

APM 462 FINAL REVIEW

- ① In principle, first half material.
- (a) unconstrained minimization problems in E^n or in a subset Ω of E^n .
 - (b) convex sets/functions
 - (c) algorithms for finding minima (steepest descent etc.)
(see About midterm pdf for details)

- ② minimization problems with equality constraints.
- (a) first order conditions & Lagrange multipliers

FIRST ORDER NECESSARY CONDITION.

Let \vec{x}^* be a regular point of the constraints $\vec{h}(\vec{x}) = \vec{0}$ and a local extremum point (a minimum or maximum) of f subject to those constraints. Then all $\vec{y} \in E^n$ satisfying

$$\vec{\nabla} \vec{h}(\vec{x}^*) \vec{y} = \vec{0}$$

must also satisfy

$$\vec{\nabla} f(\vec{x}^*) \vec{y} = 0$$

- $\vec{\nabla} f(\vec{x}^*)$ is orthogonal to the tangent plane. $\Rightarrow \vec{\nabla} f(\vec{x}^*)$ is a linear combination of the gradients of \vec{h} at \vec{x}^* .

So: Thm: Let \vec{x}^* be a local extremum point of f subject to the constraints $\vec{h}(\vec{x}) = \vec{0}$. Assume further that \vec{x}^* is a regular point of these constraints. Then \exists a $\vec{\lambda} \in E^m$ such that:

$$\vec{\nabla} f(\vec{x}^*) + \vec{\lambda}^T \vec{\nabla} \vec{h}(\vec{x}^*) = \vec{0}$$

- (b) regular points, ~~tan~~ tangent spaces.

Consider all differentiable curves on S passing through a point \vec{x}^* . The tangent plane at \vec{x}^* is the collection of the derivatives at \vec{x}^* of all these differentiable curves. The tangent plane is subspace of E^n .

Def of regular point: A point \vec{x}^* satisfying the constraint $\vec{h}(\vec{x}^*) = \vec{0}$ is said to be a regular point of the constraint if the gradient vectors $\vec{\nabla} h_1(\vec{x}^*), \vec{\nabla} h_2(\vec{x}^*), \dots, \vec{\nabla} h_m(\vec{x}^*)$ are linearly independent.

Thm: At a regular point \vec{x}^* of the surface S defined by $\vec{h}(\vec{x}) = \vec{0}$ the tangent plane is equal to $M = \{ \vec{y} : \vec{\nabla} \vec{h}(\vec{x}^*) \vec{y} = \vec{0} \}$

(c). second-order conditions

SECOND-ORDER NECESSARY CONDITIONS

$f, \vec{h} \in C^2$
 Sps \vec{x}^* is a local minimum of f subject to $\vec{h}(\vec{x}) = \vec{0}$ and that \vec{x}^* is a regular point of these constraints. Then there is a $\vec{\lambda} \in E^m$ s.t.

$$\vec{\nabla} f(\vec{x}^*) + \vec{\lambda}^T \vec{\nabla} \vec{h}(\vec{x}^*) = \vec{0}$$

If we denote by M the tangent plane $M = \{ \vec{y} : \vec{\nabla} \vec{h}(\vec{x}^*) \vec{y} = \vec{0} \}$ then the matrix $\vec{L}(\vec{x}^*) = \vec{F}(\vec{x}^*) + \vec{\lambda}^T \vec{H}(\vec{x}^*)$

is positive ~~defi~~ semidefinite on M , that is, $\vec{y}^T \vec{L}(\vec{x}^*) \vec{y} \geq 0 \quad \forall \vec{y} \in M$

SECOND-ORDER SUFFICIENT CONDITIONS:

Sps $\exists \vec{x}^*$ satisfying $\vec{h}(\vec{x}^*) = \vec{0}$ & a $\vec{\lambda} \in E^m$ s.t.

$$\vec{\nabla} f(\vec{x}^*) + \vec{\lambda}^T \vec{\nabla} \vec{h}(\vec{x}^*) = \vec{0}$$

Sps also that the matrix $\vec{L}(\vec{x}^*) = \vec{F}(\vec{x}^*) + \vec{\lambda}^T \vec{H}(\vec{x}^*)$ is positive definite on $M = \{ \vec{y} : \vec{\nabla} \vec{h}(\vec{x}^*) \vec{y} = \vec{0} \}$, that is, for $\vec{y} \in M, \vec{y} \neq \vec{0}$ there holds $\vec{y}^T \vec{L}(\vec{x}^*) \vec{y} > 0$. Then \vec{x}^* is a strict local minimum of f subject to $\vec{h}(\vec{x}) = \vec{0}$.

