

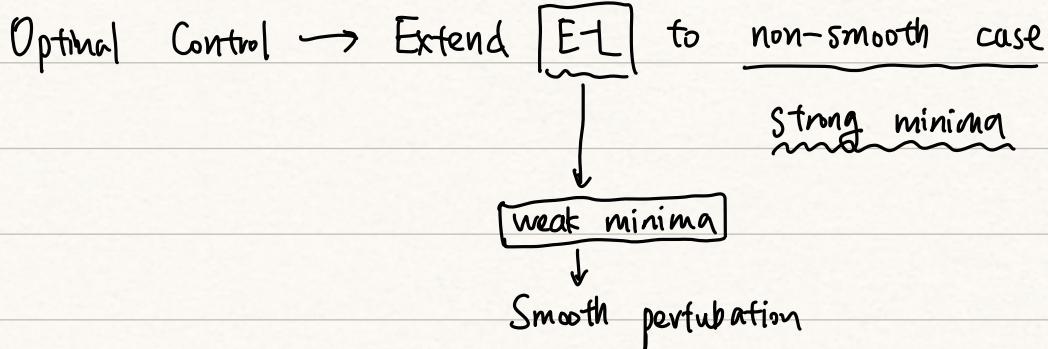
Recap: $\begin{cases} \dot{x}(t) = f(t, x(t)) \\ x(0) = x_0 \end{cases}$

$$x_0 + \varepsilon v_0 \rightarrow v_0 \rightarrow \frac{x_\varepsilon - x_0}{\varepsilon} \quad \boxed{\varepsilon \rightarrow 0}$$

$$\Rightarrow \frac{\Phi_t(x_0 + \varepsilon v_0) - \Phi_t(x_0)}{\varepsilon} \rightarrow V(t)$$

$$\begin{cases} \dot{V}(t) = P_x f(t, x(t)) V(t) \\ V(0) = V_0 \end{cases}$$

Calculation Variation



Bolza Problem

$$J[\theta] = \underbrace{\Phi(x(T))}_{\text{terminal cost}} + \underbrace{\int_0^T L(t, x(t), \theta(t)) dt}_{\text{running cost}}$$

$$\boxed{\begin{array}{ll} \inf_{\theta \in L^\infty([0,T], \Theta)} & J[\theta] \\ \text{s.t.} & \dot{x}(t) = f(t, x(t), \theta(t)) \quad t \in [0, T] \\ & x(t_0) = x_0 \end{array}}$$

- Mayer Prob: $L \equiv 0$
- Lagrange Prob: $\Phi \equiv 0$

\rightarrow E-L equation (necessary) only holds for $x^* \in C'$
 \rightarrow PMP is a necessary condition for $\theta^* \in L^\infty([0,T], \Theta)$

Goal: Derive necessary condition for Strong Optimality

[More advanced]

non-smooth perturbation is allowed

" if $\underline{\theta}^*$ is a strong minimizer,
 then $\underline{\theta}^*$ must satisfy something!
 we want to find."

Rmk: Basically, this is a constrained optimization

Lagrangian Multiplier Method

Lagrangian Multiplier Method (KKT Condition)



View Bolza Prob. as a constrained Opt. problem

$$\rightarrow \begin{cases} \inf_{\underline{\theta}, \underline{x}} J[\underline{\theta}, \underline{x}] = \underline{\Phi}(x(T)) + \int_0^T L(t, x(t), \underline{\theta}(t)) dt \\ \text{s.t. } \begin{cases} \dot{x}(t) - f(t, x(t), \underline{\theta}(t)) = 0 & \forall t \in [0, T] \\ x(0) - x_0 = 0 \end{cases} \end{cases}$$

infinitely many constraints

need infinitely many
Lagrangian Multipliers

→ For each t , there is a constraint,



introduce

a Sequence Of

(infinitely many)

