

Set up environment

```
In [1]: import gymnasium as gym
import numpy as np
import pandas as pd
import torch
```

数据准备

```
In [2]: device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
device
```

```
Out[2]: device(type='cuda')
```

```
In [3]: tech_daily = pd.read_csv(r"data\科技股票.csv")
tech_daily.set_index('date', inplace=True)
tech_daily.columns=['AAPL', 'GOOG', 'MSFT']
tech_daily
```

Out[3]:

	AAPL	GOOG	MSFT
date			
2022-01-03	178.270326	144.088458	324.504611
2022-01-04	176.007789	143.434930	318.940290
2022-01-05	171.326001	136.717897	306.696845
2022-01-06	168.465997	136.616093	304.273361
2022-01-07	168.632504	136.073308	304.428464
...
2025-11-03	268.789439	284.120000	517.030000
2025-11-04	269.778480	278.060000	514.330000
2025-11-05	269.878383	284.750000	507.160000
2025-11-06	269.508741	285.340000	497.100000
2025-11-07	268.210000	279.700000	496.820000

967 rows × 3 columns

```
In [4]: debt=pd.read_csv(r"data\无风险.csv",encoding='gbk')
debt.set_index('date', inplace=True)
debt.columns=['US_debt']
debt
```

Out[4]:

US_debt	
date	
2022-01-03	1.63
2022-01-04	1.66
2022-01-05	1.71
2022-01-06	1.73
2022-01-07	1.76
...	...
2025-11-03	4.13
2025-11-04	4.10
2025-11-05	4.17
2025-11-06	4.11
2025-11-07	4.11

963 rows × 1 columns

```
In [5]: tmp=pd.read_csv(r"data\指数和贵金属.csv", encoding='gbk')
tmp.columns=['date', 'SP500', 'Gold']
tmp.set_index('date', inplace=True)
tmp
```

Out[5]:

	SP500	Gold
date		
2022-01-03	4796.56	1801.3
2022-01-04	4793.54	1814.9
2022-01-05	4700.58	1810.6
2022-01-06	4696.05	1790.9
2022-01-07	4677.03	1796.5
...
2025-11-03	6851.97	4013.7
2025-11-04	6771.55	3941.3
2025-11-05	6796.29	3990.4
2025-11-06	6720.32	3984.8
2025-11-07	6728.80	4007.8

1001 rows × 2 columns

```
In [6]: df=pd.merge(tech_daily,debt,how='left',on='date')
df=pd.merge(df,tmp,how='left',on='date')
df['date']=pd.to_datetime(df.index)
df.set_index('date', inplace=True)
df[df.isnull().values == True]
```

Out[6]:

	AAPL	GOOG	MSFT	US_debt	SP500	Gold
date						
2022-10-10	138.103983	98.039090	223.685532	NaN	3612.39	1675.7
2022-11-11	147.475157	96.072547	241.112025	NaN	3992.93	1774.2
2023-10-09	177.082149	138.551849	324.923430	NaN	4335.66	1875.0
2024-10-14	230.005541	165.625113	416.016745	NaN	5859.85	2665.8
2024-11-11	223.220427	181.177047	414.895165	NaN	6001.35	2626.1
2025-10-13	247.420154	244.640000	514.050000	NaN	6654.72	4130.0

```
In [7]: df.interpolate(method='time', inplace=True)
df
```

Out[7]:

	AAPL	GOOG	MSFT	US_debt	SP500	Gold
date						
2022-01-03	178.270326	144.088458	324.504611	1.63	4796.56	1801.3
2022-01-04	176.007789	143.434930	318.940290	1.66	4793.54	1814.9
2022-01-05	171.326001	136.717897	306.696845	1.71	4700.58	1810.6
2022-01-06	168.465997	136.616093	304.273361	1.73	4696.05	1790.9
2022-01-07	168.632504	136.073308	304.428464	1.76	4677.03	1796.5
...
2025-11-03	268.789439	284.120000	517.030000	4.13	6851.97	4013.7
2025-11-04	269.778480	278.060000	514.330000	4.10	6771.55	3941.3
2025-11-05	269.878383	284.750000	507.160000	4.17	6796.29	3990.4
2025-11-06	269.508741	285.340000	497.100000	4.11	6720.32	3984.8
2025-11-07	268.210000	279.700000	496.820000	4.11	6728.80	4007.8