③ minimization problems with both equality & inequality constraints.
Particularly KKT Thm.

"Mixed constraints"

Def: \vec{x}^* be a point satisfying the constraints

$$\textcircled{*} \begin{cases} \vec{h}(\vec{x}^*) = \vec{0} \\ \vec{g}(\vec{x}^*) \leq \vec{0} \end{cases}$$

and let J be the set of indices j for which $g_j(\vec{x}^*) = 0$. Then \vec{x}^* is said to be a regular point of the constraints above if the gradient vectors $\nabla h_i(\vec{x}^*)$, $\nabla g_j(\vec{x}^*)$, $1 \leq i \leq m$, $j \in J$ are linearly independent.

Karush-Kuhn-Tucker conditions:

Let \vec{x}^* be a relative minimum point for the problem

minimize $f(\vec{x})$

subject to $\vec{h}(\vec{x}) = \vec{0}$, $\vec{g}(\vec{x}) \leq \vec{0}$.

and suppose \vec{x}^* is a regular point for the constraints. Then there is a vector $\vec{\lambda} \in E^m$ and a vector $\vec{\mu} \in E^p$ with $\vec{\mu} \geq \vec{0}$ s.t.

$$\left. \begin{aligned} \nabla f(\vec{x}^*) + \vec{\lambda}^T \nabla \vec{h}(\vec{x}^*) + \vec{\mu}^T \nabla \vec{g}(\vec{x}^*) &= \vec{0} \\ \vec{\mu}^T \vec{g}(\vec{x}^*) &= \vec{0} \end{aligned} \right\} \textcircled{*}$$

SECOND-ORDER CONDITIONS

NECESSARY: Suppose the function $f, \vec{g}, \vec{h} \in C^2$ & \vec{x}^* is a regular point of the constraints $\textcircled{*}$. If \vec{x}^* is a regular minimum pt

then \exists a $\vec{\lambda} \in E^m$, $\vec{\mu} \in E^p$, $\vec{\mu} \geq \vec{0}$ s.t.

the KKT holds $\textcircled{*}$

& such that

is positive $L(\vec{x}^*) = f(\vec{x}^*) + \vec{\lambda}^T H(\vec{x}^*) + \vec{\mu}^T G(\vec{x}^*)$

semidefinite on the tangent subspace of the active constraints at \vec{x}^* .

SECOND-ORDER SUFFICIENT CONDITION:

Let $f, \vec{g}, \vec{h} \in C^2$.

a point \vec{x}^* satisfying the "mixed constraints" \textcircled{A} is a strict minimum pt of problem is that there exists $\vec{\lambda} \in E^m$, $\vec{\mu} \in E^p$ such that

$$\begin{aligned} \vec{\mu} &\geq 0 \\ \vec{\mu}^T \vec{g}(\vec{x}^*) &= 0 \\ \nabla f(\vec{x}^*) + \vec{\lambda}^T \nabla \vec{h}(\vec{x}^*) + \vec{\mu}^T \nabla \vec{g}(\vec{x}^*) &= 0 \end{aligned}$$

and the Hessian matrix

$$L(\vec{x}^*) = F(\vec{x}^*) + \vec{\lambda}^T H(\vec{x}^*) + \vec{\mu}^T G(\vec{x}^*)$$

is positive ~~semi~~ definite on the subspace

$$M = \{ \vec{y} : \nabla \vec{h}(\vec{x}^*) \vec{y} = 0, \nabla g_j(\vec{x}^*) \vec{y} = 0 \forall j \in J \}$$

where $J = \{ j : g_j(\vec{x}^*) = 0, \mu_j > 0 \}$

④ The Calculus of Variations, § 4.1.1 on notes of Evans.

