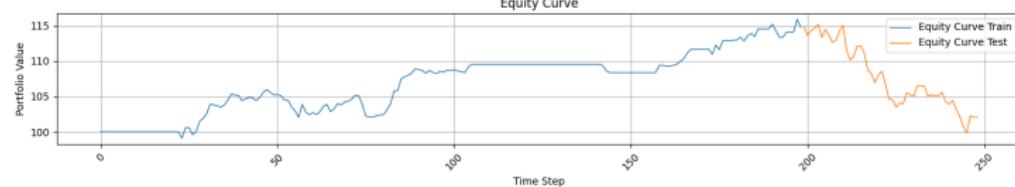
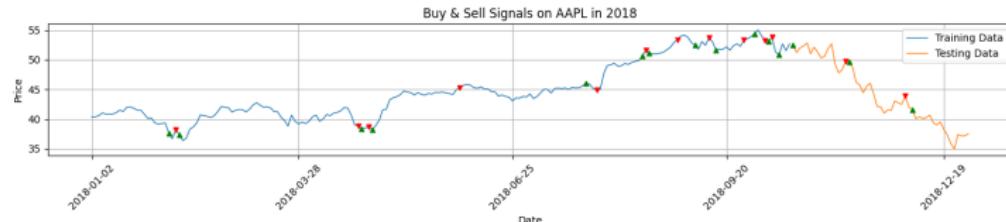
```
for episode ← 1 to N
    s ← env.reset();
    total_reward ← 0;
    while True
        Get valid actions
        Avalid ← env.get_valid_actions();
        Select a ← random choice from Avalid;
        Execute
        (s', r, done, info) ← env.step(a);
        total_reward ← total_reward + r;
        Log
            (episode, s, a, r, info["portfolio_value"]);
        s ← s';
        if done then
            break
Print episode summary : total_reward, final portfolio value;
```



Results



Results issues



Preparing PPO

- Designing and integrating a deep neural network architecture
- Compare DQN and Q-Learning greedy policy
- Expanding to more realistic market conditions
- Hyperparameterization



Thank You

