

CS164: Differential Quantities on Surfaces

Leonidas Guibas
Computer Science Dept.
Stanford University

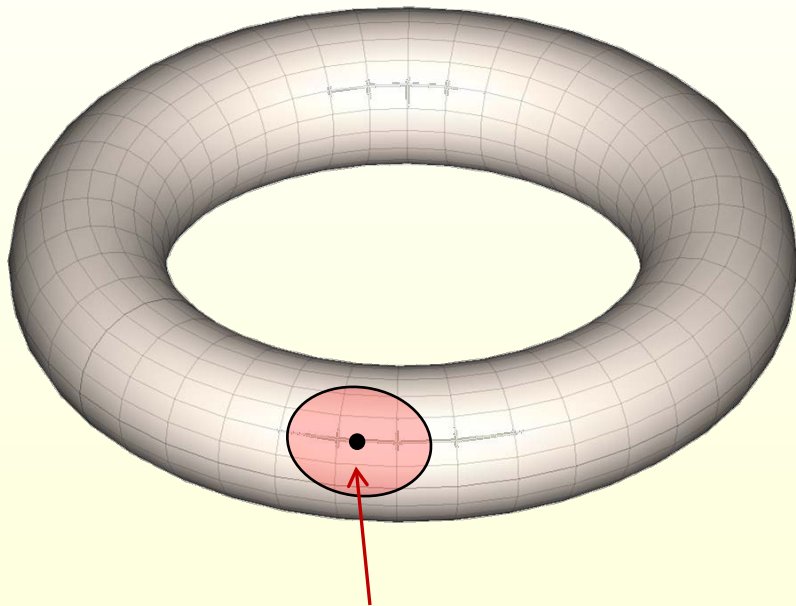


2-Manifolds and the Differential Geometry of Surfaces

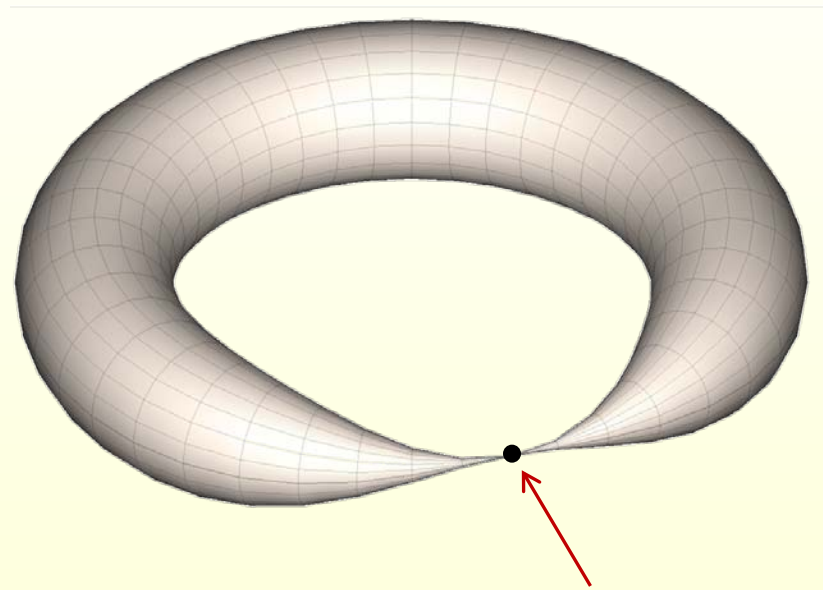
[Slides from Bronstein & Bronstein]

Manifolds

A topological space in which every point has a neighborhood homeomorphic to \mathbb{R}^n (topological disc) is called an n -dimensional (or n -) manifold



