Math 801 B107 7-Sept-11

Tuesdays for labs Amir Assadi

Distinguished guest lectures + "master class"
+ ongoing mentorship potentials

Peter Buehler
1st year, grad
neuroscien

F
learning
dis

avash (Assadi std.)
EB Sys Bio
HPC

Hamisha
med engr

Usne? 1st yr grad.
Turkey

Wu Kai 6th yr
numeric

Cheon 6th yr
dy

James ugrad
math & pn

Misha
2nd yr PhD
HPC

Beth
3rd yr

Majid
Physics major

Adel
2nd yr grad
sysb

Ali Reza
EE

Hasin
arch
neurosic

Hesam
3rd yr math
Assadi std.

Olive EB

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gee

genotype — phenotype

1 per individual
& different from
1 to another

variations →

~~everything that is the manifestation of genotype~~
- shapes
- behaviors

quantifying phenotypic variation
1/2 stat, environd

G/Ph variation Case Studies from Plant Bio.

look @ morphology & morphical variation

Charles Darwin The Movements of Plants

Plants have highly orchestrated growth responses

our problems in this course involve huge state space
and massive data sets

we will try to understand the development of the curve

study of variation manifested in mathematical structures

slide ≡ Hyperbolic Invariants of Stochastic Dynamic Networks

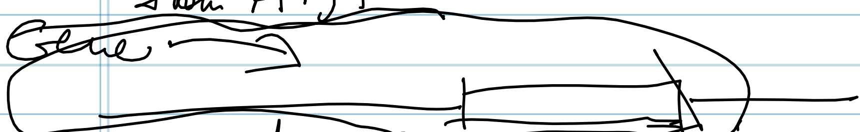
if two prob. density functions are "similar"

then the nearness Kullback-Leibler Divergence

~~Nobutaka will take over~~
Mitsuda
光田展隆 ~~Comprehensive Study of plant~~
transcription factors

~~from AIST~~

Gene



promoter
"
regulatory region

coding region

mRNA

proteins that
turn genes on/off
"TF"

bind to promoter region
& start decoding w/
partic. protein.

arabidopsis is a model organism $\boxed{\text{2000 TFs regulate 27,000 genes}}$

TFs a great target for genetic manipulation since 2K TFs regulate 27K genes

methods exist to enhance or suppress particular TFs

└ gene silencing

CRES-T is Chemeric REpressor Gene Silencing Technology
(6 amino acid sequence)

investigated function of all TFs in arabidopsis

see Fiore DB   www.cres-t.org/fiore/public_db

Math 801 Bio – Math – Bio & PCA 9-12-2011

AA presentation

Look @ examples starting w concrete & that's impossible
trick is to find probs solvable for us
w/out loosing the bio context
try broadening the question
you will be forced to go up to coarser scale

generic Q Is a particular behavior/function "programmed" w/ {specific/set elements under study} or is more than that set needed?

How can mathematical aspects of prob that can be formalized.
~~find algorithm~~

~~strategy~~ formulating a "doable" piece of research related to a "challenge" is the most creative part of the research.

perturb Ω with an environmental stimulus

?, for Wed: How do you formulate the problem of variation in bio subject / in plane curve that approximates response to gravity in short time & what happens in longer intervals of time.

~ PCA ~

9/12 4:35

Simplest of tools but one of most powerful

uses linear algebra — you can replace differential calculus w PCA; replace non-linear w linear

matrices

eigenvalues

uses SVD still about diagonalizing a matrix

PCA reduces dimensionality in high dim. data

Here's how AA would think about our assigned prob of variation

since many things can happen start w lots of identical K (roots) $r_1, \dots, r_K$

Bio fact: only root tip grows. Growth happens for at most time interval t_{int}, then stops. @ cellular level

start w $L(t_0)$ identical for all from fixed point in (A) upper root to growth (B) tip.

Vert position $= L(t)\big|_{t_0} = L_0 > 0$

$L(t)$ increases @ tip.

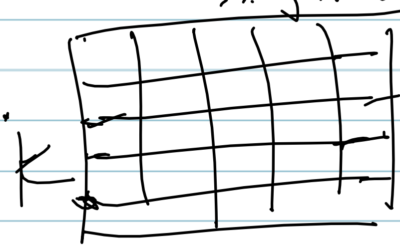
$B(t)$ is just the vert pos. of tip over time: image the tip.

(Knowing $B(t)$ stretches for a while, then fixes

imaging data set D: $B_1(t), \dots, B_K(t)$ $t = t_0, t_1, \dots t_K$

$\dots j \dots m$

Growth matrix:



call $r_{n,m}(t)$ = value of B at time k for plant m

$G \in \mathbb{R}^{K \times m}$

works on that

PCA, cont.

9/12/11

what can we say from the data in the matrix

what is best 1-dim. approx to the data.

$R^n \xrightarrow{W} R^m \quad m \ll n$

$\boxed{\text{eye research institute talk}}$

$x \xrightarrow{W} y$

$\hat{x} \xleftarrow{G} y \quad G = \text{inclusion}$

reconstruction error $\vec{\varepsilon}$

$\rho(xWG) = \|x - \hat{x}\|$

find a line K in $\mathbb{R}^k$ such that m points in K can be selected $\{Q_1, Q_2, \ldots Q_m\}$ ... such that ~~...~~ condition P holds

Keep P variable

1 case "P" av. reconstr. error smallest
"P" total rec. error smallest
"P" total " " in Sobolev norm

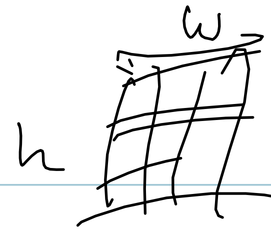
$\vec{B}_j = \vec{Q}_j + \vec{\varepsilon}_j$

$$\varepsilon_{avg} = \frac{1}{m}\sum_{j=1}^{m} \|\varepsilon_j\| \quad \frac{1}{m}\sum_{j=1}^{m} \|\vec{B}_j\|^2 = \vec{Q}_j + \vec{\varepsilon}_j$$

to minimize variance of ε.
maximize variance of approximation.

shift origin of vector space to centroid of data points

9/14/11



plant data in matlab.

find best line L that provides least sq error

$\mathbb{R}^H \longrightarrow L$

Columns

columns of A $\quad D = \{c_1, c_2, \dots c_w\} \subset \mathbb{R}^H$

matrix from image

$$(\text{mean error})^2 = \frac{1}{\#D}\sum_j \|\epsilon_j\|^2$$

Theorem: suppose mean$\{D\} = 0$ & L is a line in $\mathbb{R}^H$ such that

$$\frac{1}{\#D}\sum_j \|\epsilon_j\|^2 \text{ is minimum,}$$

then direction vector L is the ~~1st~~ eigenvector of the matrix $K = AA^T$ corresponding to the largest eigenvalue.

9/19/11

if $\boxed{K = AA^T}$, K is symmetric ~~because~~

$K^T = (AA^T)^T = AA^T = K$

and ~~positive~~ ~~semi~~definite ($\Rightarrow$ eigvals ≥ 0)

$Kv = \lambda v$ $\langle AA^T v, v\rangle$

or strong..

$\boxed{K = AA^T \text{ is the correlation matrix}}$

look @ $(A^T A)u = \lambda u$; then $\lambda \geq 0$
eigenvalue

dim of ~~large~~ eigenvector dim $v_i = n$
(A principal value

Algorithm for finding λ_1, v_1
for large matrices

eigenvalue $A \sim \det(xI - A) = f(x)$
roots of $f(x)$ are eigenvalues

doesn't work for large matrices

~~choose randomly a vector X, length 1~~

$X_0 = X$, $X_1 = (KX_0)\frac{1}{\|KX_0\|}$ ... $X_{r+1} = (KX_r)\frac{1}{\|KX_r\|}$

$\|\varepsilon_r\| = \|KX_r - a_r X_r\|$

(*) for suitable choice of sequence $a_0, a_1, \ldots a_r$

$\|\varepsilon_r\| \to 0$; so $KX_r \xrightarrow[r]{} a_r X_r$ — approx of principal vector v_1
approx of λ_1

9/14/11

goal is to control error
by ~~fixing~~ it change in angle gets you
criterion for convergence.

~~get size of~~ ~~all~~ 3 matrix

we want the mean of the columns

~~by~~ B61 = 171 x 931
r x c

do this for ourselves,

help eig

use syntax, find eig of (AA')
λ_1 = find max of eig(AA')
find v_1 from eig output corresponding to λ_1
to v_1
maybe matlab orders least to most?
make mean of columns = 0

Then
Project columns of A onto L

$A(:,j) * v'_{max}$

dot product

$A * V_{max} = Q$ where
columns are data projected
on L.
check: mean(Q) = 0
what is var Q? should be λ_1^2
if so, it's done right

compare eigvec, eigval
for 3 matrices
choose a window of width(y)
+ get eig v's
for each strip,
plot

look for PCA of a spread gives you a tangent line
a perpendicular derivative

Math 801 19-Sept-2011

Motivation: Minimize Reconstruction error

100+ frame tiff movie of growing root.