967 rows × 6 columns

```
In [8]: from math import inf

from networkx import sigma
from parsing import deque

class PortfolioOptimizationEnv(gym.Env):
    def __init__(self, tickers, window_size, start_date, end_date,
                 initial_balance, seed=None):
        super().__init__()
        self.tickers = tickers
        self.window_size = window_size
        self.initial_balance = initial_balance

        # 分别存储原始价格和指标
```

```

self.raw_data, self.feature_data = self.get_data(tickers, start_date, end_date)
self.n_features = self.feature_data.shape[1]

self.action_space = gym.spaces.Box(low=0, high=1, shape=(len(tickers),))
self.observation_space = gym.spaces.Box(low=-inf, high=inf,
                                         shape=(window_size, self.n_features))

self.return_window=deque(maxlen=window_size)
self.last_action=np.ones(len(tickers))/len(tickers)

if seed is not None:
    np.random.seed(seed)
    self.action_space.seed(seed)
    torch.manual_seed(seed)
    if torch.cuda.is_available():
        torch.cuda.manual_seed_all(seed)

def get_data(self, tickers, start_date, end_date):
    data = df.copy().dropna()
    data = data.loc[start_date:end_date, tickers]

    # 保存原始价格（用于计算投资组合收益）
    raw_data = data.copy()

    # 计算特征指标
    returns = data.pct_change()

    mom_frames = []
    for window in [5, 20]:
        mom = data / data.shift(window) - 1
        mom.columns = [f"{col}_mom_{window}" for col in data.columns]
        mom_frames.append(mom)

    vol = returns.rolling(window=20, min_periods=1).std()
    vol.columns = [f"{col}_vol_20" for col in data.columns]

    ma = data.rolling(window=20, min_periods=1).mean()
    ma_dev = data / ma - 1
    ma_dev.columns = [f"{col}_ma_dev_20" for col in data.columns]

    returns.columns = [f"{col}_ret" for col in data.columns]

```

```

# 特征数据: returns, vol, ma_dev, momentum (不包含原始价格)
feature_data = pd.concat([returns, vol, ma_dev] + mom_frames, axis=1)
raw_data = raw_data.dropna()
feature_data = feature_data.reindex(raw_data.index)
feature_data.fillna(method='ffill', inplace=True)
feature_data.fillna(method='bfill', inplace=True)

return raw_data.dropna(), feature_data.dropna()

def reset(self, seed=None):
    self.balance = self.initial_balance
    self.current_step = self.window_size

    self.return_window.clear()
    self.last_action = np.ones(len(self.tickers)) / len(self.tickers)

    # 使用特征数据作为观察
    obs = self.feature_data.iloc[self.current_step - self.window_size:self.current_step].values
    info = {"balance": self.balance}
    return obs, info

def step(self, action):
    a=np.asarray(action).ravel()
    exp_a=np.exp(a - np.max(a))
    action=exp_a/(np.sum(exp_a)+1e-8) # 归一化为权重

    prev_balance = self.balance

    # 从原始价格计算实际收益
    current_price = self.raw_data.iloc[self.current_step].values[:len(self.tickers)]
    prev_price = self.raw_data.iloc[self.current_step - 1].values[:len(self.tickers)]
    asset_returns = current_price / prev_price - 1

    self.return_window.append(asset_returns)

    # 基础奖励: 投资组合收益
    portfolio_return = np.sum(asset_returns * action)
    self.balance = self.balance * (1 + portfolio_return)
    base_reward = np.log(self.balance / prev_balance)

```



```

risk_penalty = 0
if len(self.return_window)>=5:
    R=np.vstack(self.return_window)
    cov_matrix=np.cov(R.T)
    sigma_p2= action.T @ cov_matrix @ action
    sigma_p=np.sqrt(sigma_p2)
    lambda_vol=5
    risk_penalty = -lambda_vol * sigma_p

turnover=np.sum(np.abs(action - self.last_action))
cost= 0.001 * turnover
self.last_action=action

# 总奖励
reward = base_reward + risk_penalty - cost

self.current_step += 1
done = self.current_step >= len(self.raw_data)-1

obs_end=min(len(self.feature_data),self.current_step+self.window_size)
obs_start=max(0,obs_end - self.window_size)
obs = self.feature_data.iloc[obs_start:obs_end].values

terminated = bool(done)
truncated = False
info = {'balance': self.balance}

return obs, reward, terminated, truncated, info

```

```

In [9]: tickers = df.columns.tolist()
window_size = 30
start_date = '2022-01-01'
end_date = '2025-09-01'
initial_balance = 10000
seed = 8

# Initialize the environment
env = PortfolioOptimizationEnv(
    tickers,
    window_size,

```

```

    start_date,
    end_date,
    initial_balance,
    seed)

# Get the initial state
state = env.reset(seed=seed)
# Sample and execute a random action
action = env.action_space.sample()
next_state, reward, terminated, truncated, info = env.step(action)
done = bool(terminated or truncated)
# print(f"State: {state}")
print(f"Action: {action}")
# print(f"Next state: {next_state}")
print(f"Reward: {reward}")
print(f"Balance: {info['balance']}")
print(f"Done: {done}")

```

Action: [0.32697228 0.98727685 0.31871083 0.78854895 0.86989653 0.39108482]

Reward: 0.01534999545959224

Balance: 10157.35741024358

Done: False

C:\Users\HP\AppData\Local\Temp\ipykernel_31504\3517470049.py:61: FutureWarning: DataFrame.fillna with 'method' is deprecated and will raise in a future version. Use obj.ffill() or obj.bfill() instead.

feature_data.fillna(method='ffill', inplace=True)

C:\Users\HP\AppData\Local\Temp\ipykernel_31504\3517470049.py:62: FutureWarning: DataFrame.fillna with 'method' is deprecated and will raise in a future version. Use obj.ffill() or obj.bfill() instead.

feature_data.fillna(method='bfill', inplace=True)

Training DRL agent

PPO

```

In [10]: # ===== Train PPO + plot training profile + plot cumulative wealth + print metrics =====
# Prereqs (run once in your env if needed):
#   pip install "stable-baselines3>=2.3.0" "shimmy>=2.0" matplotlib pandas

```

```

from stable_baselines3 import SAC
from stable_baselines3.common.vec_env import DummyVecEnv
from stable_baselines3.common.monitor import Monitor
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os
from stable_baselines3.common.vec_env import VecNormalize

# ----- 1) Build vectorized env (wrap with Monitor to log training rewards) -----
log_dir = "./sb3_logs"
os.makedirs(log_dir, exist_ok=True)
monitor_path = os.path.join(log_dir, "monitor.csv")

def make_env():
    env_ = PortfolioOptimizationEnv(
        tickers=tickers,
        window_size=window_size,
        start_date=start_date,
        end_date=end_date,
        initial_balance=initial_balance,
        seed=seed,
    )
    # Log episode reward/length; include "balance" from info if you want (optional)
    env_ = Monitor(env_, filename=monitor_path) # single-env -> single monitor file
    return env_

vec_env = DummyVecEnv([make_env])
vec_env = VecNormalize(vec_env, norm_obs=True, norm_reward=False, clip_obs=10.)

# ----- 2) Train SAC -----
model = SAC(
    "MlpPolicy", vec_env, verbose=1, device=device
) # SAC (软行动者评论家): 适合连续动作空间, 训练稳定, 是投资组合优化的常用算法
model.learn(total_timesteps=20000) # increase as needed
model.save("sac_portfolio_optimization")

# ----- 3) Load training profile (episode rewards) and plot -----
# SB3 Monitor CSV starts with commented metadata lines beginning with '#'
train_df = pd.read_csv(monitor_path, comment="#")
# Columns typically: r (ep reward), l (ep length), t (time)