Lagrangian Multipliers



$$\{ p(t) : t \in [0, T] \}$$

Then $\mathcal{L}(\underline{\theta}, \underline{x}, p) = J[\underline{\theta}, \underline{x}] + \int_0^T p(t)^T [\dot{x}(t) - f(t, x(t), \underline{\theta}(t))] dt$

分部积分

$$+ p(0)^T (x(0) - x_0)$$

→ Necessary Condition is:

$$0 = \nabla_{\theta} L$$

$$0 = \nabla_x L$$

$$0 = \nabla_p L$$

State

$$\textcircled{1} \quad \nabla_{p(t)} L = 0 \Rightarrow \left\{ \begin{array}{l} \dot{x}(t) = f(t, x(t), \theta(t)) \\ x(0) = x_0 \end{array} \right. \rightarrow \text{feasibility}$$

$$\textcircled{2} \quad \nabla_x L = 0 \Rightarrow \text{Rewrite } L[\theta, x, p]$$

$$= J[\theta, x] - \int_0^T p(t)^T f(t, x(t), \theta(t)) dt - p(0)^T (x(0) - x_0)$$

$$J[\theta, x] = \Phi(x(T)) + \int_0^T L(t, x(t), \theta(t)) dt$$

$$+ \int_0^T p(t)^T \dot{x}(t) dt$$

$$= [p(t)^T x(t)] \Big|_{t=0}^T - \int_0^T p(t)^T \dot{x}(t) dt$$

$$= J[\theta, x] - \int_0^T \left(p(t)^T f(t, x(t), \theta(t)) + p(t)^T \dot{x}(t) \right) dt$$

$$+ p(T)^T x(T) - p(0)^T x_0.$$

$t \in (0, T)$

$$\left\{ \begin{array}{l} \nabla_{x(t)} L = 0 \Rightarrow \dot{p}(t) = - \nabla_x [p(t)^T f(t, x(t), \theta(t)) - L(t, x(t), \theta(t))] \\ \nabla_{x(T)} L = 0 \Rightarrow p(T) = - \nabla_x \Phi(x(T)) \end{array} \right.$$

Co-state

$$\textcircled{3} \quad \nabla_{\theta(t)} L = 0 \Rightarrow \nabla_{\theta} (p(t)^T f(t, x(t), \theta(t)) - L(t, x(t), \theta(t))) = 0$$

→ want to write in a compact form

→ Hamiltonian H

$$H: [0, T] \times \mathbb{R}^d \times \mathbb{R}^d \times \mathbb{R} \rightarrow \mathbb{R}$$

$$H(t, x, p, \theta) = \underbrace{p^T f(t, x, \theta)}_{\text{Dynamic}} - \underbrace{L(t, x, \theta)}_{\text{running cost}}$$

Necessary Condition

Dynamic running cost

↑ → simplification of $\textcircled{1} \textcircled{2} \textcircled{3}$

Attain by

$$\textcircled{1} \quad \dot{x}(t) = \nabla_p H(t, x(t), p(t), \theta(t))$$

$$x(0) = x_0$$

L-M-M

$$① \dot{p}(t) = -\nabla_x H(t, x(t), p(t), \theta(t)) \quad p(T) = -\nabla \Phi(x(T))$$

$$③ \nabla_{\theta} H(t, x(t), p(t), \theta(t)) = 0$$

if control is not good \rightarrow no ∇_{θ} !

PMP

PMP

Define Hamiltonian $H(t, x(t), p(t), \theta(t))$

$$\boxed{\text{Broader Class}} = p^T f(t, x, \theta) - L(t, x, \theta)$$

Theorem:

\rightarrow Finance more

(Application / formulation)

Let $\underline{\theta^*} \in L^\infty([0, T])$ be an optimal control of the Bolza

