

Supplementary Material:

Autoregressive DRL with Learned Intrinsic Rewards for Portfolio Optimisation

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1 PSEUDOCODE FOR AUGMENTED AUTOA2C

To supplement our proposed algorithm as outlined in section 4 of the main paper, we provide pseudocodes for Augmented AutoA2C. We address the MMDP decomposition in Algorithm 1, and training and trading specifications in Algorithm 2.

Algorithm 1 Rollout for Autoregressive Model

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1: Init: initialize  $\mathcal{D} = \{\}$  and action vector  $\mathbf{a}_t = (0, 0, \dots, 0) \in \mathbb{R}^{30}$  corresponding to day  $t$  of MDP
2: for stock  $d = 1$  to 30 do
3:   Input  $u_{d-1}^{s_t} = \text{concat}(s_t, \mathbf{a}_t)$ 
4:   Sample action  $a_t^d \in \mathbb{R}$  using  $\pi_\theta$ 
5:   Update action vector  $\mathbf{a}_t[\text{position } d] \leftarrow a_t^d$ 
6:   Observe intrinsic reward  $r^{\text{in}}(u_{d-1}^{s_t}, a_t^d, u_d^{s_t}) \sim \pi_\eta$ 
7:   if  $d < 30$  then
8:     Get reward  $r^{\text{ex}}(u_{d-1}^{s_t}, a_t^d) = 0$ 
9:   else
10:    Execute action  $\mathbf{a}_t$  in environment
11:    Observe next state  $s_{t+1}$ 
12:    Observe inter-day reward  $r^{\text{ex}}(u_{29}^{s_t}, a_t^{30}) = (b_{t+1} + \mathbf{p}_{t+1}^T \mathbf{h}_{t+1}) - (b_t + \mathbf{p}_t^T \mathbf{h}_t)$ 
13:    Update  $s_t \leftarrow s_{t+1}$ 
14:   end if
15:   Append  $(u_{d-1}^{s_t}, a_t^d, u_d^{s_t}, r^{\text{ex}}, r^{\text{in}})$  to  $\mathcal{D}$ 
16: end for
17: Return trajectory  $\mathcal{D}$ 

```

For training, we maintain a reward buffer \mathcal{R} for the purpose of transforming the inter-day rewards into some external reward function $U(\cdot)$ (see section 5.2) dependent on some history of inter-day rewards.

Algorithm 2 Augmented AutoA2C

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1: Input: step size parameters  $\alpha, \beta$ 
2: for each moving window  $\mathcal{W}$  do
3:   Initialize network parameters  $\theta, \eta$ 
4:   Initialize day  $t = 0$ 
5:   Initialize reward buffer  $\mathcal{R}$ 
6:   # Train
7:   repeat
8:     Sample trajectory  $\mathcal{D} \sim \pi_\theta, \pi_\eta$  by Algorithm 1
9:     Store inter-day reward  $r^{\text{ex}}(s_t, \mathbf{a}_t)$  in  $\mathcal{R}$ 
10:    Replace  $r^{\text{ex}}(s_t, \mathbf{a}_t)$  in  $\mathcal{D}$  with  $U(s_t, \mathbf{a}_t, s_{t+1}; \mathcal{R})$  or  $U(s_{0:t+1}, \mathbf{a}_{0:t}; \mathcal{R})$ 
11:    Approximate  $\nabla_\theta J^{\text{ex+in}}(\theta; \mathcal{D})$  by Equation 6
12:    Update policy actor  $\theta' \leftarrow \theta + \alpha \nabla_\theta J^{\text{ex+in}}(\theta; \mathcal{D})$ 
13:    Update policy critic  $\theta_v$  by Equation 7
14:    Approximate  $\nabla_{\theta'} J^{\text{ex}}(\theta'; \mathcal{D})$  by Equation 11
15:    Approximate  $\nabla_\eta \theta'$  by Equation 12
16:    Compute  $\nabla_\eta J^{\text{ex}} = \nabla_{\theta'} J^{\text{ex}}(\theta'; \mathcal{D}) \nabla_\eta \theta'$ 
17:    Update intrinsic reward actor  $\eta' \leftarrow \eta + \beta \nabla_\eta J^{\text{ex}}$ 
18:    Update intrinsic reward critic  $\eta_v$  by Equation 8
19:     $t \leftarrow t + 1$ 
20:  until done
21:  # Trade
22:  for trade day  $t = 1$  to 63 do
23:    Sample  $d$  subactions  $a^1, \dots, a^d$  corresponding to  $s_t$  according to  $\pi_\theta$ 
24:    Execute action  $\mathbf{a}_t = [a^1, \dots, a^d]$  in environment
25:    Record portfolio value  $b_t + \mathbf{p}_t^T \mathbf{h}_t$ 
26:  end for
27: end for

```