Basic problem of \downarrow

Find a curve $x^*(\cdot) : [0, T] \rightarrow \mathbb{R}^n$ that minimizes the functional

~~$I[x]$~~

$$I[x(\cdot)] := \int_0^T L(x(t), x'(t)) dt$$

among all functions $x(\cdot)$ satisfying $x(0) = x^0$ and $x(T) = x^1$

§ 4.1.1 Derivation of Euler-Lagrange equations

Note: We write $L = L(x, v)$ & regard x as "position", then var v as "velocity", the partial derivatives of L are

$$\frac{\partial L}{\partial x_i} = L_{x_i}, \quad \frac{\partial L}{\partial v_i} = L_{v_i} \quad (1 \leq i \leq n)$$

& we write $\nabla_x L = (L_{x_1}, \dots, L_{x_n})$,

$$\nabla_v L = (L_{v_1}, \dots, L_{v_n})$$

Find a curve $x^*(\cdot): [0, T] \rightarrow \mathbb{R}^n$ that minimizes $I[x(\cdot)] = \int_0^T L(x(t), x'(t)) dt$ satisfying $x(0) = x^0, x(T) = x^1$

~~let~~ Write $L = L(x, v)$.

$$\frac{\partial L}{\partial x_i} = L_{x_i} \quad \frac{\partial L}{\partial v_i} = L_{v_i}$$

$$\nabla_x L = (L_{x_1}, \dots, L_{x_n}) \quad \nabla_v L = (L_{v_1}, \dots, L_{v_n})$$

Thm (E-L equations): Let $x^*(\cdot)$ solves, then $x^*(\cdot)$ solves

$$\frac{d}{dt} [\nabla_v L(x^*(t), x'^*(t))] = \nabla_x L(x^*(t), x'^*(t))$$

ith component is

$$\frac{d}{dt} [L_{v_i}(x^*(t), x'^*(t))] = L_{x_i}(x^*(t), x'^*(t))$$

select ~~any~~ curve $y[0, T] \rightarrow \mathbb{R}^n$ that $y(0) = y(T) = 0$.

$$\text{let } i(\tau) = I[x(\cdot) + \tau y(\cdot)]$$

$$\text{For } \tau \in \mathbb{R}, x(\cdot) = x^*(\cdot)$$

$x(\cdot)$ is minimizer

$$i(\tau) \geq I[x(\cdot)] = i(0)$$

$$\Rightarrow i(\cdot) \text{ has min at } \tau = 0, \text{ so } i'(0) = 0.$$

must compute $i'(\tau)$.

Note that

$$i(\tau) = \int_0^T L(x(t) + \tau y(t), x'(t) + \tau y'(t)) dt$$

$$i'(\tau) = \sum_{i=1}^n \int_0^T L_{x_i}(x(t), x'(t)) y_i(t) + L_{v_i}(x(t), x'(t)) y_i'(t) dt$$

$$y(0) = y(T) = 0$$

Integration by parts: $\int L_v(\cdot) \rightarrow y' dt = L_v(\cdot) \rightarrow y \Big|_0^T - \int \frac{d}{dt} (L_v(\cdot)) y(t) dt$

$$\text{Combine to find: } 0 = i'(0) = \int_0^T (L_x(x^*(t), x'^*(t)) - \frac{d}{dt} L_v(x^*(t), x'^*(t)) + y(t) d$$

~~is impossible if $y(t) = 0$ for all $t \in [0, T]$~~

Thm. (E-L equations):

Let $\vec{x}^*(\cdot)$ solve the calculus of variations problem, then $\vec{x}^*(\cdot)$ solves the Euler-Lagrange differential equations:

$$(E-L) \quad \frac{d}{dt} [\nabla_{\dot{x}} L(\vec{x}^*(t), \dot{\vec{x}}^*(t))] = \nabla_x L(\vec{x}^*(t), \dot{\vec{x}}^*(t))$$

(n -second-order ODE, the i th component of system reads)

$$\frac{d}{dt} [L_{\dot{x}_i}(\vec{x}^*(t), \dot{\vec{x}}^*(t))] = L_{x_i}(\vec{x}^*(t), \dot{\vec{x}}^*(t))$$

⑤ system of ordinary differential equations

$$\text{ODE has the form } \begin{cases} \dot{x}(t) = f(x(t)) & (t > 0) \\ x(0) = x^0 \end{cases}$$

initial point $x^0 \in \mathbb{R}^n$ and the function $\mathbb{R}^n \rightarrow \mathbb{R}^n$.

The unknown is the curve $x: [0, \infty) \rightarrow \mathbb{R}^n$

controlled dynamics, say f depends also upon on some "control" parameters belonging to a set $A \subset \mathbb{R}^m$, so that $f: \mathbb{R}^n \times A \rightarrow \mathbb{R}^n$. Then if we select some $a \in A$ & consider the corresponding dynamics:

$$\begin{cases} \dot{x}(t) = f(x(t), a) & (t > 0) \\ x(0) = x^0 \end{cases}$$

More generally, call a function $\alpha: [0, \infty) \rightarrow A$ is a control, corresponding to each control, we consider ODE

$$\begin{cases} \dot{x}(t) = f(x(t), \alpha(t)) & (t > 0) \\ x(0) = x^0 \end{cases}$$

and the trajectory $x(\cdot)$ is the response of the system.

