## In-Context RL

### August 2023

### 1 Data Generation

#### 1.1 5-Armed Bandit Problem

```
State space S=\{0,1,2,3,4\}; action space A=\{0,1,2,3,4\} Initialize empty pretraining dataset \mathcal B for i in [N] do p_1\sim \text{Dirchlet distribution}(\mathbb 1) p_2\sim \text{point-mass distribution} \omega\sim \text{Unif}(0.1[10]) action distribution p=(1-\omega)p_1+\omega p_2 action means \mu\sim \text{Unif}[0,1]^5 for h in [H=500] do action a_h\sim p (OHE) reward r_h\sim N(\mu_a,\sigma^2) where \sigma=0.3 append (a_h,r_h) to goal g append a_h,r_h to \mathcal B
```

# 2 Value Function Approximation

```
for i in [#iterations] do sample offline data \{s_t^i, a_t^i, s_{t+1}^i, g_t^i\}_{i=1}^N \sim \mathcal{B}, \{s_0^i\}_{i=1}^M \sim \mu_0 estimate the reward function \hat{R} for each task in the current offline data  \text{Value objective:} L_V(\theta) = \frac{1-\gamma}{M} \sum_{i=1}^M [V_\theta(s_0^i; g_0^i)] + \frac{1}{N} \sum_{i=1}^N \left[ f_\star(R_t^i + \gamma V(s_{t+1}^i; g_t^i) - V(s_t^i; g_t^i)) \right] \\ \text{update } V_\theta \colon V_\theta \leftarrow V_\theta - \alpha_V \nabla L_V(\theta)
```

For bandit data, condition V on a and s instead, and there is no  $\gamma V$  term

# 3 DT Training

```
for i in [#iterations] do sample offline data \{s_t^i, a_t^i, s_{t+1}^i, g_t^i\}_{i=1}^N \sim \mathcal{B}
```

estimate the reward function  $\hat{R}$  for each task in the current offline data

Policy chiesting,  $I_{i}(\phi) = \sum_{i=1}^{N} \int_{0}^{1} (f'_{i}(P_{i} + \alpha V_{i}(\phi_{i} + \phi_{i}) - V_{i}(\phi_{i} + \phi_{i})) \log \pi(\phi_{i} + \phi_{i})$ 

```
Policy objective: L_{\pi}(\phi) = \sum_{i=1}^{N} \left[ \left( f'_{\star} \left( R^i_t + \gamma V_{\theta}(s^i_{t+1}; g^i_t) - V_{\theta}(s^i_t; g^i_t) \right) \log \pi(a \mid s, g) \right] \right] Update \pi_{\phi}: \pi_{\phi} \leftarrow \pi_{\phi} - \alpha_{\pi}
```

For bandit data, condition V on a and s instead, and there is no  $\gamma V$  term

### 4 Test

### 4.1 Offline Test

```
\label{eq:bardinger} \begin{split} \# & \mbox{ Bandit version } \\ & \mbox{ subopt = []} \\ & \mbox{ for } i \mbox{ in [500] do } \\ & \mbox{ sample dataset } D \mbox{ with number of } i \mbox{ data} \sim \mathcal{B}_{\text{test}} \\ & s = s_0 \\ & a^* = \arg\max_{a} \mu \\ & \hat{a} = \arg\max_{a \in \mathcal{A}} \pi_{\phi}(\cdot|s, D) \\ & \mbox{ suboptimality = } \mu_{a^*} - \mu_{\hat{a}} \\ & \mbox{ append suboptimality to subopt} \end{split}
```

#### 4.2 Online Test

```
\label{eq:barbon} \begin{split} \# \; & \text{Bandit version} \\ & \text{suboptimality} = 0 \\ & \text{subopt} = [] \\ & \text{Initialize} \; \mathbf{D} = \big\{ \big\} \\ & \text{for ep in } [\max\_\text{eps=500}] \; \text{do} \\ & \text{sample dataset} \; D \sim \mathcal{B}_{\text{test}} \\ & s = s_0 \sim \text{Unif}[0,1] \\ & \hat{a} = \pi_\phi(\cdot|s,D) \\ & \text{suboptimality} \; \text{+=} \; \mu_{a^*} - \mu_{\hat{a}} \\ & \text{append suboptimality to subopt} \\ & \text{add} \; (a,r) \; \text{to} \; \mathbf{D} \end{split}
```