Set up environment

In [32]:
```
import gymnasium as gym
import numpy as np
import pandas as pd
import torch
```

数据准备

In [33]:
```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
device
```

Out[33]:
```
device(type='cuda')
```

In [34]:
```
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[34]:

date	AAPL	GOOG	MSFT
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 [35]:

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

Out[35]:

	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 [36]:

```
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[36]:

	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 [37]:

```
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[37]:

date	AAPL	GOOG	MSFT	US_debt	SP500	Gold
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 [38]:

```
df.interpolate(method='time', inplace=True)
df
```

Out[38]:

date	AAPL	GOOG	MSFT	US_debt	SP500	Gold
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 [39]:

```
from math import inf

from networkx import sigma
from pyparsing 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
```

```python
        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]
```

```python
        # 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):
        action = action / (np.sum(action) + 1e-8)

        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:
```

```python
            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 [40]:

```python
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: 0.015598913072904633
Balance: 10161.65097308565
Done: False
```

```
C:\Users\HP\AppData\Local\Temp\ipykernel_27388\2914642385.py:61: FutureWarning: DataFrame.fillna with 'method' is deprecated an
d 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_27388\2914642385.py:62: FutureWarning: DataFrame.fillna with 'method' is deprecated an
d 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 [41]:

```
# ===== 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 PPO
from stable_baselines3.common.vec_env import DummyVecEnv
```

```python
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 PPO ------------
model = PPO(
    "MlpPolicy", vec_env, verbose=1, device=device
)  # PPO（近端策略优化）：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("ppo_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:
```

```python
    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)
```

```python
    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))
```

```
C:\Users\HP\AppData\Local\Temp\ipykernel_27388\2914642385.py:61: FutureWarning: DataFrame.fillna with 'method' is deprecated an
d 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_27388\2914642385.py:62: FutureWarning: DataFrame.fillna with 'method' is deprecated an
d will raise in a future version. Use obj.ffill() or obj.bfill() instead.
  feature_data.fillna(method='bfill', inplace=True)
d:\Develop\miniconda\envs\py310\lib\site-packages\stable_baselines3\common\on_policy_algorithm.py:150: UserWarning: You are try
ing to run PPO on the GPU, but it is primarily intended to run on the CPU when not using a CNN policy (you are using ActorCriti
cPolicy which should be a MlpPolicy). See https://github.com/DLR-RM/stable-baselines3/issues/1245 for more info. You can pass `
device='cpu'` or `export CUDA_VISIBLE_DEVICES=` to force using the CPU.Note: The model will train, but the GPU utilization will
be poor and the training might take longer than on CPU.
  warnings.warn(
```

```
Using cuda device
---------------------------------
| rollout/           |          |
|    ep_len_mean     | 887      |
|    ep_rew_mean     | -53.2    |
| time/              |          |
|    fps             | 333      |
|    iterations      | 1        |
|    time_elapsed    | 6        |
|    total_timesteps | 2048     |
---------------------------------
-----------------------------------------
| rollout/                |             |
|    ep_len_mean          | 887         |
|    ep_rew_mean          | -53.1       |
| time/                   |             |
|    fps                  | 273         |
|    iterations           | 2           |
|    time_elapsed         | 14          |
|    total_timesteps      | 4096        |
| train/                  |             |
|    approx_kl            | 0.032681793 |
|    clip_fraction        | 0.245       |
|    clip_range           | 0.2         |
|    entropy_loss         | -8.52       |
|    explained_variance   | -1.17       |
|    learning_rate        | 0.0003      |
|    loss                 | -0.102      |
|    n_updates            | 10          |
|    policy_gradient_loss | -0.0612     |
|    std                  | 1           |
|    value_loss           | 0.181       |
-----------------------------------------
----------------------------------------
| rollout/                |            |
|    ep_len_mean          | 887        |
|    ep_rew_mean          | -52.8      |
| time/                   |            |
|    fps                  | 267        |
|    iterations           | 3          |
|    time_elapsed         | 22         |
```

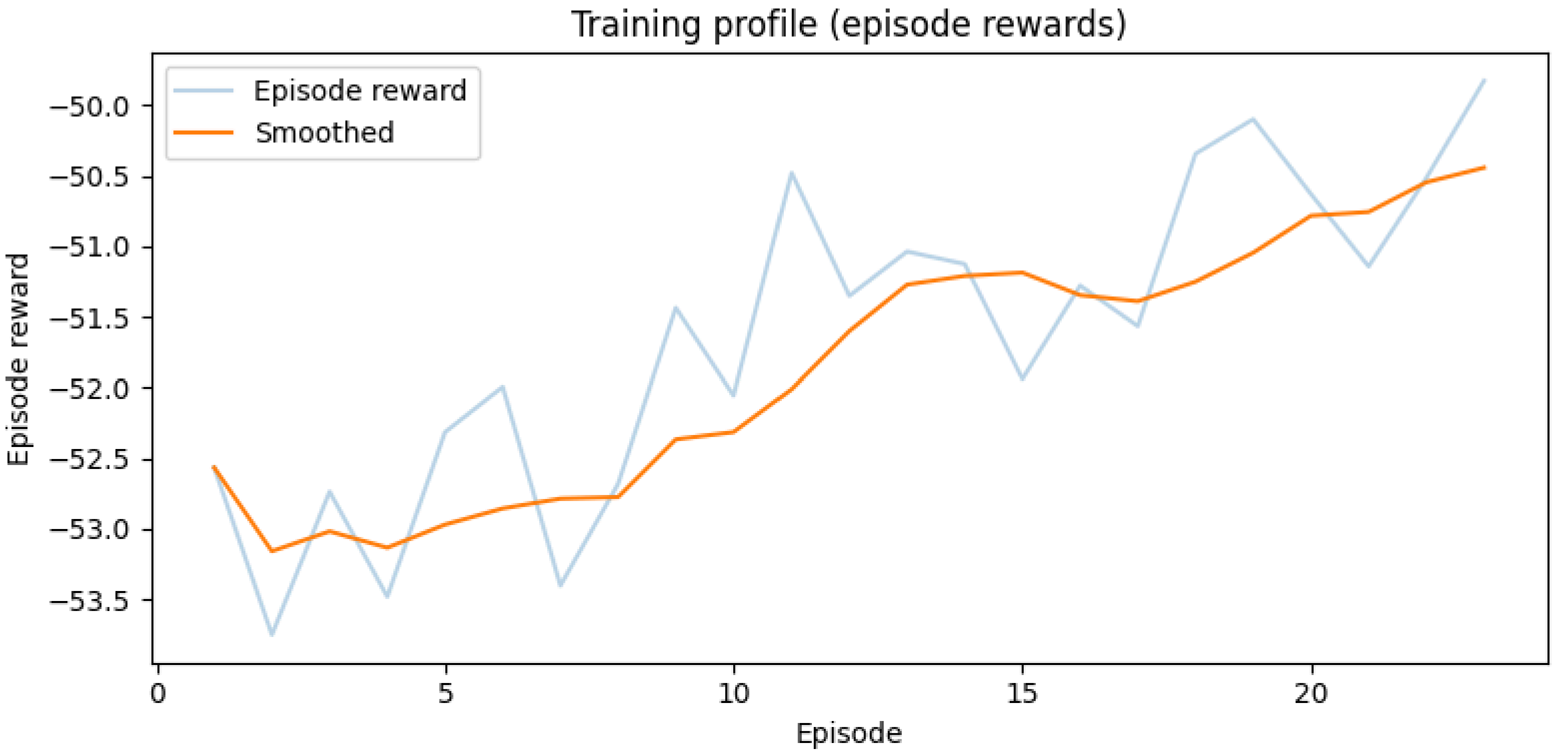
```
|    total_timesteps      | 6144         |
| train/                  |              |
|    approx_kl            | 0.03742859   |
|    clip_fraction        | 0.318        |
|    clip_range           | 0.2          |
|    entropy_loss         | -8.51        |
|    explained_variance   | 0.762        |
|    learning_rate        | 0.0003       |
|    loss                 | -0.0975      |
|    n_updates            | 20           |
|    policy_gradient_loss | -0.076       |
|    std                  | 0.993        |
|    value_loss           | 0.0565       |
-----------------------------------------
------------------------------------------
| rollout/                |              |
|    ep_len_mean          | 887          |
|    ep_rew_mean          | -52.7        |
| time/                   |              |
|    fps                  | 265          |
|    iterations           | 4            |
|    time_elapsed         | 30           |
|    total_timesteps      | 8192         |
| train/                  |              |
|    approx_kl            | 0.039297868  |
|    clip_fraction        | 0.347        |
|    clip_range           | 0.2          |
|    entropy_loss         | -8.47        |
|    explained_variance   | 0.904        |
|    learning_rate        | 0.0003       |
|    loss                 | -0.104       |
|    n_updates            | 30           |
|    policy_gradient_loss | -0.0773      |
|    std                  | 0.991        |
|    value_loss           | 0.0357       |
------------------------------------------
-----------------------------------------
| rollout/                |             |
|    ep_len_mean          | 887         |
|    ep_rew_mean          | -52.4       |
| time/                   |             |
```

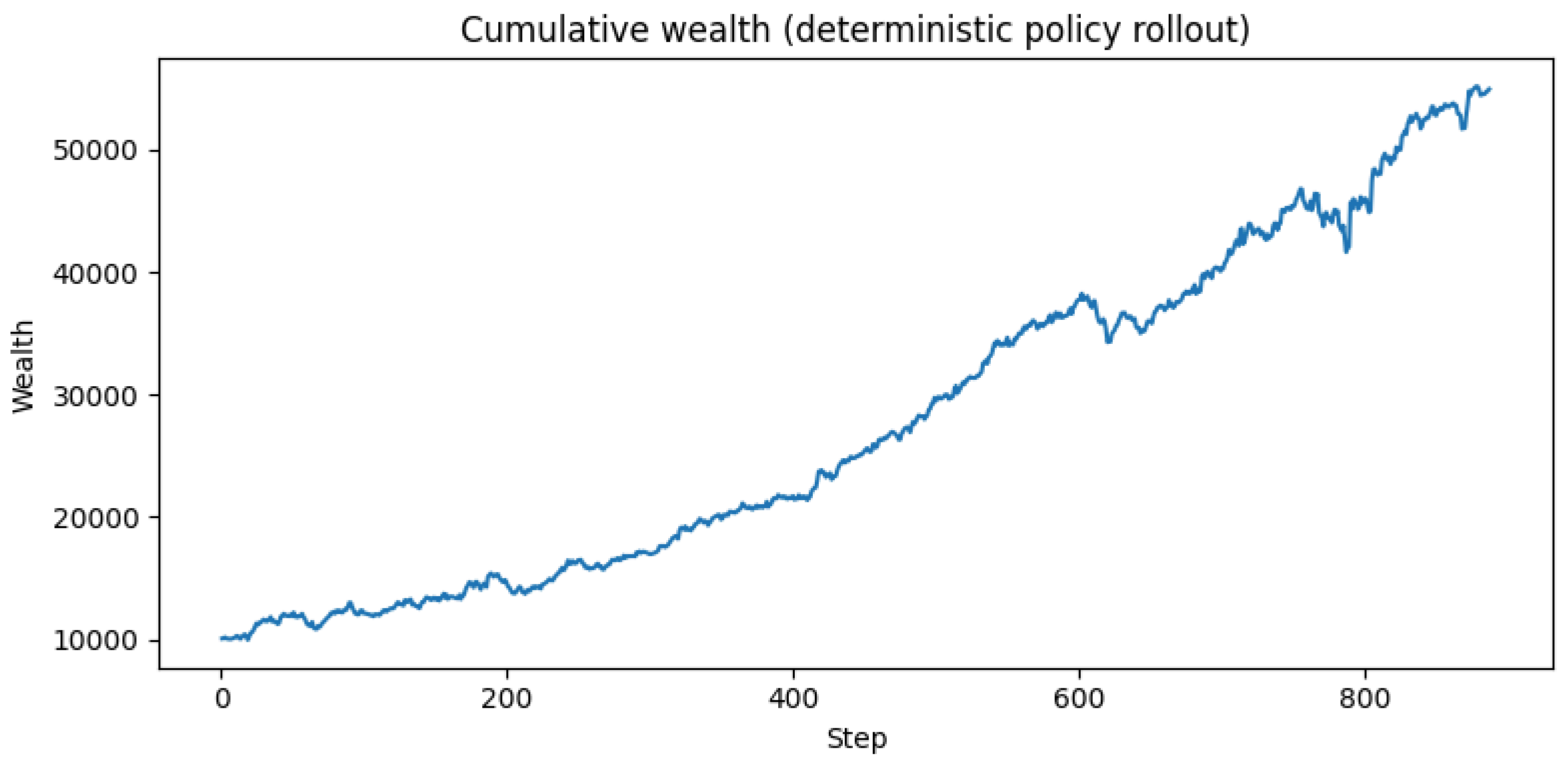
```
|    fps                  | 264        |
|    iterations           | 5          |
|    time_elapsed         | 38         |
|    total_timesteps      | 10240      |
| train/                  |            |
|    approx_kl            | 0.04230036 |
|    clip_fraction        | 0.355      |
|    clip_range           | 0.2        |
|    entropy_loss         | -8.42      |
|    explained_variance   | 0.952      |
|    learning_rate        | 0.0003     |
|    loss                 | -0.108     |
|    n_updates            | 40         |
|    policy_gradient_loss | -0.0753    |
|    std                  | 0.982      |
|    value_loss           | 0.0268     |
----------------------------------------
-----------------------------------------
| rollout/                |             |
|    ep_len_mean          | 887         |
|    ep_rew_mean          | -52.3       |
| time/                   |             |
|    fps                  | 264         |
|    iterations           | 6           |
|    time_elapsed         | 46          |
|    total_timesteps      | 12288       |
| train/                  |             |
|    approx_kl            | 0.051154993 |
|    clip_fraction        | 0.415       |
|    clip_range           | 0.2         |
|    entropy_loss         | -8.38       |
|    explained_variance   | 0.971       |
|    learning_rate        | 0.0003      |
|    loss                 | -0.108      |
|    n_updates            | 50          |
|    policy_gradient_loss | -0.0882     |
|    std                  | 0.973       |
|    value_loss           | 0.0204      |
-----------------------------------------
----------------------------------------
| rollout/                |            |
```