Quantify (Morphological) variation = Root Gravitropism

seeds from a single plant ⟹ seeds all have same genotype

but there are phenotypic morphological variation

Basic Problem: how to quantify variation in growth of root going down vertically

What we're looking @ now is 90° rotated rootling to assess effect of Δ gravitational field.

Superposition of images at time $t = t_r$ (time of rotation)

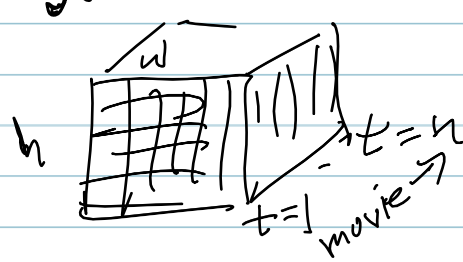
a certain space is covered.

$\vec{X}(t)$ = image of fixed size, $h \times w$.
pixels of matrix of size $h \times w$

Grey scale image will be in
$X(t) \in \mathbb{R}^{h \times w}$

area of tip gets stretched and the center of segment moved down

$X_{ij}(t) \in \mathbb{R}$ $\quad X_{ij}(t)$ where $t = \{t_0, t_1, t_2, \dots, t_m\}$



background is not significant
why?

transform arrays i.e.

300 frames × 2 mb
$X \in \mathbb{R}^{10^8 \times 6}$ $\quad D \subset \mathbb{R}^{6 \cdot 10^8}$ $\quad x_{ij}(t) = 0$ if $x_{ij}(t)$ = not plant root itself

× 1000 seedlings $= 1{,}000$

Problem (partially formulated)

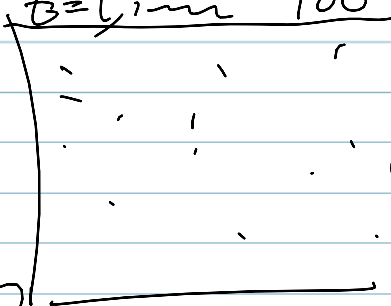
find a "parameter space" $S \subset \mathbb{R}^d$, (d small)

$S \approx \{ \vec{v} = (v_1, \dots, v_d) \; a_j \leq v_j \leq b_j, \; j = 1, \dots, d \}$

$S \sim \langle a_1, b_1, n \rangle \times \dots \langle a_d, b_d \rangle$

want to find points 1 per frame, per movie (1000)
every frame corresponds to a point
in this euclidean space

$t = 1, \dots, 100$



X_t

reduce dimension $d \ni$ points
in that space will have
enough info to reconstruct
the image or capture quantified
variation of morphology

1 way: find $\mathbb{R}^D \longrightarrow \mathbb{R}^d$

$\mathcal{D} \longrightarrow S$ (300K points in S)

it's linear so many things
are preserved in this
projection mapping

find subspace $W \subset \mathbb{R}^D \ni$ dim $W = d$
smallest d W minimum reconstruction error

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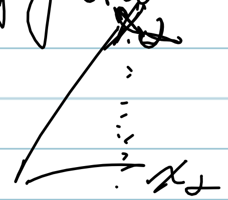
projection $\sum_\alpha |x_\alpha|^2 = \sum |x_\alpha|^2 + (\varepsilon^\alpha)^2$



$\varepsilon \downarrow 0 \Leftrightarrow$ variance of $\mathcal{D}$ goes up
since total variation
is their sum

vector $X^\alpha \in \mathbb{R}^{10^5 \times 6}$

= covariance matrix size (600m × 600m) imaging $A \cdot A^T \in \mathbb{R}^{(600m)^2}$

$K = A \cdot A^T$ is square, symmetric, pos $\Rightarrow \geq 0$

$\lambda_1 \geq \lambda_2 \geq \lambda_3 \cdots \geq \lambda_N$

look @ movie as a vector : 1000 values

$$A^T \cdot A = C \in \mathbb{R}^{1000 \times 1000}$$

Theorem: non-zero eigenvalues of $A \cdot A^T$ are same as " " of $A^T A$ corrected ~~wrong~~ ~~find~~ ~~correct theorem~~

Cond: let $\lambda_1 \cdots \lambda_{1000}$. { same eigs.

the non-zero eigvals $\{u_1 \cdots u_{1000}\}$ B eigenbasis ? orthonormal i.e. eigenvector

$W = \text{span}\{u_1 \cdots u_{1000}\} \subset \mathbb{R}^D$

we define $p : \mathbb{R}^D \to \mathbb{R}^d$

$U = (u_1 \cdots u_d) \in \mathbb{R}^{D \times d}$ rows are movies

look @ $U(A \cdot A^T)U^t =$

$$[U \vdots U_0] A \cdot A^T \begin{bmatrix} U^T \\ \hline U_0 \end{bmatrix}$$

corresp to 0 eigenvalues a block

U_0 corresp to columns of kernel of K

U corresp to image K

matrix $K \in \mathbb{R}^{D \times D}$

$\{x \in \mathbb{R}^D \mid Kx = 0\} = \text{kernel}(K) \subset \mathbb{R}^D$ Ker

$\{y \mid y = Kx \text{ for some } x\} = \text{Im}(K) \subset \mathbb{R}^D$

pick up & return to $\mathbb{R}^D$

then look for orthogonal vectors to $\text{Im}(K)$

Im & Ker make basis that corresp to pixels $u_1 \cdots u_d$ where there is a single 1 all others

19-Sep

so projection ~~from~~ $p: \mathbb{R}^D \to \mathbb{R}^d$

$$X \sum_{k=1}^{d} c_k u_k + \sum_{k=d+1}^{D} c_k U_k^{\perp}$$

$$p(X) = \sum_{k=1}^{d} c_k U_k$$ is a superposition of $c_k U_k$ vectors

c_k is a scale

U_k is a movie in pixel coord.

Matlab has tools to do these things

every eigenvector is a movie only brightness changes so we can have a 1000×1000 where each point is one growth

Biological problem is to dynamics of growth: genes $\{\gamma_1, \ldots, \gamma\}$ in DNA is expressed in certain ways that creates diff in shape.

this remains unsolved @ this point

Concl: We can quantify w/out loss; error of reconst = 0 the variation in morphology + dynamics in any imaging experiment

A priori: the larger the n of trials (movies), the bigger is d (not great!)

1 plant gave us these 1000 movies. 1 genome

so ~~losses~~ abandon 0 reconstruction error condition to approach the biological problem solutions

Improve $X = \sum_{k=1}^{d} c_k u_k + \sum_{k=d+1}^{D} c_k u_k^{\perp}$

do another projection from d to δ

so new p is $\mathbb{R}^D \to \mathbb{R}^d \to \mathbb{R}^\delta$

means cutting off some non zero eigenvalues

so we accept the error $\varepsilon(X) \sum_{k=\delta+1}^{d} c_k^2$ for a single vector

lets look @ average error $= \frac{1}{N}\sum_{\alpha=1}^{N} \varepsilon(X^\alpha) =$ msq. error

SVD

$\lambda_1 = \text{eig}_1(AA^T) =$ var proj of D onto line L | $L = \text{span}\{u_1\}$

so total variance will be sum of var for λ_1 to λ_d

$\frac{\lambda_1}{\lambda_2 \cdots + \lambda_d} =$ percentage of variation carried by L_1

var proj span $\{u_1, \dots u_\delta\} =$ Var proj $\{u_1 \cdots u_d\}$ − var proj $\{u_{\delta+1} \cdots u_d\}$

The mean approx error gives you an overall

minus

If you are looking for outliers, ~~look for~~ search algorithm for larger than avg reconstruction are the outliers

still ~~...~~ LSE can be compared to ?, will see that they are two sides of same coin

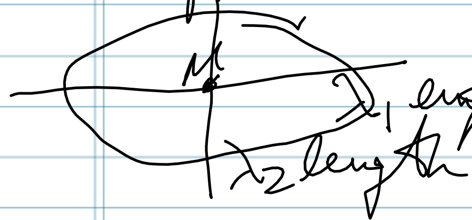
find the level of error that can be tolerated -

- ...it's tailored ~~...~~ personalized

Math 801 21-Sept. 11

~~Rxx~~ Arash did the sample code
prior knowledge of pdf
or histogram of discrete pdf — an approx.
don't get stopped by too huge data sets are complicated

whole data set → global properties
sample data set → "local" as subsets
or topological



$$\left| \frac{\lambda_1}{\lambda_1+\lambda_2} - \frac{\lambda_1^A}{\lambda_1^A+\lambda_2^A} \right| \downarrow 0$$ as sample size grows

objective function
criterion for stopping
another
$KL(f^A \| f^B) \downarrow 0$ measure of information
from stochastic analysis

projection duality vis-a-vis sampling

$S \xrightarrow{\text{injection}} D \xrightarrow{\lambda} W$ requires to replace basic set theory ZF
dual of surjection

Category C {(obj) (morphism)} that satisfy certain axioms
just symbols syntactically — arrows

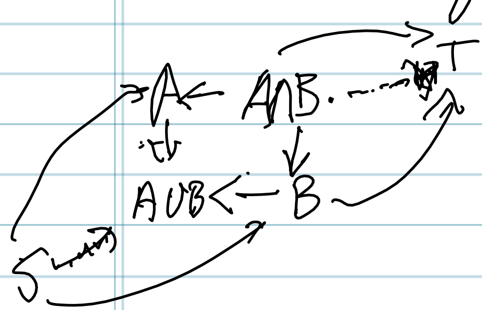
given A, B & C w $A \to B$ & $B \to C$
there is a unique morphism h that ~~xxx~~ ~~xxxx~~ (maps) $A \to C$
2nd axiom: every obj has $A \xrightarrow{I} A$
I — not necessarily I —

?,

9/21/11

dualities in category theory involve reversing arrows

in set theory



$A \partial B$ $A \cap B$

$A \cup B$

all useful in Bio Sci but they don't use this vocabulary.

large data sets that are not normal

then use topology which provides ways to deal w mins + maxs

Look @ Category theory (Cat theory for Computation)

Math 801 — 26-Sept

guest lectures

Adel: nat lang analy

Chimeric REpressor gene Silencing Tech: CRES-T

even w gene redundancy for protein,
The CRES-T approach block action of transcription factor & display expression of underlying gene

phenotypes induced by chimera repressor are dominant

arabidopsis ~2K transcription factors to study systematically.

Jernej Tonejc   U of Ljubljana, Slovenia

Analyzing growth of roots

automatic classification of phenotypes

focus on arabidopsis thaliana

focus on root midline extraction & properties of that

rotation

$$\overbrace{M = U \Sigma V^*}^{m \times n}$$

diag. scaling matrix

singular vectors = cols of U & V

related to MM^* & M^*M

eigenvectors

matrix & the maps

singular values are semiaxes of an ellipsoid

26 Sept

basic algorithm

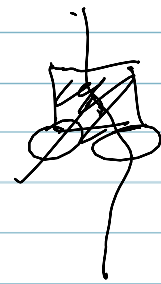
1) locate root start
set initial window size
2D SVD on window gen. an ellipse
1st PC is direction of growth
2nd value is width of root sets the window size
repeat

end up w 2x2 matrix
we scan is good enough

stop when $\sigma_1 \approx \sigma_2$ approaches
control max deviation from previous directio

better to recenter window after each cycle

detecting branching: gets intensely
block the branch base



Math 801 24-Sept-11

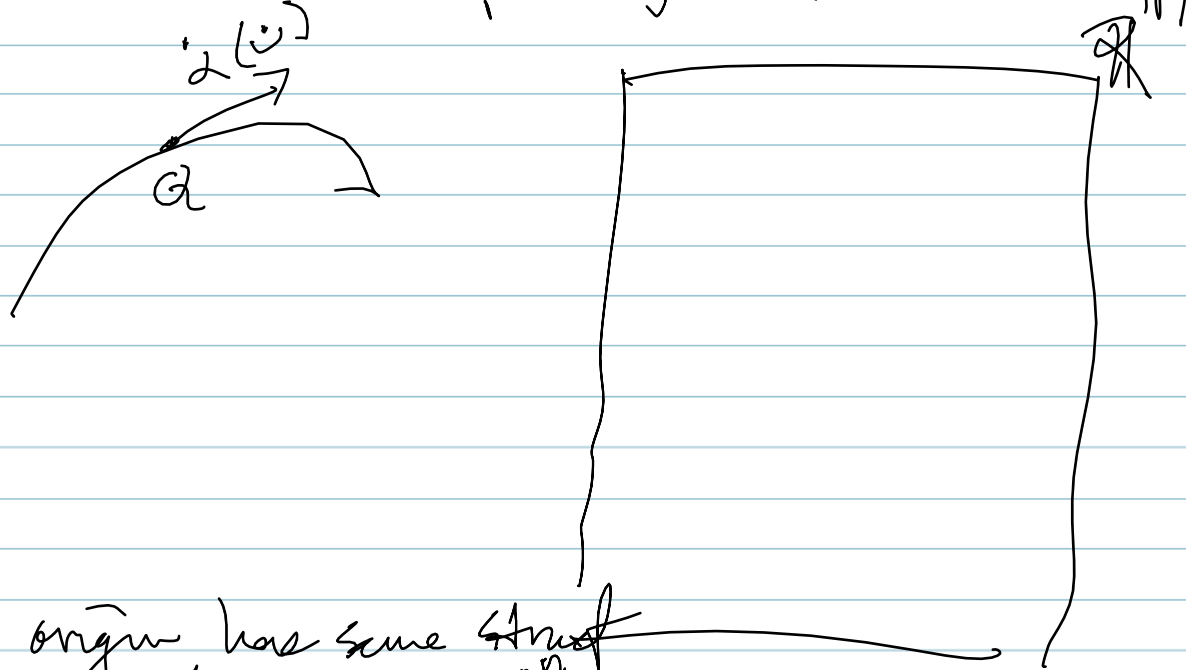
✓ diff calculus discussed (re diff. geom + using math)
- summary (rather than $\frac{d}{dx}$, think $\mathbb{R}^N \{e_1 \ldots e_N\}$)

tangent @ $T_Q \mathbb{R}^N$ is $\left\{ \frac{d\alpha}{dt}(\cdot) \Big|_{t=0} \;\middle|\; \alpha \{-\epsilon, \epsilon\},\ \epsilon > 0 \text{ is a smooth curve at } Q \right\}$

$\alpha(t) = (x_1(t), \ldots, x_n(t))$

$x_j(t)$ smooth $\quad \frac{dx_j}{dt}\Big|_{t=0} = \alpha_j$

$T_Q \mathbb{R}^N \cong \{\alpha_1, \ldots, \alpha_n \mid \alpha_j \in \mathbb{R}\} \cong \mathbb{R}^N$



@ origin has same struct everywhere as @ 0

$\mathbb{R}^n$ is a model for localization of data that we are collecting from a complex system

Tangent space to $\mathbb{R}^n$ @ any point (Q) is isomorphic to $\mathbb{R}^n$

Properties of $\mathbb{R}^n$ (locally euclidean space) 24 Oct

1) $\mathbb{R}^n$ has homogeneous struct as a manifold w local struct of having n degrees of freedom (ref to dynamics / ~~kinetics~~ ... $L(\dot{x})$)

Or when we sample points in $\mathbb{R}^n$ around any Q (dataset $D \subset \mathbb{R}^n$, mean$(D) = Q$)

we have n principal vectors & n principal values w max entropy

$\lambda_1 \cong \lambda_2 \cong \lambda_n$

There is no direction of preference (eg no "force")

Curvature

if 1 direction is normal so

straight line in hyper $\mathbb{R}^2$ for curve in $\mathbb{R}^2$

generalizing this:
start from diff calculus

n (by Laplace) is a uniform — but in bio, not so.

calc is finding dir. of max variance

$\mathbb{R}^3$; $\quad {}_Q\mathbb{R}^3 \cong \mathbb{R}^3$ classical math: mapping

X from some open subset of $(\mathcal{I}(nt))\ \mathbb{R}^2$

$X(u,v) = (X_1(u,v), X_2(u,v), \ldots)$

x_i smooth $\forall$ (u_0, v_0) $\quad X(u_0, v_0) = Q \in \mathbb{R}^3$

"at"

X_u new syntax for $= \frac{\partial X}{\partial u}(u,v)\Big|_{(u_0,v_0)}$

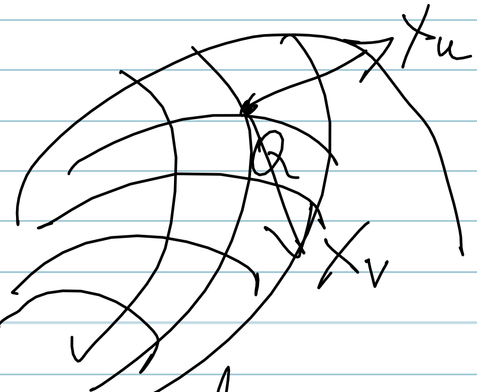
X_v $= \frac{\partial X}{\partial v}(u,v)\Big|_{(u_0,v_0)}$

with an infinite set, (timeless scaling) then

Gaussian is max. entropy distribution in a "flat" space, $\lambda_1 = \lambda_2$

prin. comp.
higher D: all the degrees of freedom that matter up to error ϵ

$\alpha(t)$ curve lies on $\subset$ Image$(X) = S$



I can sample my complex system at a projection
2 directions are maximally informative.
3rd noise will introduce rude errors + life becomes complicated
3D reduces to 2D

diff geom
$T_Q S$ tangent to surface S @ point Q $\cong \mathbb{R}^2$
use as $\cong S_Q$ @ Q

24-Oct

generalizes nicely to $\mathbb{R}^n$ $n>3$

$z=f(x,y)$ e.g. $z=x^2+y^2x+y^2+xy+y^3$

you can take x_1 as u, x_2 as v, $x_3 = z = f(u,v)$

$X_{u,v} = \{u, v, f(u,v)\}$

Case 1: if $f(u,v)$ is linear: $z = ax+by+c$

$X_u = (1,0,a)$

$X_v = (0,1,b)$

$X_u \overset{\text{cross}}{\times} X_v \neq 0 \Rightarrow$ flat

Case 2: $f(x,y)$ non-linear still get $X_u \times X_v \neq 0$

Case 3: 2nd degree polynomial

Look @ Taylor expansion, then

$f(u,v)$ expands into ——— ?

The linear piece gives the tangent plane

The quadratic term gives the quadratic approx

2nd fundamental form [of 3]

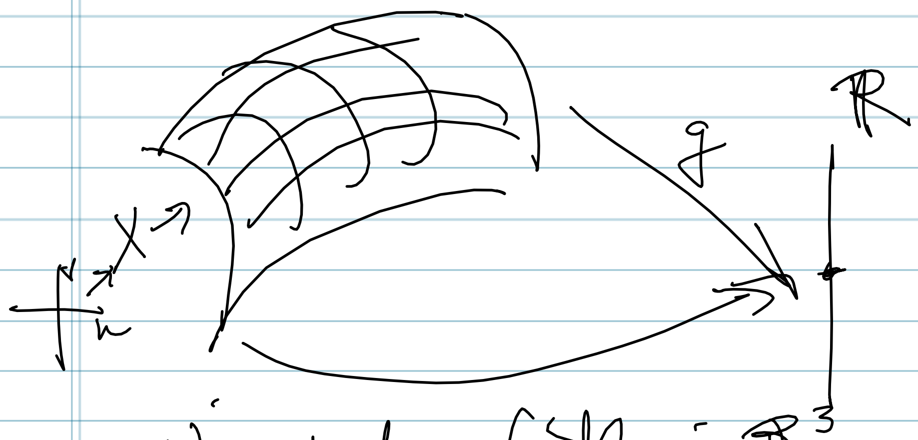
f_{uu}
f_{uv} $\quad II(u,v)$ " $f_{uu}u^2 + 2 \cdot f_{uv}uv + f_{vv} \cdot v^2$ "
f_{vv}

simple in sense that 3rd dim (z) captures the non-linearity

graph these surfaces sphere is non-linear but highly ~~der ud in exact~~ symmetric

24-Oct

directional derivative is seen as an operator
of $g(\cancel{u,v}\ X(u,v))$ shorthand $g(u,v)$



W = vector fields in $\mathbb{R}^3$
compatible w. constraints
given by S

W = linear combination of tangent vectors on S

gene perturbations as changes from homeostatic
but homeostatic is a function of all other genes

$$W(g)\Big|_{(u,v)=(u_0,v_0)} = D_{W(Q)}\, g\Big|_{(u,v)=(u_0,v_0)} = \mathrm{grad}(g)\cdot W$$

(direct deriv)

$X(u_0,v_0)=Q$

correlation of grad(g) with W.

only ~~if~~ when variation is stable ~~[illegible]~~

1^{st} fundamental form = euclidean inner prod
betw $\langle X_u + X_v$ on the Riemannian Metric

$$I(u,v) = (u,v)\langle X_u, X_v\rangle\binom{u}{v}$$

Euclidean on T_QS

24-Oct

Gauss theorem of which

$\mathrm{I}(u,v)$ is intrinsic

1st Fund Form provides a scalar function on S called curvature $K(u,v) = K(X(u,v))$

curvature does not depend on parameterization X

$K(Q) =$ product $\lambda_1 \cdot \lambda_2$ of S

$$\frac{\lambda_1 + \lambda_2}{2} = H(u,v)$$ mean curvature trace (II)

~~If $H = 0$, then locally it looks like a soap film minimum (energy) surfaces~~

Classical Story

math 812 next semester.

learning theory, etc

LOCI 26 Oct

light microscopy because ~~[illegible]~~ camera
is primarily a cellular level
Phenomenon problem
Biggest thing in informatics ~~data management~~
b/c campus ~~[illegible]~~
UG passionate abt overcoming haves/have nots.

idea: Subsidized | Buddy Backup | Jan Cheetham

KE: just show it can work by adopting
multiple labs w diff data needs.
- Robin Valenza
- LOCI
- Tevas
} 1 yr. trial?

subsidized

Primary storage @ dept level; backup could be anywhere
thumb drives & CDs now

Next Math Bio in on scale

Cloud backup is partly Jim W. Chern (adoptee?)
DoIT branded cloud data service

Could we have a UW System cloud?

shipping containers ~~[illegible]~~ of comp/storage in a warehouse?