Def we define the reachable set for time t to be
 $C(t)$ = set of initial ~~set~~ points x^0 for which
 there exists a control such that $x(t)=0$
 and overall reachable set

C = set of initial points x^0 for which there
 exists a control such that $x(t)=0$ for some
 finite time t .

Note that $C = \bigcup_{t \geq 0} C(t)$

Let $M^{n \times m}$ denote all $n \times m$ matrices.

$$\begin{cases} x'(t) = Mx(t) + N\alpha(t) & (t > 0) \\ x(0) = x^0 \end{cases}$$

Quick review for Linear ODE

$X(\cdot): \mathbb{R} \rightarrow M^{n \times n}$ be the unique solution of matrix ODE

$$\begin{cases} X'(t) = MX(t) & (t \in \mathbb{R}) \\ X(0) = I \end{cases}$$

We call $X(\cdot)$ a fundamental solution & some times
 write $X(t) = e^{tM} = \sum_{k=0}^{\infty} \frac{t^k M^k}{k!}$

$$\bullet X^{-1}(t) = X(-t)$$

* Thm 2.1 (Solving ~~the~~ Linear systems of ODE)

① The unique solution of homogeneous system of ODE

$$\begin{cases} x'(t) = Mx(t) \\ x(0) = x^0 \end{cases}$$

$$\text{is } x(t) = X(t)x^0 = e^{tM}x^0$$

② The unique solution of nonhomogeneous system

$$\begin{cases} x'(t) = Mx(t) + f(t) \\ x(0) = x^0 \end{cases}$$

$$\text{is } x(t) = X(t)x^0 + X(t) \int_0^t X^{-1}(s)f(s) dt$$

$$x(t) = e^{tM}x^0 + e^{tM} \int_0^t e^{-sM} N\alpha(s) ds$$

$$M = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} \quad e^{tM} = \begin{pmatrix} 1 & t \\ 0 & 1 \end{pmatrix} \quad M = \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix} \quad e^{tM} = \begin{pmatrix} \cos t & \sin t \\ -\sin t & \cos t \end{pmatrix} \quad M = \begin{pmatrix} a & 0 \\ 0 & b \end{pmatrix}$$

(6) CONTROLLABILITY OF LINEAR SYSTEMS

(a). In particular Thm 2.2, 2.3, 2.5.

$$e^{tM} = \begin{pmatrix} e^{at} & 0 \\ 0 & e^{bt} \end{pmatrix}$$

Thm 2.2. (Structure of reachable set)

(i) The reachable set C is symmetric & convex

(ii) Also, if $x^0 \in C(\bar{t})$, then $x^0 \in C(t)$ for all times $t \geq \bar{t}$.

def: (i). symmetric if $x \in S \Rightarrow -x \in S$

(ii). convex if $x, \hat{x} \in S$ & $0 \leq \lambda \leq 1$, imply $\lambda x + (1-\lambda)\hat{x} \in S$

Definition: the controllability matrix is

$$G = G(M, N) = [N, MN, M^2N, \dots, M^{n-1}N]$$

$n \times (mn) \text{ matrix}$

Thm 2.3 (CONTROLLABILITY MATRIX)

We have $\text{rank } G = n$ iff $0 \in C^0$.

Def: linear system (ODE) is controllable if $C = \mathbb{R}^n$.

Thm 2.5 (CRITERION FOR CONTROLLABILITY)

Let A be the cube $[-1, 1]^m$ in \mathbb{R}^m ,

Sp. as well $\text{rank } G = n$, and $\text{Re } \lambda \leq 0$ for each eigenvalue λ of the matrix M .

Then the system (ODE) is controllable.

(b). Bang-bang controls (Thm 2.8)

take A to be the cube $[-1, 1]^m$ in \mathbb{R}^m

Def: A control $\alpha(\cdot) \in A$ is called bang-bang if each time $t \geq 0$ & each index $i=1, \dots, m$ we have $|\alpha^i(t)| = 1$

where

$$\alpha(t) = \begin{pmatrix} \alpha^1(t) \\ \vdots \\ \alpha^m(t) \end{pmatrix}$$

Thm 2.8: Let $t > 0$, suppose $x^0 \in C(t)$, for the system

$$\dot{x}(t) = Mx(t) + N\alpha(t)$$

Then \exists a bang-bang control $\alpha(\cdot)$ which steers x^0 to 0 at time t .

