## 平衡k臂赌博机问题

## 10臂赌博机实验

 $\mathbf{k}$  = 10, 动作的期望价值 $q_*(a)$ 通过均值为0,方差为1的正态分布随机得到, $\mathbf{a}$  = 1,2,3 . . . ,10

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In [20]:
        import numpy as np
         import matplotlib.pyplot as plt
         import seaborn as sns
         #设置中文字体与美化样式
         plt.rcParams["font.sans-serif"] = ["SimHei"]
         plt.rcParams["axes.unicode_minus"] = False
         sns.set(style="whitegrid")
In [21]: #定义赌博机环境
         class KArmedBandit:
            def __init__(self, k = 10, seed = None):
                初始化k臂赌博机
                K: 动作数量
                seed: 随机种子, 使实验可复现
                self.k = k
                if seed is not None:
                    np.random.seed(seed)
                self.q_star = np.random.randn(k)
                self.best_action = np.argmax(self.q_star)
            def get_q_star(self):
                return self.q star
            def step(self,action):
                执行动作, 返回奖励
                奖励 ~ N(q_star[action],1)
                return np.random.randn()+self.q_star[action]
         # 定义 \varepsilon-贪婪智能体
         class EpsilonGreedyAgent:
            def __init__(self,k, epsilon, seed=None):
                k: 动作数量
                epsilon: 探索概率
                self.k = k
                self.epsilon = epsilon
                if seed is not None:
                    np.random.seed(seed)
                self.Q = np.zeros(k) # 定义奖励函数
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self.N = np.zeros(k) # 保存每个动作被选择的次数,方便计算状态奖励
            def select_action(self):
                动作选择
                if np.random.rand()<self.epsilon:</pre>
                    # exploration 探索,选择随机动作
                    return np.random.randint(self.k)
                else:
                    # exploitation
                    max_Q = np.max(self.Q)
                    best actions = np.where(self.Q==max Q)[0] #where函数返回满足条件的位
                    return np.random.choice(best_actions) #当有多个最大奖励时,随机返回
            def update(self,action,reward):
                更新
                self.N[action] += 1
                self.Q[action] += (reward-self.Q[action])/self.N[action]
In [27]: # 运行单次实验
        def run_expriment(bandit, agent, steps=1000):
            运行一次实验
            返回:每一步的奖励,是否选择了最优动作
            rewards = np.zeros(steps)
            is_best_actions = np.zeros(steps,dtype=bool)
            for t in range(steps):
                action = agent.select action()
                reward = bandit.step(action)
                agent.update(action, reward)
                rewards[t] = reward
                is_best_actions[t] = (action == bandit.best_action)
            return rewards, is best actions
In [28]: # 主实验
        def main expriment(epsilons = [0,0.01,0.1], runs = 2000, steps = 1000, k = 10, s
            对每一个epsilon,运行runs次实验,每次steps步。
            return: 平均奖励矩阵, 最优动作选择矩阵
            average_rewards = np.zeros((len(epsilons), steps))
            average best actions = np.zeros((len(epsilons), steps))
            for i,epsilon in enumerate(epsilons):
                print(f"running expriments for E = {epsilon}...")
                total_rewards = np.zeros(steps)
                total_best_actions = np.zeros(steps)
                for run in range(runs):
                    为每次运行创建新的赌博机
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bandit = KArmedBandit(k = k, seed=seed +run)
    agent = EpsilonGreedyAgent(k = k, epsilon=epsilon, seed = seed+run)
# print(bandit.get_q_star())
    rewards, is_best = run_expriment(bandit,agent,steps)
    total_rewards += rewards
    total_best_actions += is_best

average_best_actions[i] = total_best_actions/runs
    average_rewards[i] = total_rewards/runs

return average_rewards, average_best_actions
```

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In [29]: def plot_results(avg_rewards, avg_best_action_rates, epsilons, steps=1000):
             fig, axes = plt.subplots(2, 1, figsize=(12, 8))
             # 平均奖励
             for i, epsilon in enumerate(epsilons):
                 axes[0].plot(range(1, steps + 1), avg_rewards[i], label=f'ε = {epsilon}'
             axes[0].set_xlabel('Steps')
             axes[0].set_ylabel('Average Reward')
             axes[0].legend()
             axes[0].set title('Average Reward over Time')
             # 最优动作选择率
             for i, epsilon in enumerate(epsilons):
                 axes[1].plot(range(1, steps + 1), avg_best_action_rates[i], label=f'ε =
             axes[1].set xlabel('Steps')
             axes[1].set_ylabel('% Optimal Action')
             axes[1].legend()
             axes[1].set_title('Optimal Action Selection Rate over Time')
             plt.tight_layout()
             plt.show()
```

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In [30]: if __name__ == "__main__":
            # 设置参数
            EPSILONS = [0, 0.01, 0.1]
            RUNS = 2000
            STEPS = 1000
            # 运行实验
            avg_rewards, avg_best_action_rates = main_expriment(
                epsilons=EPSILONS,
                runs=RUNS,
                steps=STEPS,
                k=10,
                seed=42 # 为了复现性, 你可以改变或移除
            print(avg rewards.shape,avg best action rates.shape)
            print(avg_best_action_rates,avg_rewards)
            plot results(avg rewards, avg best action rates, EPSILONS, STEPS)
            # 打印长期(最后100步)平均表现
            print("\n=== 长期表现(最后100步平均) ===")
            for i, eps in enumerate(EPSILONS):
                last_100_reward = np.mean(avg_rewards[i, -100:])
                last_100_optimal = np.mean(avg_best_action_rates[i, -100:])
                print(f"ε = {eps:.2f}: 平均奖励 = {last_100_reward:.3f}, 最优动作率 = {1
```

```
running expriments for E = 0...
  running expriments for E = 0.01...
  running expriments for E = 0.1...
   (3, 1000) (3, 1000)
   [[0.1065 0.1635 0.196 ... 0.3765 0.3765 0.3765]
      [0.1065 0.1625 0.1935 ... 0.6185 0.6195 0.6205]
      [0.1065 0.159 0.1845 ... 0.8235 0.8205 0.8205]] [[0.07387915 0.31048855 0.49677
  893 ... 1.03448335 1.01456309 0.99924449]
      [0.07387915 0.30822287 0.49773834 ... 1.34087822 1.35666832 1.33263078]
      [0.07387915 \ 0.28742308 \ 0.46430849 \ \dots \ 1.37327314 \ 1.37787789 \ 1.36039334]]
                                                                                                                                  Average Reward over Time
                                          polating of the second and the second of the
       1.4
       1.2
Average Reward
      0.4
                                                                                                                                                                                                                                                                                       \varepsilon = 0.01
      02
                                                                                                                                                                                                                                                                                    - ε = 0.1
                          0
                                                                            200
                                                                                                                               400
                                                                                                                                                                                   600
                                                                                                                                                                                                                                      800
                                                                                                                                                                                                                                                                                        1000
                                                                                                                                                       Steps
                                                                                                                       Optimal Action Selection Rate over Time
                         - ε = 0
      0.8
                            ε = 0.01
      0.7
                          -\epsilon = 0.1
Optimal Action
 ° 0.3
       0.2
      0.1
                                                                                                                                                                                                                                      800
                                                                                                                                                                                                                                                                                         1000
  === 长期表现(最后100步平均) ===
  \epsilon = 0.00: 平均奖励 = 1.022, 最优动作率 = 0.377
  \varepsilon = 0.01: 平均奖励 = 1.318, 最优动作率 = 0.610
  \epsilon = 0.10: 平均奖励 = 1.362, 最优动作率 = 0.813
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In [ ]: