

① Update in grading policy:

better. →

①	Draft	5	lowest	HW.
②	@ Better	mid term :	30%	, Final 50%
③	Each	mid term :	20%	, final 40%
④				Final 80%

Midterm 2 : " in class (at Home!) of an book, open notes

Scanning :
Android : Adobe Scan
iPhone : Notes app / Cam Scanner
(Scanner Pro \$4).

Math: Lagrange multipliers (constrained optimization).

Need to know first ① Manifolds:

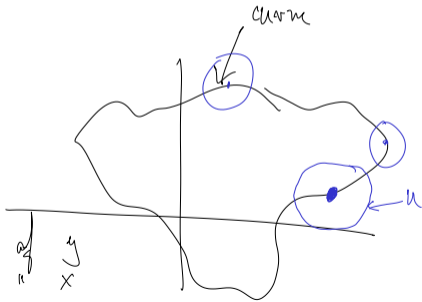
② 1 dim manifold \rightarrow curves

Curve in \mathbb{R}^2 :

$\Gamma \subseteq \mathbb{R}^2$ is a C^1 curve if

$\forall a \in \Gamma, \exists$ an open set $U \ni$

on $\Gamma \cap U$, either x is a C^1 fn of y
or y is a C^1 fn of x



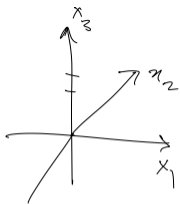
(b) Curve in \mathbb{R}^3 : $\Gamma \subseteq \mathbb{R}^3$ (x_1, x_2, x_3) .

$\forall a \in \Gamma$, $\exists U \ni a$ on $\Gamma \cap U$ either

① x_1, x_2 are C^1 fns of x_3

OR ② x_1, x_3 " " " " x_2

OR ③ x_2, x_3 " " " " x_1



(b) We say $\Gamma \subseteq \mathbb{R}^n$ is a surface if
 $\forall a \in \Gamma$, $\exists U$ open such that on $U \cap \Gamma$
 $\exists 2$ coordinates, x_i & x_j ∇ on $U \cap \Gamma$ all other coordinates are
 C^1 fns of x_i & x_j ∇ (i.e. x_3, \dots, x_n are C^1 fns of x_1, x_2
or x_2, x_4, \dots, x_n " " " " etc.) ∇ x_1, x_3
etc.).

(c) $M \subset \mathbb{R}^n$ is a d -dimensional manifold if
 $\forall a \in M, \exists U \subset \mathbb{R}^n$ open & d -coordinates
 $x_{i_1}, x_{i_2}, \dots, x_{i_d}$ on $U \cap M$ the remaining $n-d$
 coordinates are C^1 func of x_{i_1}, \dots, x_{i_d} .

Prime examples: $f: \mathbb{R}^{n+d} \rightarrow \mathbb{R}^n$ is C^1 .
 $c \in \mathbb{R}^n$.

Let $M = \{f = c\}$. Assume $\forall x \in M, \text{Rank}(Df_x) = n$.
 Then by the implicit fn theorem M is a d -dim manifold.

Need: If $a \in M$, Then Tgt space of M at a is $\text{Ker}(Df_a)$

Lagrange multipliers: Maximise a fun f given the constraint $g=0$

$$f: \mathbb{R}^d \rightarrow \mathbb{R}, \quad C^1$$

$$g: \mathbb{R}^d \rightarrow \mathbb{R}^m, \quad \boxed{\{g=0\}} \text{ is (typically) } d-n \text{ dim manifold.}$$

Condition: at a local constrained max/min.
 $\exists \lambda_1, \dots, \lambda_n + \nabla f(a) = \sum_{i=1}^n \lambda_i \nabla g_i(a)$