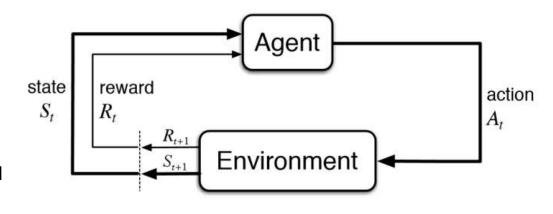
Parallel Reinforcement Learning Parallel Design

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Refresher: Reinforcement Learning

- At each time t, the agent receives current state S_t and reward R_t
- The agent then choose action A_i
- The action is sent to the environment, which moves to a new state S_{t+1} and reward R_{t+1}
- Goal is to learn a **policy** π which maximizes the cumulative reward

$$\pi(a,s) = Pr(A_t = a \mid S_t = s)$$



Sequential Baseline Results

- Learning performance of a single RL agent with a 10-armed bandit
- We use an ε -greedy policy (ε = 0.1) to average 500 different experiments where each contain 100 trials
- n=10 arms are created randomly from N(1.0, 1.0)
- As the agent gains more experience
 - Reward for each arm approaches the true mean
 - The agent is more likely to select the optimal action

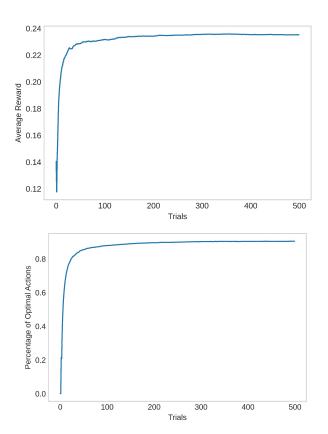
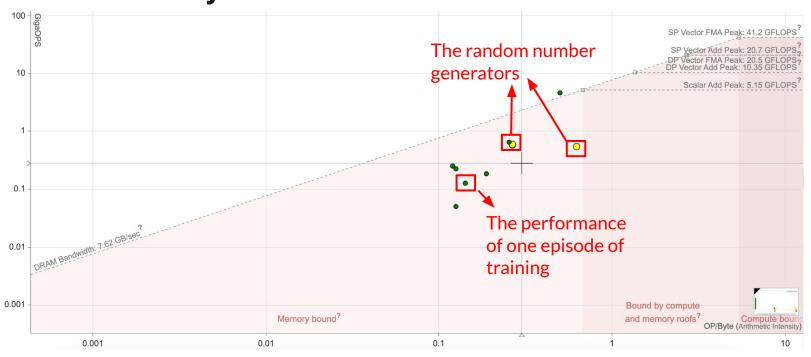


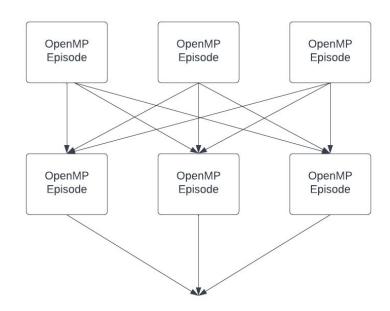
Figure: Single Agent in 10-armed Bandit Task

Roofline Analysis



Parallel programming models

- We cannot make the random number generators perform better
- Parallelize both the agents and the training within each episode
- Parallelize the agents with MPI; parallelize the episodes with OpenMP



Plan to implement parallel code

- Flow of computational steps:
 - Define an initial best action
 - Run the 500 episodes with 100 trials each
- Synchronization must occur:
 - Between agents, after a set number of episodes to share the information among agents and optimally update for learning
 - Within an agent, between each episode
- No load imbalance will be expected due to the random and repeated nature of the RL

Hiding Latency

- Latency will likely occur largely when sharing information between agents:
 - Small size of information makes latencies even more apparent
 - Must determine optimal frequency in which to share between agents to hide latencies
 - Want to send information between agents while calculations continue to happen