```

```

# Make a simple moving average of episode rewards for a smooth training curve
if len(train_df) > 0:
    train_df["ep"] = np.arange(1, len(train_df) + 1)
    train_df["reward_smooth"] = train_df["r"].rolling(window=max(5, len(train_df)//50), min_periods=1).mean()

    plt.figure(figsize=(8, 4))
    plt.plot(train_df["ep"], train_df["r"], alpha=0.3, label="Episode reward")
    plt.plot(train_df["ep"], train_df["reward_smooth"], label="Smoothed")
    plt.xlabel("Episode")
    plt.ylabel("Episode reward")
    plt.title("Training profile (episode rewards)")
    plt.legend()
    plt.tight_layout()
    plt.show()
else:
    print("No episodes logged in monitor file (did training terminate too early?).")

# ----- 4) Roll out a full episode deterministically and record balances -----
obs = vec_env.reset()
dones = [False]
balances = []
rewards = []
weights_seq = []

while not dones[0]:
    action, _ = model.predict(obs, deterministic=True)
    obs, reward, dones, infos = vec_env.step(action)
    rewards.append(float(reward[0]))
    balances.append(float(infos[0].get("balance", np.nan)))
    weights_seq.append(infos[0].get("weights", None))

# Try to build a date index for nicer plotting/annualization
try:
    # Access the underlying single env inside DummyVecEnv -> Monitor -> PortfolioOptimizationEnv
    base_env = vec_env.envs[0].env
    # For safety if nested wrappers differ:
    while hasattr(base_env, "env"):
        base_env = base_env.env
    price_index = base_env.data.index # pandas.DatetimeIndex from your env
    # The first balance corresponds to the first step after initial window
    # Align dates accordingly:

```

```

start_idx = window_size
end_idx = start_idx + len(balances)
dates = price_index[start_idx:end_idx]
except Exception:
    dates = pd.RangeIndex(start=1, stop=len(balances) + 1) # fallback to simple index

# ----- 5) Plot cumulative wealth curve -----
plt.figure(figsize=(8, 4))
plt.plot(dates, balances)
plt.xlabel("Date" if isinstance(dates, pd.DatetimeIndex) else "Step")
plt.ylabel("Wealth")
plt.title("Cumulative wealth (deterministic policy rollout)")
plt.tight_layout()
plt.show()

# ----- 6) Compute portfolio performance metrics -----
# Step simple returns from balance path
balances_arr = np.asarray(balances, dtype=float)
rets = balances_arr[1:] / balances_arr[:-1] - 1.0 if len(balances_arr) > 1 else np.array([])

# Infer periods per year from dates if possible; else default 252
def infer_ppy(idx):
    if isinstance(idx, pd.DatetimeIndex) and len(idx) >= 2:
        # Use median days between points
        deltas = np.diff(idx.view("int64")) / 1e9 / 86400.0 # ns -> days
        median_days = np.median(deltas) if len(deltas) else 1.0
        if median_days <= 0:
            return 252.0
        return 365.25 / median_days
    return 252.0

PPY = infer_ppy(dates)

def max_drawdown(equity):
    peak = np.maximum.accumulate(equity)
    dd = (equity - peak) / peak
    return float(dd.min()) if len(dd) else 0.0

if len(rets) > 0:
    total_growth = balances_arr[-1] / balances_arr[0]
    N = len(rets)

```

```

CAGR = total_growth ** (PPY / N) - 1.0 # PPY: 每年交易天数; CAGR: 年复合增长率
mean_r = float(np.mean(rets))
std_r = float(np.std(rets, ddof=1)) if N > 1 else 0.0
ann_return = (1.0 + mean_r) ** PPY - 1.0 if mean_r > -1 else np.nan # geometric approx alternative below
ann_vol = std_r * np.sqrt(PPY) if std_r > 0 else 0.0
# Sharpe (rf=0 for simplicity; replace with your risk-free rate if desired)
rf = 0.0
sharpe = (mean_r - rf/PPY) / std_r * np.sqrt(PPY) if std_r > 0 else np.nan
mdd = max_drawdown(balances_arr)
calmar = (CAGR / abs(mdd)) if mdd != 0 else np.nan

# Alternative geometric annualized return from total growth (more stable):
ann_return_geom = total_growth ** (PPY / N) - 1.0

print("\n=== Portfolio Performance (deterministic rollout) ===")
print(f"Periods per year (inferred): {PPY:.2f}")
print(f"Start wealth: {balances_arr[0]:.2f}")
print(f"End wealth: {balances_arr[-1]:.2f}")
print(f"Total growth: {total_growth:.6f}")
print(f"CAGR: {CAGR:.6%}")
print(f"Ann. Return (geom from equity): {ann_return_geom:.6%}")
print(f"Ann. Vol: {ann_vol:.6%}")
print(f"Sharpe (rf=0): {sharpe:.4f}")
print(f"Max Drawdown: {mdd:.2%}")
print(f"Calmar: {calmar:.4f}")
else:
    print("Not enough steps to compute metrics (need at least 2 balances).")

# ----- 7) (Optional) Inspect last action weights -----
if any(w is not None for w in weights_seq):
    last_w = [w for w in weights_seq if w is not None][-1]
    print("\nLast portfolio weights:", np.round(last_w, 4))