Problem, and x^* is controlled trajectory, then there exists a co-state (state)

process $\{p^*(t) : t \in [0, T]\}$ absolutely continuous & satisfy :

$$x^*(0) = x_0$$

$$\left\{ \begin{array}{l} ① \dot{x}^*(t) = f(t, x^*(t), \theta^*(t)) = \nabla_p H(t, x^*(t), p^*(t), \theta^*(t)) \\ ② \dot{p}^*(t) = -\nabla_x H(t, x^*(t), p^*(t), \theta^*(t)) \quad p^*(t) = -\nabla \Phi(x^*(t)) \\ ③ H(t, x^*(t), p^*(t), \theta^*(t)) \geq H(t, x^*(t), p^*(t), \theta) \end{array} \right.$$

for $\forall t \in [0, T]$ & $\forall \theta \in \Theta$

a.e. \rightarrow almost every

relax our condition on $H \leftrightarrow \theta$ \rightarrow no need have $\nabla_{\theta} H$

② Stronger Condition \rightarrow rule out more candidates

Fixed-End-Time

Pf (Simplest One) \rightarrow terminal time fixed

- Step 1 \rightarrow conversion to Mayer Problem (From Bolza Prob to $L=0$)

Method: Define an auxiliary variable $\{x^*(t)\}$ satisfy an ODE

$$\underbrace{\dot{x}^*(t) = L(t, x(t), \theta(t))}_{\Downarrow} \quad x^*(0) = 0$$

$$\text{Sol}^2 : x^*(t) = \int_0^t L(t, x(z), \theta(z)) dz$$

$\Rightarrow x^*(T) \rightarrow \text{Running cost!}$

Therefore, define new variables

$$\begin{cases} \tilde{x} = \begin{pmatrix} x^* \\ x \end{pmatrix} \\ \tilde{f} = \begin{pmatrix} L \\ f \end{pmatrix} \\ \tilde{\Phi}(\tilde{x}) = \underline{\Phi}(x) + x^* \\ \tilde{x}(0) = \begin{pmatrix} 0 \\ x_0 \end{pmatrix} = \tilde{x}_0 \end{cases}$$

Then Bolza Prob. becomes:

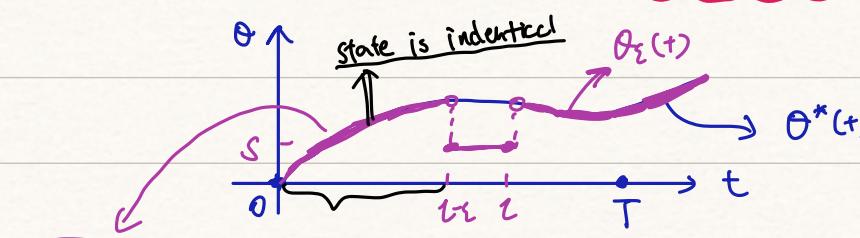
$$\begin{cases} \inf_{\underline{\theta}} \tilde{\Phi}(\tilde{x}(T)) \\ \text{s.t. } \begin{cases} \dot{\tilde{x}} = \tilde{f} \\ \tilde{x}(0) = \tilde{x}_0 \end{cases} \end{cases} \rightarrow \boxed{\text{Mayer Problem}}$$

drop the ' \sim ' and consider

Mayer Problem only W.L.O.G

- Step 2: Introduce 'Non-smooth' Perturbation

(Needle Perturbation)