⑦ LINEAR TIME-OPTIMAL CONTROL

Particularly, Pontryagin Maximum Principle.

Def: the control theory Hamiltonian is the function

$$H(x, p, a) = f(x, a) \cdot p + r(x, a) \quad (x, p \in \mathbb{R}^n, a \in A)$$

Thm: Assume $d^*(\cdot)$ is optimal for (ODE), (P) & $x^*(\cdot)$ is the corresponding trajectory.

Then \exists a function $p^*: [0, T] \rightarrow \mathbb{R}^n$ s.t.

$$(ODE) \quad x'^*(t) = \nabla_p H(x^*(t), p^*(t), d^*(t)),$$

$$(ADJ) \quad p'^*(t) = -\nabla_x H(x^*(t), p^*(t), d^*(t)),$$

&

$$(M) \quad H(x^*(t), p^*(t), d^*(t)) = \max_{a \in A} H(x^*(t), p^*(t), a) \quad (0 \leq t \leq T)$$

In addition, the mapping

$$t \mapsto H(x^*(t), p^*(t), d^*(t)) \text{ is a constant}$$

Finally, we have the terminal condition,

$$p^*(T) = \nabla g(x^*(T)).$$

$$\int_0^T e^{-\rho t} \alpha = \max_{a \in A} \left\{ \int_0^T e^{-\rho t} N a \right\} \quad (\text{Ch 3.33-35})$$

§ 3.1 Existence of time-optimal controls

$$\begin{cases} x'(t) = Mx(t) + Na(t) \\ x(0) = x^0 \end{cases}$$

Optimal time problem

given starting pt $x^0 \in \mathbb{R}^n$, wts an optimal control $d^*(\cdot)$

s.t.

$$P[d^*(\cdot)] = \max_{d(\cdot) \in A} P[d(\cdot)]$$

Then $\tau^* = -P[d^*(\cdot)]$ is the minimum time to steer to origin.

§3.2 The maximum principle for linear time-optimal control.

def: $K(t, x^0)$ be the reachable set for time t ,

$$K(t, x^0) = \{x' \mid \exists \alpha(\cdot) \in A \text{ which steers from } x^0 \text{ to } x' \text{ at time } t\}$$

Since $x(\cdot) \in \text{ODE}$, have $x' \in K(t, x^0)$ iff

$$x' = X(t)x^0 + X(t) \int_0^t X^{-1}(s) N \alpha(s) ds = x(t)$$

for some control $\alpha(\cdot) \in A$

Thm: Pontryagin Maximum principle for LTO control.

$\exists \vec{h} \neq \vec{0}$ s.t.

$$(11) \quad h^T X^{-1}(t) N \alpha^*(t) = \max_{a \in A} \{h^T X^{-1}(t) N a\}$$

for each time $t \in [0, T^*]$

Reachable set.

set of initial pts x^0 for
which \exists a control such that
 $x(t) = 0$

Practice problem minimization with equality

minimize $f(x) = \frac{1}{2}(x^2 + y^2) - z$

~~subject to $h(x) = \frac{1}{2}(y^2 + z^2) - x = 0$ and $d^T x + e = 0$.~~

~~A positive definite, b.d column vector.~~

subject to $h(x) = \frac{1}{2}(y^2 + z^2) - x = 0$

$$x - \lambda = 0$$

$$y + \lambda y = 0$$

$$-1 + \lambda z = 0$$

$$h(x, y, z) = 0$$

$$(x, y, z) =$$

$$x = \lambda = -1$$

$$\lambda = -1 \quad \frac{1}{2}(y^2 + 1) + 1 = 0$$

$$z = \frac{1}{-1} = -1$$

Impossible!

