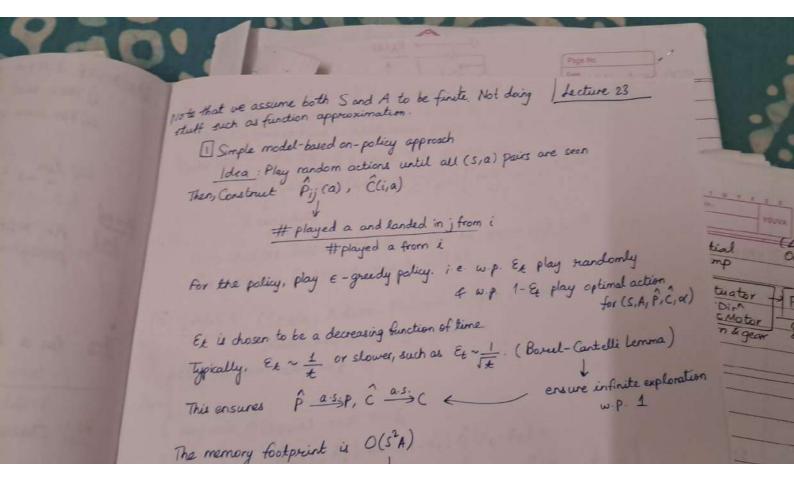
hypothesis of Thm X holds was proof, where there was he policy TT, all inequalities EE6106 LECTURE 23 Date: 2177Apr 2024 (dassical RL -> Q-learning, SARSA Discounted Cost Setting (S, A, P, C, a) Assumption: Underlying MDP is unichain. For average cost MDP, so such assumption was made when the horizon was assumed to be made. t factor x) "solves" In the RL setting, we require a connectivity assumption or mistakes are compulsory and sub-optimal actions have to be taken. Flavours of RL: 1) On-policy learning a) vá (3)] 2) Off-policy learning Ourpality - The learning algorithm is in control and decides which action to take. Off-policy -> The entity which decides what action to take is different suference state that the learning agent. We can still learn from the feedback signals received by someone else. + XZPijhx(j)7 better using this format Flavours of RL algorithms: D Model-based 2) Model- free Model-based -> Algorithm is learning a "model" and hence learning (P,C) Model-free -> Not learning P. C but directly trying to learn optimal policy. learn value functions directly



Et is down to be a decreasing function of sume.

This insures  $\hat{P}$  as  $\hat{P}$ ,  $\hat{C}$  as  $\hat{C}$  ensure infinite exploration

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The memory footprint is  $O(s^2A)$ Storing estimates of  $\hat{P}$ .

[2] O-Learning (model-free off-policy algorithm)

Acans the Q-function, with a memory requirement of O(sA).  $Q^*(i,a) = C(i,a) + \alpha \sum P_{ij}(a) V^*(j)$   $= C(i,a) + \alpha \sum P_{ij}(a) \sum_{a} V^*(j)$ This is the Bellman equation in terms of the Q function  $\hat{Q}(\mathcal{H}_{L}, A_{L}) \leftarrow (1 - V_{L}) \hat{Q}(\mathcal{H}_{L}, A_{L}) + V_{L}[Q + V_{min} \hat{Q}(\mathcal{H}_{L}, a_{d})]$ If u the step-size parameter, gives memory of the eacher event v is also chosen as a decreasing function of time.

Note that v in  $\hat{Q}(\mathcal{H}_{L}, a_{d})$  is an estimate of  $v^*(X_{L}, a_{d})$ .

Need:  $\sum V_{L} = 0$ ,  $\sum V_{L}^{2} < \infty$ 

g: what do we need for g to converge to Q? fecture 23.

In the long run, every (s, a) - pair should be visited almost surely Thus, we cannot have a stationary policy which drives Q-learning "Tracks ODE":  $\dot{g} = Tg - g$ , where T is an operator Tu(i,a) = C(i,a) + of Epy(a) [min u(j,a')] Note that the Bellman equation can be expressed as \$ T9=9 The memory footprint now is O(s,a). (State, Action, Reward, State, Action) Model-free, on-policy algorithm -Play random action w.p. Et aug min ĝ (xt, a) w.p. 1- & ĝ(Xt, At) ← (1-1/t) ĝ(Xt, At) + 7+ [C+ + & Q(X++1/A++1)] There is no minimization term in SARSA. Note that the next step we WILL perform minimization w.p. 1-Et

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tilla

At any min  $\hat{g}(x_t, a)$  w.p.  $1 - \xi_t$   $\hat{g}(x_t, A_t) \leftarrow (1 - \gamma_t) \hat{g}(x_t, A_t) + \\
Y_t \left[ (\xi_t + \alpha_t \hat{g}(x_{t+1}, A_{t+1}) \right]$ There is no minimization term in SARSA. Note that the next step we will perform minimization w.p.  $1 - \xi_t$ Note that for g-learning, we can use any action selection algorithm as long as it performs infinite exploration.

Typically choose  $\xi_t \sim \frac{1}{t} \ell + \delta_t \sim \frac{1}{t}$   $\Rightarrow \hat{g} \stackrel{q.s.}{=} g$ Note that these algorithms are notoriously slow. This is because only entry gets filled in one time-step only entry gets filled in one time-step function as a linear combination of some basis function.

Actor-Critic algorithm

GPI  $\rightarrow$  Generalized Policy Iteration

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Original policy iteration searches for greedy inprovements on the policy

Actor: Policy improvement (slower timescale)

(ritic: Policy evaluation (factor timescale)

You have two timescales, one with a small & one with a large step size In practice, use step size  $Y_t$  for actor &  $P_t$  for uritic.

BY=a(Y\_t)  $Y_t = O(P_t)$ Libble of Oh

SARSA

If we do, off-policy SARSA, under some Stationary policy TI, we will hearn

the value function corresponding to the policy TI -> QTI and VTI

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All of these algorithms can be generalized for a time-average MDP setting.