Let θ^* be an optimal control

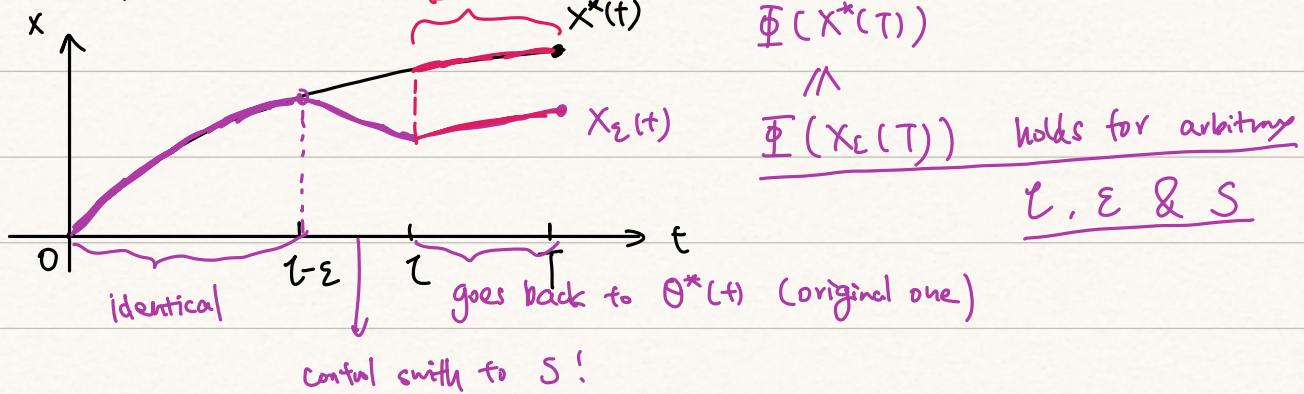
Fix arbitrary some $\textcircled{1} t \in (0, T)$ & $\textcircled{2} s \in \mathbb{U}$ & $\textcircled{3} \varepsilon > 0$

Define a perturbed control as $\theta_\varepsilon(t) = \begin{cases} s & t \in [t-\varepsilon, t] \\ \theta^*(t) & \text{otherwise} \end{cases}$

and corresponding trajectory X_ε defined by

$$\begin{cases} \dot{x}_\varepsilon(t) = f(t, x(t), \theta_\varepsilon(t)) \\ x_\varepsilon(\cdot) = x_0 \end{cases}$$

What happens to state?



CRUCIAL PART !!! → Needle Perturb

• Step 3: Variation Equation → how perturbation transfer

perturbate,

Define $v(t) := \lim_{\varepsilon \rightarrow 0} \frac{x_\varepsilon(t) - x^*(t)}{\varepsilon}$ $t \in [L, T]$

↓ Variation Equation Points!

Note that on $[L, T]$, control is the same, ODE same



x_ε & x^* satisfy the same eqn.

$$\dot{x}(t) = f(t, x(t), \theta(t))$$

Thus, use Variational Equation Result,

$\{v(t)\}$ satisfy : (ODE)

$$\begin{cases} \dot{v}(t) = \nabla_x f(t, x^*(t), \theta^*(t)) v(t) & t \in [L, T] \\ v(L) = V_0 \end{cases}$$

→ haven't determined yet!

To calculate $v(t)$, by defn:

$$v(t) = \lim_{\epsilon \rightarrow 0^+} \frac{1}{\epsilon} \left[\underbrace{\left(x_0 + \int_0^t f(t, x(s), \theta^*(s)) ds \right)}_{x_\epsilon(t)} - \underbrace{\left(x_0 + \int_0^t f(t, x(s), \theta^*(s)) ds \right)}_{x^*(t)} \right]$$

$\int_0^{t-\epsilon}$ → the same

$$\int_{t-\epsilon}^t \rightarrow \text{different} = \lim_{\epsilon \rightarrow 0^+} \frac{1}{\epsilon} \left[\int_{t-\epsilon}^t f(s, x(s), s) ds - \int_{t-\epsilon}^t f(s, x(s), \theta^*(s)) ds \right]$$

Lebesgue Differential Thm

$$\underline{f}(t, x(t), s) - \overline{f}(t, x(t), \theta^*(t))$$



Thus, Needle Perturbation travels as:

to reach this,
we make use
of the arbitrariness

$$\left\{ \begin{array}{l} \dot{V}(t) = \nabla_x f(t, x^*(t), \theta^*(t)) V(t) \quad t \in [t, T] \\ V(t) = f(t, x^*(t), s) - f(t, x^*(t), \theta^*(t)) \end{array} \right.$$

of ϵ to characterize

the initial perturbation $\rightarrow V(t)$

$$\Phi: \mathbb{R}^d \rightarrow \mathbb{R}$$

• Step 4. make use of $\underline{\Phi}(x^*(T)) \leq \underline{\Phi}(x_\epsilon(T))$