So $y = 0$,

$$\frac{1}{2}z^2 - x = 0 \quad x = \lambda, \quad z = \frac{1}{\lambda}$$

$$\frac{1}{2} \cdot \frac{1}{\lambda^2} - \lambda = 0$$

$$\lambda \cdot 2\lambda^2 = 1$$

$$2\lambda^3 = 1$$

$$\lambda^3 = \frac{1}{2}$$

$$\text{So } \vec{x} = (\quad, \quad), \lambda = 0.$$

minimization with inequality constraints

$$\begin{aligned} \min f(x) &= x^2 + 2y^2 + z^2 \\ \text{subject to } g(x) &= x + 3y \geq 5 \end{aligned}$$

$$\Rightarrow \cancel{g(x)} \quad g_0(x) = -x - 3y + 5 \leq 0$$

~~$$2x - \mu = 0$$~~

~~$$4y - 3\mu = 0$$~~

~~$$2z = 0$$~~

$$\mu \geq 0$$

~~$$2x - \mu = 0$$~~

$$2x - \mu = 0$$

$$4y - 3\mu = 0$$

$$2z = 0$$

$$\mu(-x - 3y + 5) = 0$$

$$\Rightarrow x = \frac{\mu}{2}$$

$$\Rightarrow y = \frac{3}{4}\mu$$

$$\Rightarrow z = 0$$

$$\left(-\frac{\mu}{2} - \frac{9}{4}\mu + 5\right) \mu = 0$$

$$\mu = 0 \text{ or } -\frac{11}{4}\mu + 5 = 0$$

$$\mu = 5 \times \frac{4}{11} = \frac{20}{11}$$

$$\min f(x) = x^2 + 2y^2 + z^2$$

$$\begin{aligned} \text{subject to } h(x) &= x + 2y + z = 5 \\ g(x) &= x + 3y \geq 5 \end{aligned}$$

$$\Rightarrow \begin{aligned} h(x) &= x + 2y + z - 5 = 0 \\ g(x) &= -x - 3y + 5 \leq 0 \end{aligned}$$

$$2x + \lambda - \mu = 0$$

$$4y + 2\lambda - 3\mu = 0$$

$$2z + \lambda = 0$$

$$\lambda \geq 0, \mu \geq 0$$

$$x + 2y + z - 5 = 0$$

$$\mu(-x - 3y + 5) = 0$$

$$x = \frac{\mu - \lambda}{2}$$

$$y = \frac{3\mu - 2\lambda}{4}$$

$$\Rightarrow z = -\frac{1}{2}\lambda$$

$$\frac{\mu - \lambda}{2} + \frac{3\mu - 2\lambda}{2} - \frac{1}{2}\lambda = 5$$

$$\left(-\frac{\mu - \lambda}{2} - \frac{3(3\mu - 2\lambda)}{4} + 5\right) \mu = 0$$

Second order conditions for constrained minimization problems.

$$\min f(x, y, z) = \frac{1}{2}(x^2 + y^2 - z^2)$$

$$\text{Subject to } h(x) = x + 2y + 3z - 4 = 0.$$

$$x + \lambda = 0 \Rightarrow x = -\lambda$$

$$y + 2\lambda = 0 \Rightarrow y = -2\lambda$$

$$-z + 3\lambda = 0 \Rightarrow z = 3\lambda$$

$$\lambda \geq 0$$

$$x + 2y + 3z = 4 \Rightarrow -\lambda - 4\lambda + 9\lambda = 4\lambda = 4 \Rightarrow \lambda = 1$$

~~→~~

$$\text{so, } \vec{x}(x, y, z) = (-1, -2, 3), \lambda = 1.$$

Check:

Whether $L(x) = F(x) + \lambda^T H(x)$ is positive ^{semi} definite
 $= \nabla^2 f(x) + \lambda \nabla^2 h(x)$

$$= \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \end{pmatrix} + 1 \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \end{pmatrix}$$

Check this with a vector on tangent space plane.

Step ① Choose basis

$$\text{so } \nabla h(x) \cdot \vec{V} = 0$$

$$1v_1 + 2v_2 + 3v_3 = 0.$$

$$\vec{V}_1 = (2, -1, 0)$$

$$\vec{V}_2 = (3, 0, -1)$$

~~check~~ better

Step ② Write 2x2 matrix

whose entry i, j is $\vec{V}_i^T M \vec{V}_j$

$$\begin{pmatrix} 5 & 6 \\ 6 & 10 \end{pmatrix}$$

positive definite

✓

so local min

$$\vec{V}_1^T M \vec{V}_1 = (2, -1, 0) \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \end{pmatrix} \begin{pmatrix} 2 \\ -1 \\ 0 \end{pmatrix} = \begin{pmatrix} 2 \\ -1 \\ 0 \end{pmatrix} \begin{pmatrix} 2 & -1 & 0 \end{pmatrix} = 5$$