```
|    ep_len_mean          | 887        |
|    ep_rew_mean          | -52.1      |
| time/                   |            |
|    fps                  | 263        |
|    iterations           | 7          |
|    time_elapsed         | 54         |
|    total_timesteps      | 14336      |
| train/                  |            |
|    approx_kl            | 0.05654466 |
|    clip_fraction        | 0.435      |
|    clip_range           | 0.2        |
|    entropy_loss         | -8.33      |
|    explained_variance   | 0.973      |
|    learning_rate        | 0.0003     |
|    loss                 | -0.0883    |
|    n_updates            | 60         |
|    policy_gradient_loss | -0.0903    |
|    std                  | 0.967      |
|    value_loss           | 0.0184     |
----------------------------------------
----------------------------------------
| rollout/                |            |
|    ep_len_mean          | 887        |
|    ep_rew_mean          | -52        |
| time/                   |            |
|    fps                  | 262        |
|    iterations           | 8          |
|    time_elapsed         | 62         |
|    total_timesteps      | 16384      |
| train/                  |            |
|    approx_kl            | 0.06213968 |
|    clip_fraction        | 0.452      |
|    clip_range           | 0.2        |
|    entropy_loss         | -8.29      |
|    explained_variance   | 0.982      |
|    learning_rate        | 0.0003     |
|    loss                 | -0.0996    |
|    n_updates            | 70         |
|    policy_gradient_loss | -0.0884    |
|    std                  | 0.959      |
|    value_loss           | 0.0146     |
```

```
---------------------------------------
-----------------------------------------
| rollout/                |             |
|    ep_len_mean          | 887         |
|    ep_rew_mean          | -51.8       |
| time/                   |             |
|    fps                  | 261         |
|    iterations           | 9           |
|    time_elapsed         | 70          |
|    total_timesteps      | 18432       |
| train/                  |             |
|    approx_kl            | 0.060942143 |
|    clip_fraction        | 0.469       |
|    clip_range           | 0.2         |
|    entropy_loss         | -8.24       |
|    explained_variance   | 0.988       |
|    learning_rate        | 0.0003      |
|    loss                 | -0.108      |
|    n_updates            | 80          |
|    policy_gradient_loss | -0.0907     |
|    std                  | 0.951       |
|    value_loss           | 0.0132      |
-----------------------------------------
---------------------------------------
| rollout/                |           |
|    ep_len_mean          | 887       |
|    ep_rew_mean          | -51.6     |
| time/                   |           |
|    fps                  | 261       |
|    iterations           | 10        |
|    time_elapsed         | 78        |
|    total_timesteps      | 20480     |
| train/                  |           |
|    approx_kl            | 0.0653253 |
|    clip_fraction        | 0.467     |
|    clip_range           | 0.2       |
|    entropy_loss         | -8.17     |
|    explained_variance   | 0.984     |
|    learning_rate        | 0.0003    |
|    loss                 | -0.108    |
|    n_updates            | 90        |
```

```
|    policy_gradient_loss | -0.0894    |
|    std                  | 0.939      |
|    value_loss           | 0.0126     |
---------------------------------------
```






```
=== 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
```

A2C

In [42]:

```
# ===== Train PPO + plot training profile + plot cumulative wealth + print metrics =====
# Prereqs (run once in your env if needed):
```

```python
#   pip install "stable-baselines3>=2.3.0" "shimmy>=2.0" matplotlib pandas

from stable_baselines3 import A2C

# ------------ 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=10.0)

# ------------ 2) Train A2C ------------
model = A2C(
    "MlpPolicy", vec_env, verbose=1, device=device
)  # A2C（优势行动者评论家）：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("a2c_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)
```

```python
    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):
```

```python
    last_w = [w for w in weights_seq if w is not None][-1]
    print("\nLast portfolio weights:", np.round(last_w, 4))
```

```
Using cuda device
```

```
C:\Users\HP\AppData\Local\Temp\ipykernel_27388\2914642385.py:61: FutureWarning: DataFrame.fillna with 'method' is deprecated an
d 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_27388\2914642385.py:62: FutureWarning: DataFrame.fillna with 'method' is deprecated an
d will raise in a future version. Use obj.ffill() or obj.bfill() instead.
  feature_data.fillna(method='bfill', inplace=True)
d:\Develop\miniconda\envs\py310\lib\site-packages\stable_baselines3\common\on_policy_algorithm.py:150: UserWarning: You are try
ing to run A2C on the GPU, but it is primarily intended to run on the CPU when not using a CNN policy (you are using ActorCriti
cPolicy which should be a MlpPolicy). See https://github.com/DLR-RM/stable-baselines3/issues/1245 for more info. You can pass `
device='cpu'` or `export CUDA_VISIBLE_DEVICES=` to force using the CPU.Note: The model will train, but the GPU utilization will
be poor and the training might take longer than on CPU.
  warnings.warn(
```