```

Gym has been unmaintained since 2022 and does not support NumPy 2.0 amongst other critical functionality. Please upgrade to Gymnasium, the maintained drop-in replacement of Gym, or contact the authors of your software and request that they upgrade.

Users of this version of Gym should be able to simply replace 'import gym' with 'import gymnasium as gym' in the vast majority of cases.

See the migration guide at https://gymnasium.farama.org/introduction/migration_guide/ for additional information.

```
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    feature_data.fillna(method='bfill', inplace=True)
```

Using cuda device

rollout/	
ep_len_mean	887
ep_rew_mean	-42.8
time/	
episodes	4
fps	39
time_elapsed	90
total_timesteps	3548
train/	
actor_loss	-35.5
critic_loss	0.0731
ent_coef	0.356
ent_coef_loss	-10.3
learning_rate	0.0003
n_updates	3447

rollout/	
ep_len_mean	887
ep_rew_mean	-42.8
time/	
episodes	8
fps	38
time_elapsed	182
total_timesteps	7096
train/	
actor_loss	-40.5
critic_loss	0.0264
ent_coef	0.123
ent_coef_loss	-20.8
learning_rate	0.0003
n_updates	6995

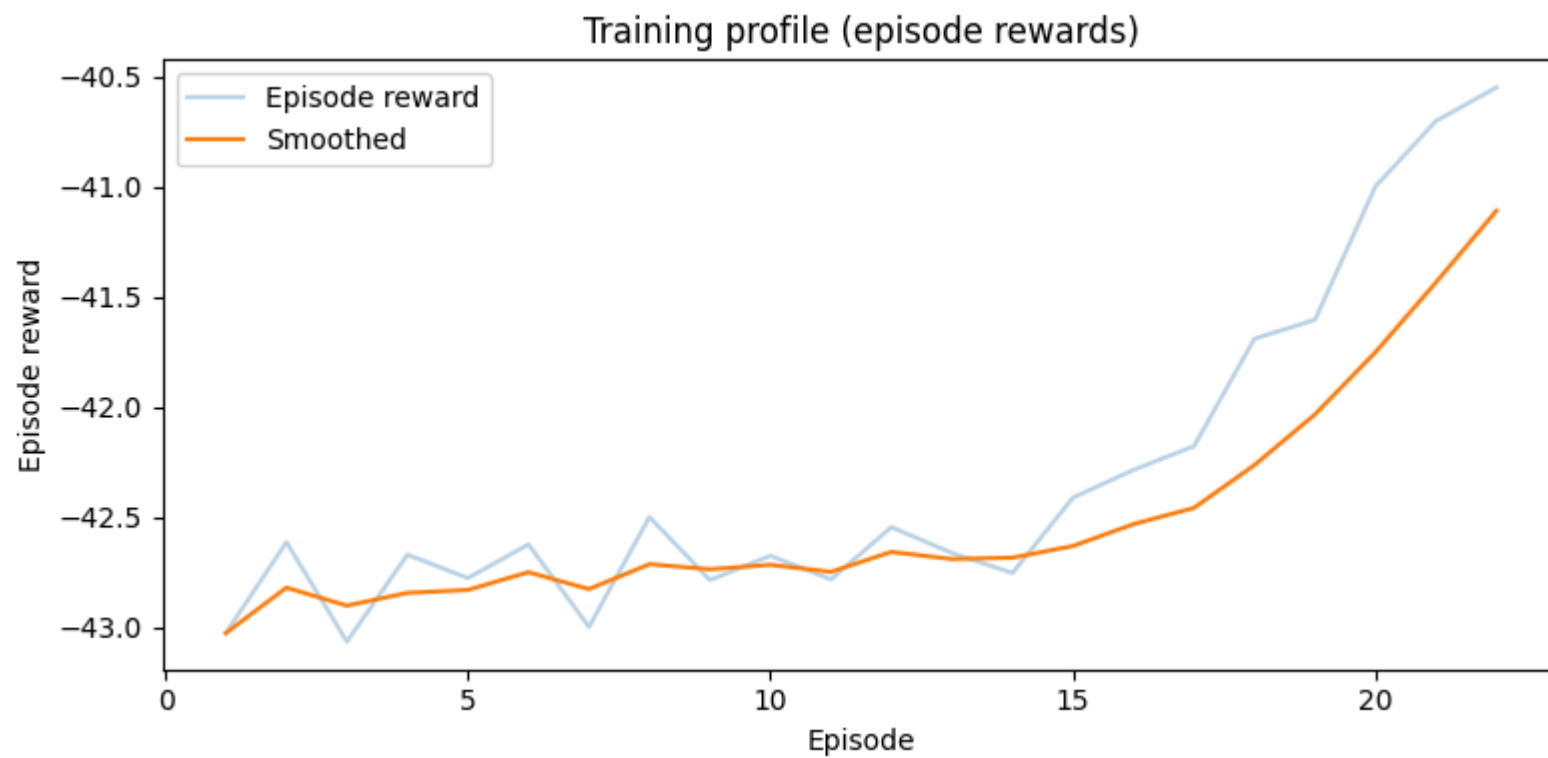
rollout/	
ep_len_mean	887
ep_rew_mean	-42.8
time/	
episodes	12

