goal: determine dynamics of finite MP/SDE

Neuro-Dynamic Programming

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chapter 2

Reinforcement Learning

An Introduction

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Chapter 3

o consider a finite MP/SDE (X,U,P), i.e. IXI,  $IUI < \infty$   $x^+ \sim P(x,u)$ ,  $P: X \times U \to \Delta(X)$   $\to \Delta(X)$   $\to \Delta$  starting from state  $P \in \Delta(X)$  and applying policy  $T: X \to \Delta(U)$  determine next state  $P^+ \in \Delta(X)$  (it can help to regard  $P: X \to [0,1]$  — determine  $P^+(x^+)$ , all  $X^+ \in X$ ) — we can compte  $P^+(x^+)$  for each  $X^+ \in X$  using rules of probability:  $P^+(x^+) = \sum_{X \in X} (P(X) \left[ \sum_{U \in U} T(u \mid X) P(X^+ \mid X, u) \right] \right)$   $\sum_{X \in X} (P(X) \left[ \sum_{U \in U} T(u \mid X) P(X^+ \mid X, u) \right] \right)$   $\sum_{X \in X} (P(X) \left[ \sum_{U \in U} T(u \mid X) P(X^+ \mid X, u) \right]$   $\sum_{X \in X} (P(X) \left[ \sum_{U \in U} T(u \mid X) P(X^+ \mid X, u) \right]$   $\sum_{X \in X} (P(X) \left[ \sum_{U \in U} T(u \mid X) P(X^+ \mid X, u) \right]$ 

\* this determines a deterministic (?) difference equation:  $P^{+}=F(P)$ ,  $(P:X \rightarrow [0,1]) \in \Delta(X) \subset [0,1]^{X} \subset \mathbb{R}^{X}=\mathbb{R}^{N}$ PE [0,1]X - more generally we let  $\Rightarrow p \in \mathbb{R}^{X} = \mathbb{R}^{N} \quad \mathbb{R}^{A} = \{ f : A \Rightarrow B \}$ e.g.  $IR^{N} = \{ V : \{ 1, \dots, N \} \rightarrow R \}$ -> show that F is linear (?) (i.e. find  $\Gamma \in \mathbb{R}^{N \times N}$ , N = |X|, s.t.  $F(p) = \Gamma p = p^{+}$ ) -  $[\Gamma]_{x+,x} = \sum_{n \in \mathbb{N}} \tau(u|x) P(x+|x,u)$  yields  $p^+ = \Gamma p$ \* we can use linear systems throug to characterize "solutions" / trajectories including their asymptotic properties ? -> were studying discrete-time linear time-invariant DE Pt= TP o first of all, we know trajectories  $P_t = \Gamma^t P_0$ , any  $t \in \mathbb{N}$ C t-fold makrix moltiplication . furthermore,  $\Gamma$  has special properties:  $1\Gamma\Gamma = 1\Gamma \implies 1 \in \text{spec}\Gamma$   $\uparrow 1\Gamma = (1, \dots, 1) \in \mathbb{R}^N$ i.e.  $\Gamma$  is "left-stochastic"  $\Rightarrow$   $\forall \lambda \in \operatorname{spec} \Gamma : |\lambda| \leq 1$ 

\* if  $\Gamma = \overline{p} = \overline{p}$  is unique  $\Gamma = \overline{p} = \overline{p}$  is unique.

so all trajectories asymptotically converge to unique P o