```
------------------------------------
| time/                 |          |
|    fps                | 236      |
|    iterations         | 100      |
|    time_elapsed       | 2        |
|    total_timesteps    | 500      |
| train/                |          |
|    entropy_loss       | -8.55    |
|    explained_variance | -39.1    |
|    learning_rate      | 0.0007   |
|    n_updates          | 99       |
|    policy_loss        | 0.959    |
|    std                | 1.01     |
|    value_loss         | 0.0216   |
------------------------------------
------------------------------------
| rollout/              |          |
|    ep_len_mean        | 887      |
|    ep_rew_mean        | -50.7    |
| time/                 |          |
|    fps                | 237      |
|    iterations         | 200      |
|    time_elapsed       | 4        |
|    total_timesteps    | 1000     |
| train/                |          |
|    entropy_loss       | -8.57    |
|    explained_variance | -2.61    |
|    learning_rate      | 0.0007   |
|    n_updates          | 199      |
|    policy_loss        | 2.19     |
|    std                | 1.01     |
|    value_loss         | 0.123    |
------------------------------------
------------------------------------
| rollout/              |          |
|    ep_len_mean        | 887      |
|    ep_rew_mean        | -50.7    |
| time/                 |          |
|    fps                | 237      |
|    iterations         | 300      |
|    time_elapsed       | 6        |
```

```
|    total_timesteps    | 1500      |
| train/                |           |
|    entropy_loss       | -8.59     |
|    explained_variance | -3        |
|    learning_rate      | 0.0007    |
|    n_updates          | 299       |
|    policy_loss        | 0.0161    |
|    std                | 1.01      |
|    value_loss         | 0.0308    |
------------------------------------
------------------------------------
| rollout/              |           |
|    ep_len_mean        | 887       |
|    ep_rew_mean        | -51.4     |
| time/                 |           |
|    fps                | 236       |
|    iterations         | 400       |
|    time_elapsed       | 8         |
|    total_timesteps    | 2000      |
| train/                |           |
|    entropy_loss       | -8.59     |
|    explained_variance | -0.395    |
|    learning_rate      | 0.0007    |
|    n_updates          | 399       |
|    policy_loss        | -0.245    |
|    std                | 1.01      |
|    value_loss         | 0.0133    |
------------------------------------
------------------------------------
| rollout/              |           |
|    ep_len_mean        | 887       |
|    ep_rew_mean        | -51.4     |
| time/                 |           |
|    fps                | 236       |
|    iterations         | 500       |
|    time_elapsed       | 10        |
|    total_timesteps    | 2500      |
| train/                |           |
|    entropy_loss       | -8.6      |
|    explained_variance | -70.4     |
|    learning_rate      | 0.0007    |
```

```
|    n_updates           | 499      |
|    policy_loss         | 0.539    |
|    std                 | 1.01     |
|    value_loss          | 0.0213   |
------------------------------------
------------------------------------
| rollout/               |          |
|    ep_len_mean         | 887      |
|    ep_rew_mean         | -50.7    |
| time/                  |          |
|    fps                 | 236      |
|    iterations          | 600      |
|    time_elapsed        | 12       |
|    total_timesteps     | 3000     |
| train/                 |          |
|    entropy_loss        | -8.6     |
|    explained_variance  | -3.98    |
|    learning_rate       | 0.0007   |
|    n_updates           | 599      |
|    policy_loss         | 0.38     |
|    std                 | 1.01     |
|    value_loss          | 0.00893  |
------------------------------------
------------------------------------
| rollout/               |          |
|    ep_len_mean         | 887      |
|    ep_rew_mean         | -50.7    |
| time/                  |          |
|    fps                 | 236      |
|    iterations          | 700      |
|    time_elapsed        | 14       |
|    total_timesteps     | 3500     |
| train/                 |          |
|    entropy_loss        | -8.6     |
|    explained_variance  | 0.211    |
|    learning_rate       | 0.0007   |
|    n_updates           | 699      |
|    policy_loss         | -0.558   |
|    std                 | 1.01     |
|    value_loss          | 0.00812  |
------------------------------------
```

```
------------------------------------
| rollout/                |          |
|    ep_len_mean          | 887      |
|    ep_rew_mean          | -50.9    |
| time/                   |          |
|    fps                  | 236      |
|    iterations           | 800      |
|    time_elapsed         | 16       |
|    total_timesteps      | 4000     |
| train/                  |          |
|    entropy_loss         | -8.65    |
|    explained_variance   | -9.32    |
|    learning_rate        | 0.0007   |
|    n_updates            | 799      |
|    policy_loss          | -2.41    |
|    std                  | 1.02     |
|    value_loss           | 0.125    |
------------------------------------
------------------------------------
| rollout/                |          |
|    ep_len_mean          | 887      |
|    ep_rew_mean          | -51      |
| time/                   |          |
|    fps                  | 237      |
|    iterations           | 900      |
|    time_elapsed         | 18       |
|    total_timesteps      | 4500     |
| train/                  |          |
|    entropy_loss         | -8.66    |
|    explained_variance   | 0.626    |
|    learning_rate        | 0.0007   |
|    n_updates            | 899      |
|    policy_loss          | -1.24    |
|    std                  | 1.02     |
|    value_loss           | 0.0264   |
------------------------------------
------------------------------------
| rollout/                |          |
|    ep_len_mean          | 887      |
|    ep_rew_mean          | -51      |
| time/                   |          |
```

```
|    fps                  | 236      |
|    iterations           | 1000     |
|    time_elapsed         | 21       |
|    total_timesteps      | 5000     |
| train/                  |          |
|    entropy_loss         | -8.68    |
|    explained_variance   | -2.18    |
|    learning_rate        | 0.0007   |
|    n_updates            | 999      |
|    policy_loss          | 0.269    |
|    std                  | 1.03     |
|    value_loss           | 0.0052   |
------------------------------------
------------------------------------
| rollout/                |          |
|    ep_len_mean          | 887      |
|    ep_rew_mean          | -51.1    |
| time/                   |          |
|    fps                  | 236      |
|    iterations           | 1100     |
|    time_elapsed         | 23       |
|    total_timesteps      | 5500     |
| train/                  |          |
|    entropy_loss         | -8.72    |
|    explained_variance   | -6.87    |
|    learning_rate        | 0.0007   |
|    n_updates            | 1099     |
|    policy_loss          | -1.91    |
|    std                  | 1.04     |
|    value_loss           | 0.102    |
------------------------------------
------------------------------------
| rollout/                |          |
|    ep_len_mean          | 887      |
|    ep_rew_mean          | -51.1    |
| time/                   |          |
|    fps                  | 236      |
|    iterations           | 1200     |
|    time_elapsed         | 25       |
|    total_timesteps      | 6000     |
| train/                  |          |
```