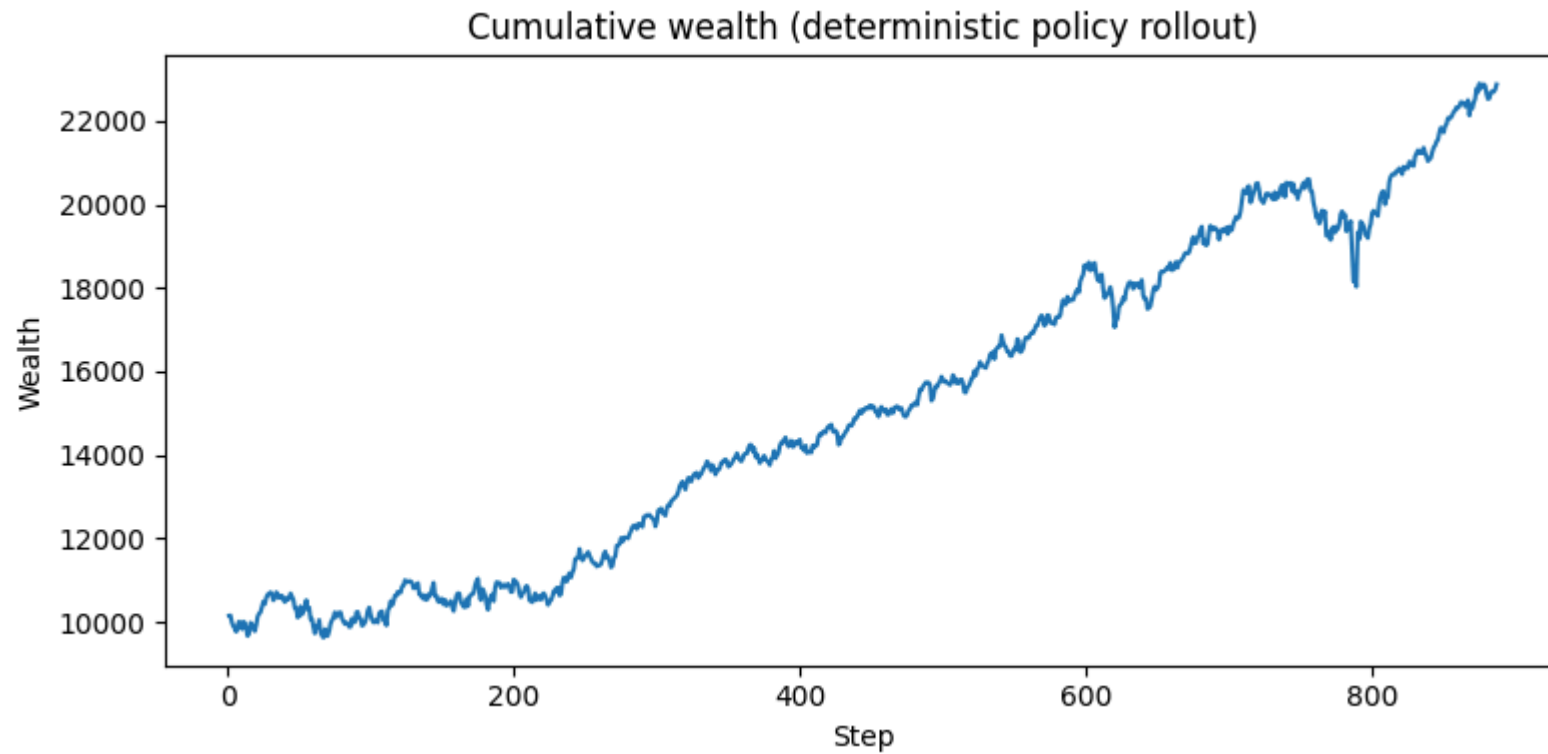
fps	38
time_elapsed	277
total_timesteps	10644
train/	
actor_loss	-36.5
critic_loss	0.811
ent_coef	0.0425
ent_coef_loss	-31
learning_rate	0.0003
n_updates	10543

rollout/	
ep_len_mean	887
ep_rew_mean	-42.7
time/	
episodes	16
fps	38
time_elapsed	369
total_timesteps	14192
train/	
actor_loss	-30.3
critic_loss	0.00687
ent_coef	0.0147
ent_coef_loss	-40.5
learning_rate	0.0003
n_updates	14091

rollout/	
ep_len_mean	887
ep_rew_mean	-42.5
time/	
episodes	20
fps	38
time_elapsed	462
total_timesteps	17740
train/	
actor_loss	-24.7
critic_loss	0.00514
ent_coef	0.00514

ent_coef_loss	-48.7
learning_rate	0.0003
n_updates	17639





=== Portfolio Performance (deterministic rollout) ===

Periods per year (inferred): 252.00

Start wealth: 10145.52

End wealth: 22875.43

Total growth: 2.254731

CAGR: 26.016893%

Ann. Return (geom from equity): 26.016893%

Ann. Vol: 14.523819%

Sharpe (rf=0): 1.6653

Max Drawdown: -12.48%

Calmar: 2.0840

修改部分

添加了科技股票、国债、标普500和黄金等数据作为环境输入特征

收益严重偏大，进行修改：

=== Portfolio Performance (deterministic rollout) === Periods per year (inferred): 252.00 Start wealth: 10297.47 End wealth: 23731074.08 Total growth: 2304.553868 CAGR: 804.485651% Ann. Return (geom from equity): 804.485651% Ann. Vol: 22.710210% Sharpe (rf=0): 9.8502 Max Drawdown: -5.59% Calmar: 143.9561

1、对vec_env进行了归一化处理

=== Portfolio Performance (deterministic rollout) === Periods per year (inferred): 252.00 Start wealth: 10180.25 End wealth: 1013360.39 Total growth: 99.541782 CAGR: 270.067928% Ann. Return (geom from equity): 270.067928% Ann. Vol: 22.074986% Sharpe (rf=0): 6.0514 Max Drawdown: -8.50% Calmar: 31.7818

2、调整奖励函数

用协方差矩阵估计组合波动 添加每次交易成本千一

=== Portfolio Performance (deterministic rollout) === Periods per year (inferred): 252.00 Start wealth: 10055.45 End wealth: 54941.09 Total growth: 5.463811 CAGR: 62.092061% Ann. Return (geom from equity): 62.092061% Ann. Vol: 17.712724% Sharpe (rf=0): 2.8174 Max Drawdown: -11.18% Calmar: 5.5563

3、更换为sac算法

=== Portfolio Performance (deterministic rollout) === Periods per year (inferred): 252.00 Start wealth: 10145.52 End wealth: 22875.43 Total growth: 2.254731 CAGR: 26.016893% Ann. Return (geom from equity): 26.016893% Ann. Vol: 14.523819% Sharpe (rf=0): 1.6653 Max Drawdown: -12.48% Calmar: 2.0840