1st HTC
2nd put $ on the prob, but we want more
unified alliance? diverge per space

Strategic Planning & Af Sorto
Hidako:
start w simple use cases, low hanging fruit?
eg CIO office ID's res ~~priority~~ & ~~[illegible]~~
alliance

26-08

take adoption strategy
DoIT showcase

here's what we can do
pick a modest dept.
research but not
resource rich.

2) At cant & network has given DoIT a better rep.

[IAM part is solved by OS depts.

LOCI use LDAP & Net ID,
w current sys is down cant authN.

KE Port us catalog
DoIT as partner in metadata - too domain specific
Could lead to a service for all
1st TB is free.
w/-Fed : Scott Koranda
Botany, Mat Sci, LOCI, KSK
Waisman MEL
17 total groups 2 mbc, 2 msn, etc.
(LOCI)
primary/backup. entry level
all imaging labs + all
w/in Bruce's power to fund
image repository
indiv researchers
LOCI would like to participate because of time & spending
multiple collaborators.
20 extra $ in from grants. Because of the pol. skills
on hard $.
plug-ins for fee services across campus
maybe even fundable by
NIH & NSF

[Box.net?]
non of imaging orgs has
data mgmt

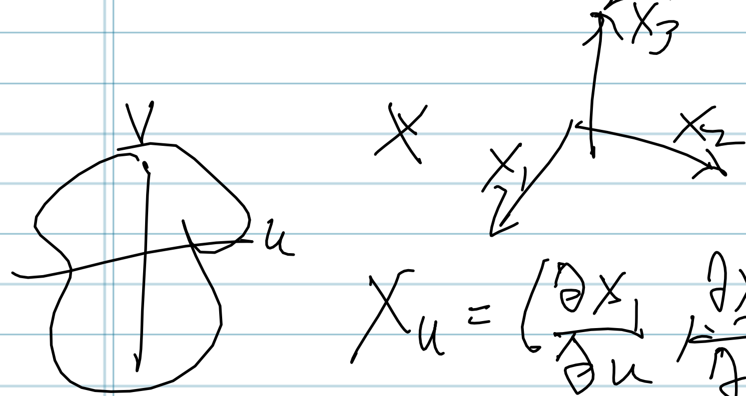
26-Oct

LOCI is free for the newbies
then they w
$40 hrs, or $44 for data
or ~~$~~ avi over all.

research? | grant funded
funding model | central campus budgets | [illegible]
sustainability | fee based
101 funds

do you need a backstop plan B ≤ if it's not fundable
the data group - for sb, by request?

$X(u,v) = (X_1(u,v), X_2(u,v), X_3(u,v))$



$X_u = \left(\frac{\partial X_1}{\partial u}, \frac{\partial X_2}{\partial v}, \frac{\partial X_3}{\partial v}\right)$

S is curve

$X_v = \left(\frac{\partial X_1}{\partial v}, \frac{\partial X_2}{\partial v}, \frac{\partial X_3}{\partial v}\right)$

$X_u \times X_v = N(u,v)$ unit normal to S if only 1 determine curve (surface)

$\Rightarrow S$ has codim of 1

curve in plane

$N \perp$ to tangent plane of S @ u,v.

both $\frac{\partial N}{\partial u} \in T_Q S$. $\frac{\partial N}{\partial v} \in T_Q S$

sphere $S^2 = \{Y \in \mathbb{R}^3 \mid \|Y\| = 1\}$

N can be seen as vector or map

as map. $N: S \to S^2$ $N(X_{u,v}) = N(u,v)$

the Gauss map

Jacobian of N $J(N) = \left(\frac{\partial N}{\partial u}\right.$

$N = (N_1(x_1, x_2, x_3), N_2(x_1, x_2, x_3), N_3(x_1, x_2, x_3))$

Cov. ~~Derivative~~ are beginning of Riemannian —

take tangent space, & tangent space

~~take~~ derivative, get a 3rd tangent space

(in stochastic problems, we look @ pdfs

eg take deriv. of $V = X_n$ in terms of $W = X_m$

Remember chain rule of vector calculus

geometry of circadian rhythms is a direct application of this stuff

~~are there~~ numerical soln of Frobenius Theorem

Shamus Series on vector calc.

& diff. geom.