```
|    entropy_loss        | -8.71     |
|    explained_variance  | -79.2     |
|    learning_rate       | 0.0007    |
|    n_updates           | 1199      |
|    policy_loss         | 0.222     |
|    std                 | 1.03      |
|    value_loss          | 0.0798    |
------------------------------------
------------------------------------
| rollout/               |           |
|    ep_len_mean         | 887       |
|    ep_rew_mean         | -51       |
| time/                  |           |
|    fps                 | 235       |
|    iterations          | 1300      |
|    time_elapsed        | 27        |
|    total_timesteps     | 6500      |
| train/                 |           |
|    entropy_loss        | -8.71     |
|    explained_variance  | -3.72     |
|    learning_rate       | 0.0007    |
|    n_updates           | 1299      |
|    policy_loss         | -2.22     |
|    std                 | 1.03      |
|    value_loss          | 0.0805    |
------------------------------------
------------------------------------
| rollout/               |           |
|    ep_len_mean         | 887       |
|    ep_rew_mean         | -51       |
| time/                  |           |
|    fps                 | 235       |
|    iterations          | 1400      |
|    time_elapsed        | 29        |
|    total_timesteps     | 7000      |
| train/                 |           |
|    entropy_loss        | -8.7      |
|    explained_variance  | -26.7     |
|    learning_rate       | 0.0007    |
|    n_updates           | 1399      |
|    policy_loss         | -4.21     |
```

```
|    std                 | 1.03     |
|    value_loss          | 0.301    |
------------------------------------
------------------------------------
| rollout/               |          |
|    ep_len_mean         | 887      |
|    ep_rew_mean         | -50.9    |
| time/                  |          |
|    fps                 | 233      |
|    iterations          | 1500     |
|    time_elapsed        | 32       |
|    total_timesteps     | 7500     |
| train/                 |          |
|    entropy_loss        | -8.7     |
|    explained_variance  | -4.16    |
|    learning_rate       | 0.0007   |
|    n_updates           | 1499     |
|    policy_loss         | -1.03    |
|    std                 | 1.03     |
|    value_loss          | 0.0279   |
------------------------------------
------------------------------------
| rollout/               |          |
|    ep_len_mean         | 887      |
|    ep_rew_mean         | -50.7    |
| time/                  |          |
|    fps                 | 232      |
|    iterations          | 1600     |
|    time_elapsed        | 34       |
|    total_timesteps     | 8000     |
| train/                 |          |
|    entropy_loss        | -8.72    |
|    explained_variance  | 0.834    |
|    learning_rate       | 0.0007   |
|    n_updates           | 1599     |
|    policy_loss         | 0.349    |
|    std                 | 1.03     |
|    value_loss          | 0.00311  |
------------------------------------
------------------------------------
| rollout/               |          |
```

```
|    ep_len_mean         | 887      |
|    ep_rew_mean         | -50.7    |
| time/                  |          |
|    fps                 | 231      |
|    iterations          | 1700     |
|    time_elapsed        | 36       |
|    total_timesteps     | 8500     |
| train/                 |          |
|    entropy_loss        | -8.72    |
|    explained_variance  | 0.265    |
|    learning_rate       | 0.0007   |
|    n_updates           | 1699     |
|    policy_loss         | -0.136   |
|    std                 | 1.04     |
|    value_loss          | 0.00113  |
------------------------------------
------------------------------------
| rollout/               |          |
|    ep_len_mean         | 887      |
|    ep_rew_mean         | -50.6    |
| time/                  |          |
|    fps                 | 229      |
|    iterations          | 1800     |
|    time_elapsed        | 39       |
|    total_timesteps     | 9000     |
| train/                 |          |
|    entropy_loss        | -8.7     |
|    explained_variance  | 0.559    |
|    learning_rate       | 0.0007   |
|    n_updates           | 1799     |
|    policy_loss         | -1.17    |
|    std                 | 1.03     |
|    value_loss          | 0.0196   |
------------------------------------
------------------------------------
| rollout/               |          |
|    ep_len_mean         | 887      |
|    ep_rew_mean         | -50.6    |
| time/                  |          |
|    fps                 | 228      |
|    iterations          | 1900     |
```

```
|    time_elapsed       | 41         |
|    total_timesteps    | 9500       |
| train/                |            |
|    entropy_loss       | -8.69      |
|    explained_variance | -1.71      |
|    learning_rate      | 0.0007     |
|    n_updates          | 1899       |
|    policy_loss        | -0.359     |
|    std                | 1.03       |
|    value_loss         | 0.0114     |
------------------------------------
------------------------------------
| rollout/              |            |
|    ep_len_mean        | 887        |
|    ep_rew_mean        | -50.4      |
| time/                 |            |
|    fps                | 227        |
|    iterations         | 2000       |
|    time_elapsed       | 43         |
|    total_timesteps    | 10000      |
| train/                |            |
|    entropy_loss       | -8.69      |
|    explained_variance | -122       |
|    learning_rate      | 0.0007     |
|    n_updates          | 1999       |
|    policy_loss        | -2.79      |
|    std                | 1.03       |
|    value_loss         | 0.196      |
------------------------------------
------------------------------------
| rollout/              |            |
|    ep_len_mean        | 887        |
|    ep_rew_mean        | -50.4      |
| time/                 |            |
|    fps                | 228        |
|    iterations         | 2100       |
|    time_elapsed       | 46         |
|    total_timesteps    | 10500      |
| train/                |            |
|    entropy_loss       | -8.7       |
|    explained_variance | -7.54      |
```