$$\vec{V}_1^T M \vec{V}_2 = (2, -1, 0) \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \end{pmatrix} \begin{pmatrix} 3 \\ 0 \\ -1 \end{pmatrix} = \begin{pmatrix} 2 & -1 & 0 \end{pmatrix} \begin{pmatrix} 3 \\ 0 \\ -1 \end{pmatrix} = 6$$

$$\vec{V}_2^T M \vec{V}_2 = (3, 0, -1) \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \end{pmatrix} \begin{pmatrix} 3 \\ 0 \\ -1 \end{pmatrix} = \begin{pmatrix} 3 \\ 0 \\ -1 \end{pmatrix} \begin{pmatrix} 3 & 0 & -1 \end{pmatrix} = 10$$

Calculus of variations.

Find a function $x(\cdot)$ that minimizes

$$I[x(\cdot)] = \frac{1}{2} \int_0^1 (x'(t) - t^2)^2 \text{ in the set } A = \{x(\cdot) \in C^1([0,1]) : x(0)=0, x(1)=0\}$$

~~Let~~ Sps: $y^* \min I[x(\cdot)]$

$$T(s) = I[y^*(\cdot) + sz(\cdot)] \geq I[y^*(\cdot)] = i(0)$$

$$i'(0) = 0$$

$$T(s) = \frac{1}{2} \int_0^1 (y' + \cancel{sz'} - t^2)^2 dt = \frac{1}{2} \int_0^1 [sz' + (y' - t^2)]^2 dt$$

$$= \frac{1}{2} \int_0^1 [s^2 z'^2 + 2sz'(y' - t^2) + (y' - t^2)^2] dt$$

$$\frac{d}{ds} T(s) = \frac{1}{2} \int_0^1 \cancel{2sz'} + 2z'(y' - t^2) dt$$

$$= \int_0^1 s z'^2 + z'(y' - t^2) dt$$

$$\text{So } T'(0) = \int_0^1 z'(y' - t^2) dt = 0$$

Also $y + sz$ satisfies constraints

& $y(0) = y(1) = 0$ since optimality

$$y(0) + sz(0) = y(1) + sz(1) = 0$$

$$\Rightarrow z(0) = z(1) = 0$$

$$\int_0^1 z'(y' - t^2) dt = 0$$

Systems of ODE & matrix exponentials.

$$M = \begin{pmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} \quad (a) \quad e^{tM} = ?$$

$$M^2 = \begin{pmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$M^3 = \begin{pmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$M^4 = \begin{pmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} = I$$

$$\text{so } M^{j+4k} = M^j \quad \forall k \text{ \& } j \in \{0, 1, 2, 3\}$$

Then $e^{tM} = \begin{pmatrix} \cos t & \sin t & 0 \\ -\sin t & \cos t & 0 \\ 0 & 0 & e^t \end{pmatrix}$

$$M = \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix} \Rightarrow e^{tM} = \begin{pmatrix} \cos t & \sin t \\ -\sin t & \cos t \end{pmatrix}$$

$$M = \begin{pmatrix} a & 0 \\ 0 & b \end{pmatrix} \Rightarrow e^{tM} = \begin{pmatrix} e^{at} & 0 \\ 0 & e^{bt} \end{pmatrix}$$

b. Write down a formula for solution of $\frac{d}{dt} x(t) = Mx(t) + \begin{pmatrix} 0 \\ 0 \\ \alpha(t) \end{pmatrix}$

$$\text{sps } x(0) = x^0$$

$$\text{general solution is } x(t) = e^{tM} x^0 + e^{tM} \int_0^t e^{-sM} \begin{pmatrix} 0 \\ 0 \\ \alpha(s) \end{pmatrix} ds$$

Note: $e^{tM} = \sum \frac{t^k M^k}{k!} \quad M = \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix}$

$$= I \left(1 - \frac{t^2}{2!} + \frac{t^4}{4!} - \frac{t^6}{6!} + \dots \right) - M \left(t - \frac{t^3}{3!} + \frac{t^5}{5!} - \dots \right)$$

$$= \cos t I - \sin t M$$

$$= \begin{pmatrix} \cos t & \sin t \\ -\sin t & \cos t \end{pmatrix}$$

$$e^{tM} = I + M + \frac{(tM)^2}{2!} + \frac{(tM)^3}{3!} + \dots$$

Controllability:

Consider equation

$$\frac{d}{dt}x(t) = Mx(t) + Na(t), \quad a(t) \in [-1, 1] \text{ for all } t.$$

where $M = \begin{pmatrix} 0 & \frac{1}{2} & 0 & 3 & 0 \\ 0 & 2 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 3 \end{pmatrix}$ $N = \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}$ or $N = \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 1 \end{pmatrix}$

For every $k=0, 1, \dots$, $M^k N$ has the form $\begin{pmatrix} \vdots \\ 0 \end{pmatrix}$

So the controllability matrix G has the form $G = [N, MN, \dots, M^4 N] = \begin{pmatrix} \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}$

$\text{rank } G = 4 \neq 5$ so not controllable

Pontryagin Max Principle.

! Sps $a^*(\cdot)$ is an optimal control, steering the system of equations from x^0 to the origin in the minimum possible time.

What can we deduce ~~from~~ $a^*(t)$ from PMP?
about

• $\frac{d}{dt}x(t) = Mx(t) + Na(t), \quad a(t) \in [-1, 1] \text{ for all } t.$

$$M = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{pmatrix} \quad N = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$$

• Says that $\exists h = (h_1, h_2, h_3)^T$ s.t.

$$h^T e^{-tM} Na(t) = \left(\frac{1}{2}h_1 t^2 + h_2 t + h_3\right) a(t) = \max_{|a| \leq 1} \left(h^T e^{-tM} N a\right)$$

$$= \max_{|a| \leq 1} \left(\frac{1}{2}h_1 t^2 + h_2 t + h_3\right) a$$

$$\Rightarrow a(t) = \max_{|a| \leq 1} \text{sign}\left(\frac{1}{2}h_1 t^2 + h_2 t + h_3\right)$$

So $a(t) = \pm 1 \quad \forall t$ That is not a root of poly $\frac{1}{2}h_1 t^2 + h_2 t + h_3$
change sign we t is a root, (at most twice)

• Another e.g.

$$\frac{d}{dt} x_1(t) = x_2(t) + u_1(t)$$

$$\frac{d}{dt} x_2(t) = -x_1(t) + u_2(t)$$

$$\text{with } u_1^2(t) + u_2^2(t) \leq 1 \quad \forall t.$$

a. What can be deduced?

~~take~~ the constraint is unusual,

$$\text{rewrite } \frac{d}{dt} x(t) = Mx(t) + Nu(t), \quad u_1^2(t) + u_2^2(t) \leq 1 \quad \forall t$$

$$M = \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix} \quad N = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

it's easy to check the system is controllable.

$$\text{PMP says exists a vector } h = \begin{pmatrix} h_1 \\ h_2 \end{pmatrix} \text{ s.t. } \forall t \in [0, \tau^*] \\ h^T e^{-tM} N u(t) = \max_{\{a: a_1^2 + a_2^2 \leq 1\}} h^T e^{-tM} N a$$

N is identity

$$\text{i.e., } h^T e^{-tM} u(t) = \max_{\{a\}} h^T e^{-tM} a$$

$$\Rightarrow (e^{+tM} h)^T u(t) = \max (e^{+tM} h)^T a$$

$$\text{max occurs when } a = \frac{e^{+tM} h}{|e^{+tM} h|}, \text{ in fact equal to } e^{+tM} \frac{h}{|h|}$$

$$\Rightarrow \forall t \in [0, \tau^*], \quad u(t) = e^{+tM} \tilde{h} \quad \text{where } \tilde{h} = \frac{h}{|h|}$$

b. What's optimal control? could figure out without PMP?

$$\text{Note } x(t) = e^{tM} x^0 + e^{tM} \int_0^t e^{-sM} d(s) ds$$

substitute what
we know about $d(t)$ into \uparrow

$$\begin{aligned} &= e^{tM} \left[x^0 + \int_0^t e^{-sM} e^{sM} \tilde{h} \right] \\ &= e^{tM} [x^0 + t\tilde{h}] \end{aligned}$$

How to quickly make this 0?

$$\tilde{h} = \frac{-x^0}{|x^0|}$$

$$\text{Then } x(t) = e^{tM} \left[\left(1 - \frac{t}{|x^0|}\right) x^0 \right] = \left(1 - \frac{t}{|x^0|}\right) e^{tM} x^0$$

$$d(t) = -\frac{1}{|x^0|} e^{tM} x^0 = -\frac{x(t)}{|x(t)|}$$