

State Agent Control

remand

Env (State)

next state

Descriptive unsupervised No decision Predictive Supervised Predictive decision No loop

Control
Reinforced
Control devision

Multi Armed Bandits

Agent

action Treward

EM

aval: To look at the challenges in the control or reinforcement learning setting and slice out the multi-armed bandits

(learning to play)

Contre

Application of: playing chess/Gw, autonomons doiving, robotics (Mujoco), play viduo games

> inventory control, traffic bignal control, optimal imestment, on eine ad

challenge 1:

env: deterministic,

revoids: 010 00010 left Right

> rt Z (0.9) 2 2 L

t= 5 cm night

Say T=2, go east $\int switched$. T=3, go right : T=8, go right T=9, Go right for 3 steps then left

(Yoral: Immediate VS Future

challenge 2'. Say I play a game of ches, and
I win, is it possible to pin point the
winning move ?

Moral: Temporal credit assignment

Chauarge 3! Environment is not deterministic max & [] at]

* you have to visit each of these places multiple times

I say I visit each location 10 times, Collect samples, look at sample mean and decide

C few good samples at left excation and few bad samples at night location can screw US)

Moral: Cannot explore and commit

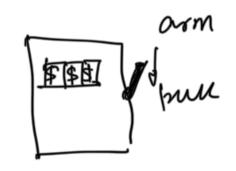
in order to gain information we actually need a samples (keep exploring)

It while we explore, we should not over explore bad choices, Cexploit what we know)

Exploration VS Exploitation

Notation for Multi-Armed Bandits

• $A = \{1, ..., k3\}$ arms



- o arm a is associated with distribution P_a
- at time t, we pick At C puelling arm)

e Reward
$$X_{t} \sim P_{A_{t}}$$

Best reward
$$\mu_{x} = max \mu(a)$$

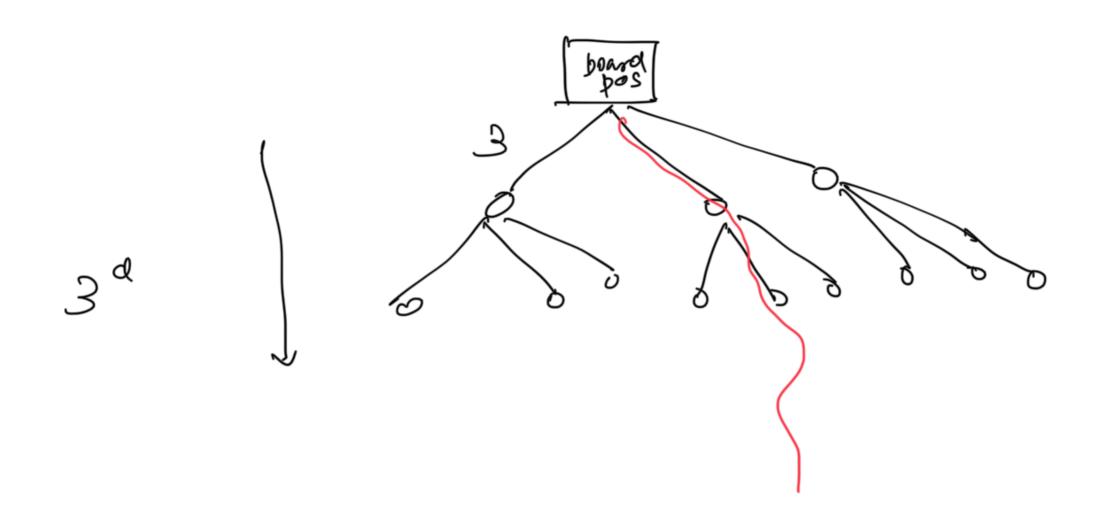
Best arm
$$a_{*} = arg max \mu(a)$$

Suboptimality
$$\Delta a = f_{*} - \mu(a)$$
Gaps

$$R_n = Regret_n = E\left[\sum_{t=1}^n (\mu_t - x_t)\right]$$
 $n = 10$

why / where do we see the impact of expeone VS explorit

Example: Game



How to so eve the MAB problem

Seavence/

Seavence/

Convergence > $X_i Y_{i7,0}$ iid $X_i \rightarrow F[X_i]$ random variables

Probability concentrates around true mean Concenbration > 070 babi-lity

Tone Mean

device from one mean