```
|    learning_rate       | 0.0007   |
|    n_updates           | 2099     |
|    policy_loss         | -0.931   |
|    std                 | 1.03     |
|    value_loss          | 0.0152   |
------------------------------------
------------------------------------
| rollout/               |          |
|    ep_len_mean         | 887      |
|    ep_rew_mean         | -50.3    |
| time/                  |          |
|    fps                 | 228      |
|    iterations          | 2200     |
|    time_elapsed        | 48       |
|    total_timesteps     | 11000    |
| train/                 |          |
|    entropy_loss        | -8.69    |
|    explained_variance  | -36.5    |
|    learning_rate       | 0.0007   |
|    n_updates           | 2199     |
|    policy_loss         | -1.36    |
|    std                 | 1.03     |
|    value_loss          | 0.0371   |
------------------------------------
------------------------------------
| rollout/               |          |
|    ep_len_mean         | 887      |
|    ep_rew_mean         | -50.3    |
| time/                  |          |
|    fps                 | 228      |
|    iterations          | 2300     |
|    time_elapsed        | 50       |
|    total_timesteps     | 11500    |
| train/                 |          |
|    entropy_loss        | -8.66    |
|    explained_variance  | -14.1    |
|    learning_rate       | 0.0007   |
|    n_updates           | 2299     |
|    policy_loss         | 0.185    |
|    std                 | 1.03     |
|    value_loss          | 0.00567  |
```

```
------------------------------------
------------------------------------
| rollout/              |          |
|    ep_len_mean        | 887      |
|    ep_rew_mean        | -50.2    |
| time/                 |          |
|    fps                | 227      |
|    iterations         | 2400     |
|    time_elapsed       | 52       |
|    total_timesteps    | 12000    |
| train/                |          |
|    entropy_loss       | -8.61    |
|    explained_variance | -11.1    |
|    learning_rate      | 0.0007   |
|    n_updates          | 2399     |
|    policy_loss        | -0.0271  |
|    std                | 1.02     |
|    value_loss         | 0.000686 |
------------------------------------
------------------------------------
| rollout/              |          |
|    ep_len_mean        | 887      |
|    ep_rew_mean        | -50.1    |
| time/                 |          |
|    fps                | 226      |
|    iterations         | 2500     |
|    time_elapsed       | 55       |
|    total_timesteps    | 12500    |
| train/                |          |
|    entropy_loss       | -8.61    |
|    explained_variance | -1.05    |
|    learning_rate      | 0.0007   |
|    n_updates          | 2499     |
|    policy_loss        | 1.14     |
|    std                | 1.02     |
|    value_loss         | 0.0328   |
------------------------------------
------------------------------------
| rollout/              |          |
|    ep_len_mean        | 887      |
|    ep_rew_mean        | -50.1    |
```

```
| time/                   |          |
|    fps                  | 225      |
|    iterations           | 2600     |
|    time_elapsed         | 57       |
|    total_timesteps      | 13000    |
| train/                  |          |
|    entropy_loss         | -8.62    |
|    explained_variance   | -1.15    |
|    learning_rate        | 0.0007   |
|    n_updates            | 2599     |
|    policy_loss          | -2.4     |
|    std                  | 1.02     |
|    value_loss           | 0.0751   |
------------------------------------
------------------------------------
| rollout/                |          |
|    ep_len_mean          | 887      |
|    ep_rew_mean          | -50.1    |
| time/                   |          |
|    fps                  | 225      |
|    iterations           | 2700     |
|    time_elapsed         | 59       |
|    total_timesteps      | 13500    |
| train/                  |          |
|    entropy_loss         | -8.61    |
|    explained_variance   | -0.863   |
|    learning_rate        | 0.0007   |
|    n_updates            | 2699     |
|    policy_loss          | -3.43    |
|    std                  | 1.02     |
|    value_loss           | 0.153    |
------------------------------------
------------------------------------
| rollout/                |          |
|    ep_len_mean          | 887      |
|    ep_rew_mean          | -50.1    |
| time/                   |          |
|    fps                  | 226      |
|    iterations           | 2800     |
|    time_elapsed         | 61       |
|    total_timesteps      | 14000    |
```

```
| train/                  |           |
|    entropy_loss         | -8.62     |
|    explained_variance   | -223      |
|    learning_rate        | 0.0007    |
|    n_updates            | 2799      |
|    policy_loss          | -1.41     |
|    std                  | 1.02      |
|    value_loss           | 0.0549    |
-----------------------------------
-----------------------------------
| rollout/                |           |
|    ep_len_mean          | 887       |
|    ep_rew_mean          | -50       |
| time/                   |           |
|    fps                  | 226       |
|    iterations           | 2900      |
|    time_elapsed         | 63        |
|    total_timesteps      | 14500     |
| train/                  |           |
|    entropy_loss         | -8.62     |
|    explained_variance   | -0.293    |
|    learning_rate        | 0.0007    |
|    n_updates            | 2899      |
|    policy_loss          | 0.117     |
|    std                  | 1.02      |
|    value_loss           | 0.00357   |
-----------------------------------
-----------------------------------
| rollout/                |           |
|    ep_len_mean          | 887       |
|    ep_rew_mean          | -50       |
| time/                   |           |
|    fps                  | 227       |
|    iterations           | 3000      |
|    time_elapsed         | 66        |
|    total_timesteps      | 15000     |
| train/                  |           |
|    entropy_loss         | -8.62     |
|    explained_variance   | -0.398    |
|    learning_rate        | 0.0007    |
|    n_updates            | 2999      |
```

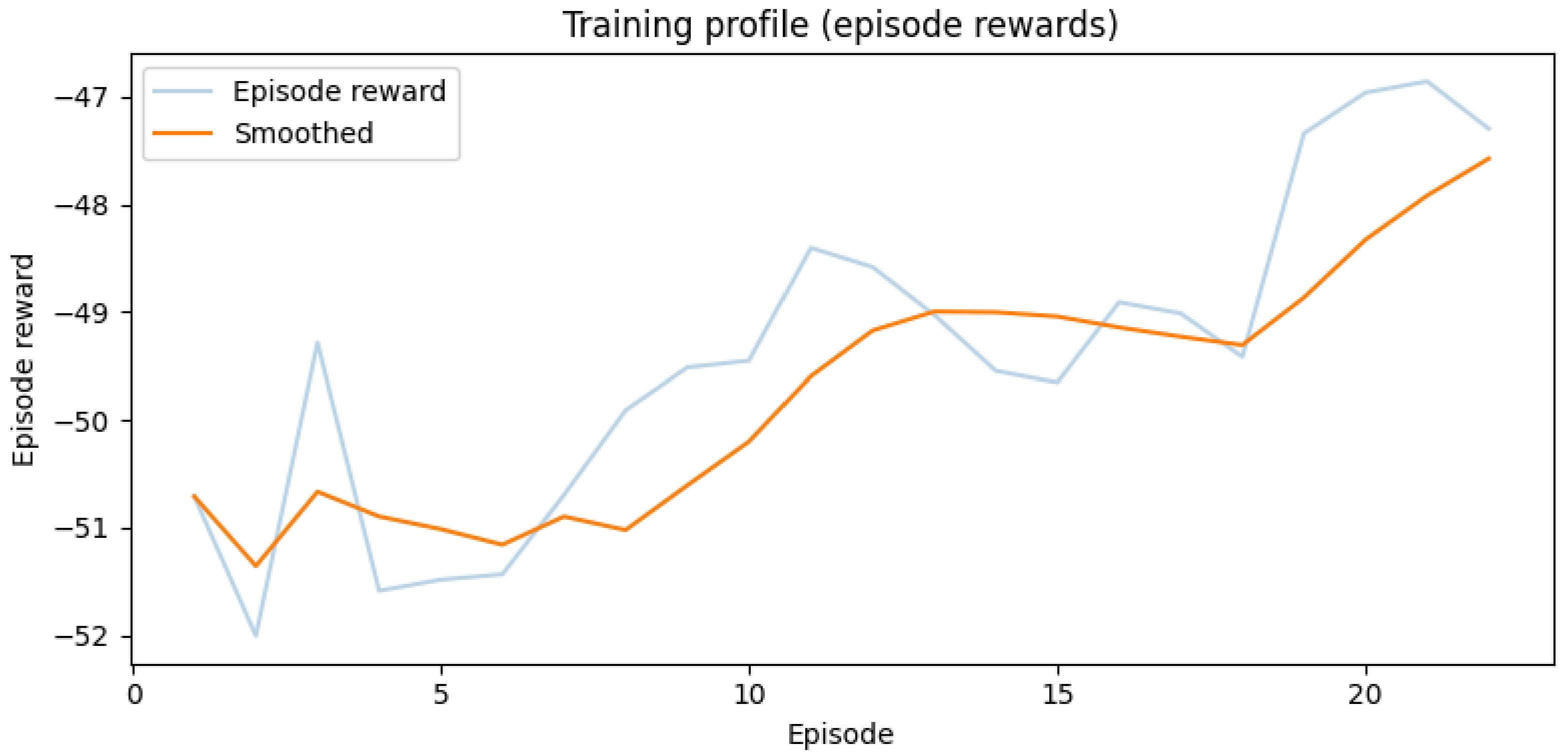
```
|    policy_loss        | -0.401   |
|    std                | 1.02     |
|    value_loss         | 0.0301   |
------------------------------------
------------------------------------
| rollout/              |          |
|    ep_len_mean        | 887      |
|    ep_rew_mean        | -50      |
| time/                 |          |
|    fps                | 227      |
|    iterations         | 3100     |
|    time_elapsed       | 68       |
|    total_timesteps    | 15500    |
| train/                |          |
|    entropy_loss       | -8.63    |
|    explained_variance | -24.8    |
|    learning_rate      | 0.0007   |
|    n_updates          | 3099     |
|    policy_loss        | -2.99    |
|    std                | 1.02     |
|    value_loss         | 0.141    |
------------------------------------
------------------------------------
| rollout/              |          |
|    ep_len_mean        | 887      |
|    ep_rew_mean        | -49.9    |
| time/                 |          |
|    fps                | 227      |
|    iterations         | 3200     |
|    time_elapsed       | 70       |
|    total_timesteps    | 16000    |
| train/                |          |
|    entropy_loss       | -8.61    |
|    explained_variance | -3.88    |
|    learning_rate      | 0.0007   |
|    n_updates          | 3199     |
|    policy_loss        | 0.765    |
|    std                | 1.02     |
|    value_loss         | 0.0097   |
------------------------------------
-------------------------------------
```