→ Optimality condition at End-Point

By defn of strong local optimality

→ $\underline{\Phi}(x^*(T)) \leq \underline{\Phi}(x_\epsilon(T))$ for ϵ sufficient small

→ $\underline{\Phi}(x_\epsilon(T)) - \underline{\Phi}(x^*(T)) \geq 0 \quad \epsilon \rightarrow 0^+$

→ optimality condition

treat as function of ϵ
 \Rightarrow Direction Derivative ≥ 0

$$x_\epsilon(T) \approx x^*(T) + \epsilon V(T) + o(\epsilon)$$

$$\underbrace{\left(\lim_{\epsilon \rightarrow 0^+} \frac{x_\epsilon(T) - x^*(T)}{\epsilon} \right)^T}_{V(T)} \nabla \underline{\Phi}(x^*(T)) \geq 0$$

$$\Leftrightarrow \underbrace{V(T)^T}_{\sim} \nabla \underline{\Phi}(x^*(T)) \geq 0$$

(*)

implicitly depends on t & s (arbitrary)

Goal: 'Push Back' $(*)$ to time t to say 'something'
about $x^*(t)$ & $\theta^*(t)$

Adjoint Equation:

Consider a linear ODE system given by

$$\dot{v}(t) = A(t) v(t)$$

Its adjoint equation is

$$\dot{p}(t) = -A(t)^T p(t)$$

$$g_t(\cdot) : \mathbb{R}^d \rightarrow \mathbb{R}^d$$

$$\begin{pmatrix} g_{t1} \\ \vdots \\ g_{td} \end{pmatrix} \quad g_{ti} : \mathbb{R}^d \rightarrow \mathbb{R}$$

Key property:

$$\frac{d}{dt} (p(t)^T v(t)) = p(t)^T \dot{v}(t) + \dot{p}(t)^T v(t)$$

$$= p(t)^T A(t) v(t) + (-A(t)^T p(t))^T v(t)$$

$$\equiv 0 \quad !!!$$

$\Rightarrow p(t)^T v(t) \equiv \text{constant with respect } t!$



→ use Adjoint equation on ; (ODE)

$$\begin{cases} \dot{v}(t) = \nabla_x f(t, x^*(t), \theta^*(t)) v(t) \\ v(T) = f(t, x^*(t), s) - f(t, x^*(t), \theta^*(t)) \end{cases}$$

we define the adjoint equation (co-state) is $\{ p^*(t) : t \in [t, T] \}$

$$\begin{cases} \dot{p}(t) = -\nabla_x f(t, x^*(t), \theta^*(t))^T p(t) \\ p^*(T) = -\nabla \Phi(x^*(T)) \end{cases}$$

$$\Rightarrow p^*(t)^T v(t) = \text{constant} = \underbrace{p^*(T)^T v(T)}_{-\nabla \Phi(x^*(T))} \leq 0$$

$$-\nabla \Phi(x^*(T))$$

holds for $\forall t \in [t, T]$.

$$\Rightarrow p^*(z)^T V(z) \leq 0 \leftarrow \text{choose } t = z$$

$$(V(z) = f(z, x^*(z), s) - f(z, x^*(z), \theta^*(z)))$$

$$\Rightarrow \boxed{p^*(z)^T f(z, x^*(z), s) \leq p^*(z)^T f(z, x^*(z), \theta^*(z))}$$

holds for a.e. $z \in [0, T]$

→ Mayer Problem Result

for all $s \in \mathbb{S}$



Transform to the Bolza Problem Version!

• Step 5: convert Back to Bolza Problem! ($L \neq 0$)

Mayer

Bolza

$$\begin{cases} \tilde{\Phi}(x) \rightarrow \bar{\Phi}(x) + x^0 \\ \tilde{p}^* \rightarrow (p^*, p^{*0}) \\ f \rightarrow (f, L) \end{cases}$$

check this term

has no relation to x^0

$$\rightarrow \begin{cases} \dot{p}^{*0} = \nabla_{x^0} L(t, x(t), \theta(t)) \equiv 0 \\ p^*(T) = -\nabla_{x^0} \tilde{\Phi}(\bar{x}) = -1 \end{cases} \Rightarrow p^{*0}(t) \equiv -1$$

$$\boxed{\text{Mayer}} \rightarrow \boxed{\text{Bolza}}$$

$$\Rightarrow \tilde{p}^* \tilde{f} \rightarrow p^*(z) f(z, x^*(z), \theta^*(z)) - L(z, x^*(z), \theta^*(z))$$

$$\Rightarrow \tilde{p}^* \tilde{f}(s) \leq \tilde{p}^* \tilde{f}(\theta^*(z))$$

$$\Leftrightarrow \boxed{H(z, x^*(z), p^*(z), \theta^*(z)) \geq H(z, x^*(z), p^*(z), s)}$$

③

For Bolza-Problem !!!

holds for a.e. $\forall z \in [0, T]$

and $\forall s \in \mathbb{S}$

#

Rmk:

PMP \rightarrow has many versions for different problems
(not just 2 then)

Bolza Problem with fixed end point & variable time
↓ previously is fixed-end-time

$$\inf_{\Theta, T} J[\Theta] = \int_0^T L(t, x(t), \Theta(t)) dt + \Phi(x(T))$$

s.t. $\dot{x}(t) = f(t, x(t), \Theta(t))$

$$x(0) = x_0$$

$$x(T) = x_f$$

Physics More!
(formulation)!

PMP: Variant

$$\dot{x}^*(t) = D_p H(t, x^*(t), p^*(t), \Theta^*(t))$$

$$\dot{p}^*(t) = -\nabla_x H(t, x^*(t), p^*(t), \Theta^*(t))$$

$$H(t, x^*(t), p^*(t), \Theta^*(t)) \geq H(t, x^*(t), p^*(t), s)$$

for $\forall t \in [0, T]$

& $\forall \theta \in \Theta$

New

$$x^*(0) = x_0$$

$$x^*(T) = x_f$$

~~Vanish!~~

since $\Phi \equiv 0$

2小節

→ Brachistochrone \Rightarrow terminal state only fixed halfly!



$$\begin{cases} u(t_i) = b \\ x(t_i) \rightarrow \text{not fixed} \end{cases}$$

Application:

piece-wise curve (example of PMP)

$$J[x] = \int_1^1 x(u)^2 (x'(u) - 1)^2 du$$

$$\min_x J[x]$$

$$\begin{cases} x(1) = 0 \\ x(1) = 1 \end{cases}$$

Calculus Variation Prob.

global minimizer (not in C^1)

$$\boxed{x^* = \begin{cases} 0, & -1 \leq t \leq 0 \\ u, & 0 < t \leq 1 \end{cases}}$$

only applied when $x \in C^1$

E-L equation is not a necessary condition

\Rightarrow Method: Reformulate into a controlled problem!

$$\min_{\theta \in \Theta} \int_{-1}^1 x(t)^2 (\theta(t) - 1)^2 dt$$

$L \rightarrow$ running cost

$\underline{\theta} = 0 \rightarrow$ no terminal cost

s.t. $\dot{x}(t) = \theta(t)$

$x(-1) = 0$

$x(1) = 1$

$\Theta = \mathbb{R}$

PMP Variation

\rightarrow Hamiltonian: $H(t, x, p, \theta) = p\theta - x^2(\theta - 1)^2$

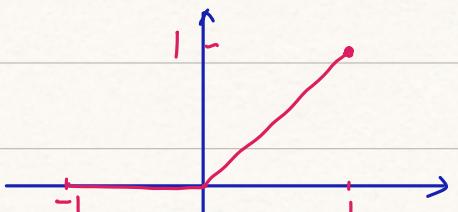
\Rightarrow apply PMP:

① $\dot{x}^*(t) = \theta^*(t)$

② $\dot{p}^*(t) = -2x^*(t)(\theta^*(t) - 1)^2 \quad x^*(-1) = 0 \quad x^*(1) = 1$

③ $\theta^*(t) \in \underset{\theta \in \Theta}{\operatorname{argmax}} \{ p^*(t)\theta - x^*(t)^2(\theta - 1)^2 \}$

The solution we found by observation is:



$$x^*(t) = \begin{cases} 0, & -1 \leq t \leq 0 \\ t, & 0 < t \leq 1 \end{cases}$$

$$\theta^*(t) = \begin{cases} 0, & -1 \leq t \leq 0 \\ 1, & 0 < t \leq 1 \end{cases} \rightarrow \text{optimal control}$$

$$\dot{p}^*(t) \equiv 0 \quad \text{from} \quad \begin{cases} x^*(t) \\ \theta^*(t) \end{cases}$$

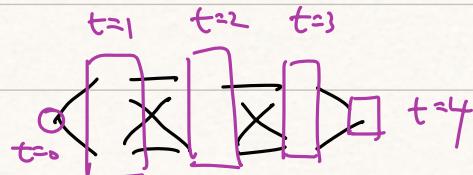
↓

$$p^*(t) \equiv \text{Constant}$$

Sufficient & Necessary Condition (Dynamic Program)

Motivation:

- ① Greedy
- ② Recursive



Goal: Maximize the final score

$$\rightarrow \text{Total # of paths} = 2^3 = 8$$

\rightarrow More generally, if we have N circles at each step

(Brute Force) and T steps

\rightarrow total # of paths N^T (exponential in T)

We can use DP to solve the problem more efficiently.

↳ Define • $X(t)$ → state of player at time (stage) t

* • Define $V(t, x) = \max_{x \in \text{time } t}$ score starting at state x (Value Function)

observe that $V(0, 1)$ → Best score we can get

DP Strategy → extend our problems

• Derive a recursion on $\{V(t, x)\}_{t, x}$

↳ solve for all t & x

↳ construct our optimal sol⁺

Q1: How to determine max score? \Rightarrow Backwards!

$$\begin{cases} v(3,2) = 3 \\ v(3,1) = -3 \end{cases} \rightarrow \begin{cases} v(2,2) = \max \{-1 + v(3,2), 4 + v(3,1)\} = 2 \\ v(2,1) = \max \{-1 + v(3,1), -2 + v(3,2)\} = 1 \end{cases}$$

↓
at time 3

↓
at time 2

$$\begin{cases} v(1,2) = \max \{2 + v(2,2), 1 + v(2,1)\} = 4 \\ v(1,1) = \max \{3 + v(2,2), 5 + v(2,1)\} = 6 \end{cases}$$

↓ at time 1

$$v(0,1) = \max \{0 + v(1,1), 1 + v(1,2)\} = 6$$

↳ Better than GREEDY

Q2: How to attain the path? (Forward)

Since we know $\{v(t,x)\}_{t,x}$

at time 0 $\rightarrow x_0 = \underset{x}{\operatorname{argmax}} \{ \text{score}(x) + v(1,x) \}$

at time 1 $\rightarrow x_1 = \underset{x}{\operatorname{argmax}} \{ \text{score}(x_0, x) + v(2,x) \}$

⋮

Punchline:

we can apply "Greedy Strategy" on $\{v(t,x)\}$ to achieve the
optimal path

Complexity $O(N^2 T)$

Brute Force $\rightarrow N^T$

→ Apply to Optimal Control thm!

↳ Define Value Func $V(t, x)$

↳ Define Recursion On $V(t, x) \leftrightarrow$ PDE

↳ Solve for $\{V(t, x)\} \rightarrow$ Greedy Search

⇒ Hamilton - Jacobi - Bellman Equation !