```
| rollout/              |             |
|    ep_len_mean        | 887         |
|    ep_rew_mean        | -49.9       |
| time/                 |             |
|    fps                | 228         |
|    iterations         | 3300        |
|    time_elapsed       | 72          |
|    total_timesteps    | 16500       |
| train/                |             |
|    entropy_loss       | -8.63       |
|    explained_variance | -2.03e+03   |
|    learning_rate      | 0.0007      |
|    n_updates          | 3299        |
|    policy_loss        | -1.09       |
|    std                | 1.02        |
|    value_loss         | 0.0229      |
-------------------------------------
------------------------------------
| rollout/              |            |
|    ep_len_mean        | 887        |
|    ep_rew_mean        | -49.8      |
| time/                 |            |
|    fps                | 228        |
|    iterations         | 3400       |
|    time_elapsed       | 74         |
|    total_timesteps    | 17000      |
| train/                |            |
|    entropy_loss       | -8.61      |
|    explained_variance | -15.1      |
|    learning_rate      | 0.0007     |
|    n_updates          | 3399       |
|    policy_loss        | -2.48      |
|    std                | 1.02       |
|    value_loss         | 0.0803     |
------------------------------------
------------------------------------
| rollout/              |            |
|    ep_len_mean        | 887        |
|    ep_rew_mean        | -49.8      |
| time/                 |            |
|    fps                | 228        |
```

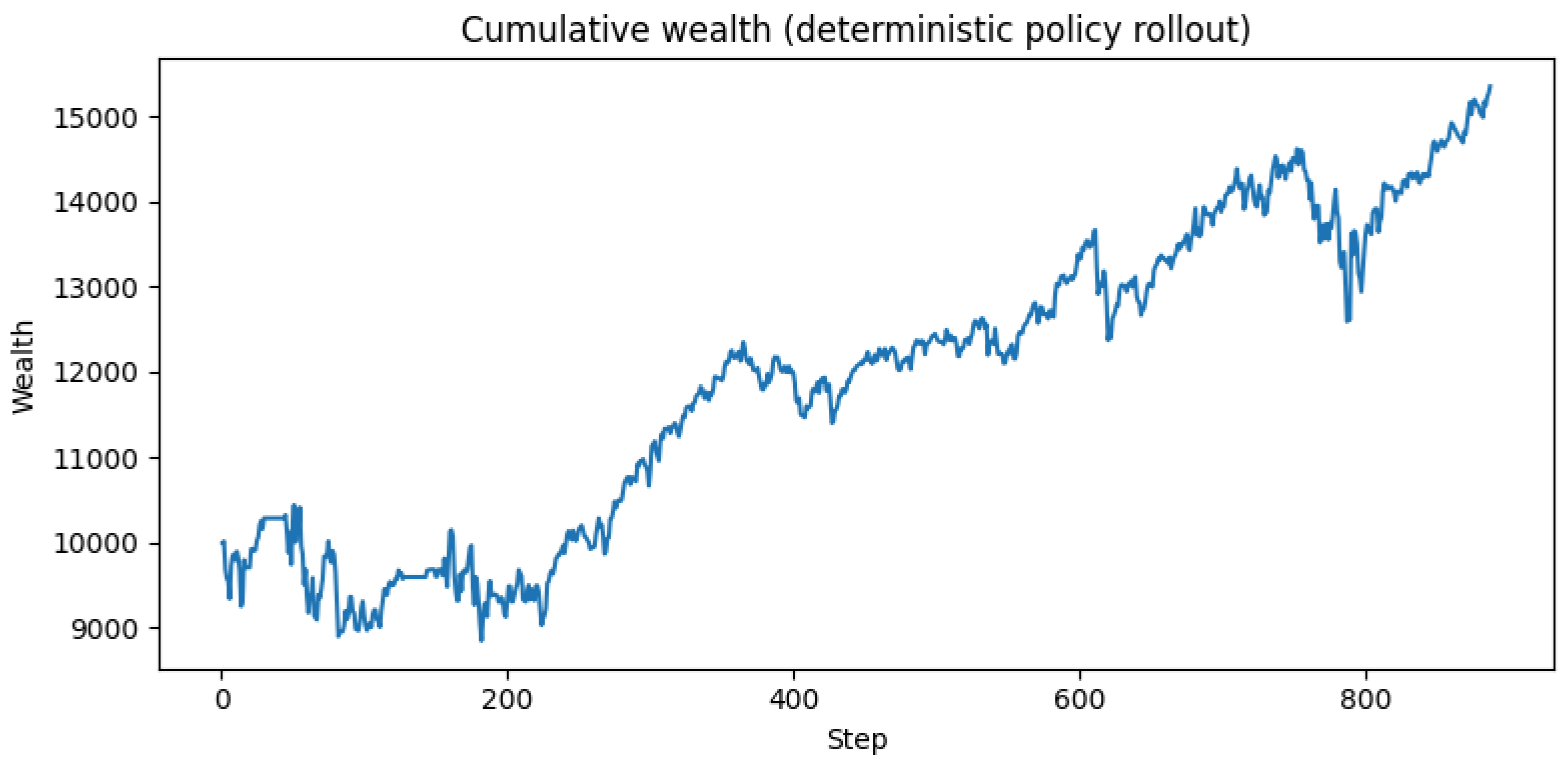
```
|    iterations          | 3500      |
|    time_elapsed        | 76        |
|    total_timesteps     | 17500     |
| train/                 |           |
|    entropy_loss        | -8.63     |
|    explained_variance  | -13.3     |
|    learning_rate       | 0.0007    |
|    n_updates           | 3499      |
|    policy_loss         | 1.84      |
|    std                 | 1.02      |
|    value_loss          | 0.0455    |
------------------------------------
------------------------------------
| rollout/               |           |
|    ep_len_mean         | 887       |
|    ep_rew_mean         | -49.6     |
| time/                  |           |
|    fps                 | 229       |
|    iterations          | 3600      |
|    time_elapsed        | 78        |
|    total_timesteps     | 18000     |
| train/                 |           |
|    entropy_loss        | -8.64     |
|    explained_variance  | -121      |
|    learning_rate       | 0.0007    |
|    n_updates           | 3599      |
|    policy_loss         | 0.621     |
|    std                 | 1.02      |
|    value_loss          | 0.0186    |
------------------------------------
-------------------------------------
| rollout/               |            |
|    ep_len_mean         | 887        |
|    ep_rew_mean         | -49.6      |
| time/                  |            |
|    fps                 | 229        |
|    iterations          | 3700       |
|    time_elapsed        | 80         |
|    total_timesteps     | 18500      |
| train/                 |            |
|    entropy_loss        | -8.63      |
```

```
|    explained_variance | -1.49e+03 |
|    learning_rate      | 0.0007    |
|    n_updates          | 3699      |
|    policy_loss        | 2.26      |
|    std                | 1.02      |
|    value_loss         | 0.196     |
-------------------------------------
------------------------------------
| rollout/              |          |
|    ep_len_mean        | 887      |
|    ep_rew_mean        | -49.5    |
| time/                 |          |
|    fps                | 229      |
|    iterations         | 3800     |
|    time_elapsed       | 82       |
|    total_timesteps    | 19000    |
| train/                |          |
|    entropy_loss       | -8.61    |
|    explained_variance | -223     |
|    learning_rate      | 0.0007   |
|    n_updates          | 3799     |
|    policy_loss        | -0.365   |
|    std                | 1.02     |
|    value_loss         | 0.00611  |
------------------------------------
-------------------------------------
| rollout/              |           |
|    ep_len_mean        | 887       |
|    ep_rew_mean        | -49.5     |
| time/                 |           |
|    fps                | 229       |
|    iterations         | 3900      |
|    time_elapsed       | 84        |
|    total_timesteps    | 19500     |
| train/                |           |
|    entropy_loss       | -8.61     |
|    explained_variance | -5.81e-05 |
|    learning_rate      | 0.0007    |
|    n_updates          | 3899      |
|    policy_loss        | -0.0142   |
|    std                | 1.02      |
```

```
|    value_loss         | 1.5e-05   |
-------------------------------------
------------------------------------
| rollout/              |          |
|    ep_len_mean        | 887      |
|    ep_rew_mean        | -49.4    |
| time/                 |          |
|    fps                | 230      |
|    iterations         | 4000     |
|    time_elapsed       | 86       |
|    total_timesteps    | 20000    |
| train/                |          |
|    entropy_loss       | -8.57    |
|    explained_variance | -41.2    |
|    learning_rate      | 0.0007   |
|    n_updates          | 3999     |
|    policy_loss        | 0.288    |
|    std                | 1.01     |
|    value_loss         | 0.0169   |
------------------------------------
```



Training profile (episode rewards)
Episode reward
Smoothed
−47
−48
−49
−50
−51
−52
0
5
10
15
20
Episode
Episode reward




```
=== Portfolio Performance (deterministic rollout) ===
Periods per year (inferred): 252.00
Start wealth:  10000.00
End wealth:    15353.61
Total growth:  1.535361
CAGR:          12.969926%
Ann. Return (geom from equity): 12.969926%
Ann. Vol:      17.650193%
Sharpe (rf=0): 0.7793
Max Drawdown:  -15.29%
Calmar:        0.8483
```

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、添加了a2c算法