2-manifold



Not a manifold

The earth is an example of a 2-manifold

Charts and Atlases

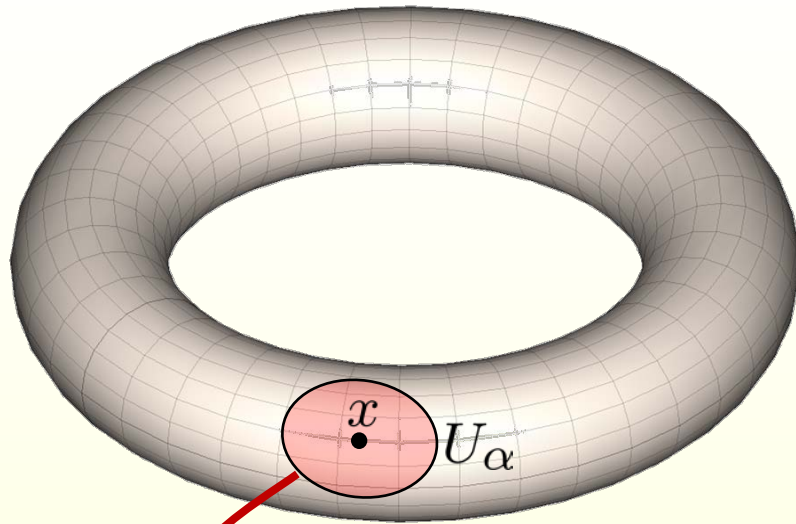
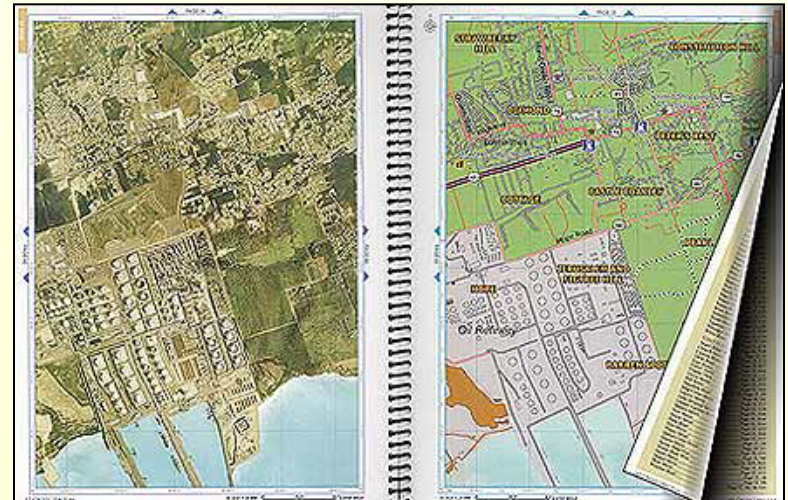


Chart $\alpha : U_\alpha \rightarrow \mathbb{R}^2$

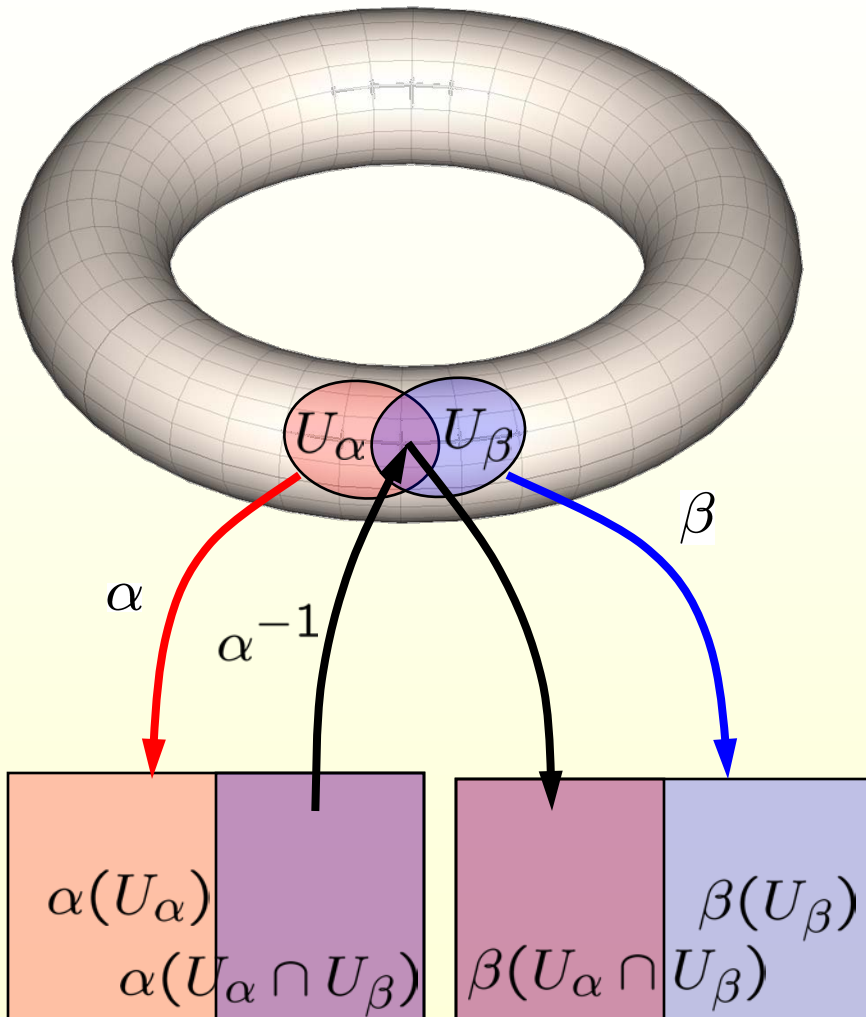
$$\alpha(U_\alpha) \subset \mathbb{R}^2$$

A homeomorphism $\alpha : U_\alpha \rightarrow \mathbb{R}^n$ from a neighborhood U_α of $x \in X$ to \mathbb{R}^n is called a **chart**

A collection of charts whose domains cover the manifold is called an **atlas**



Smooth Manifolds



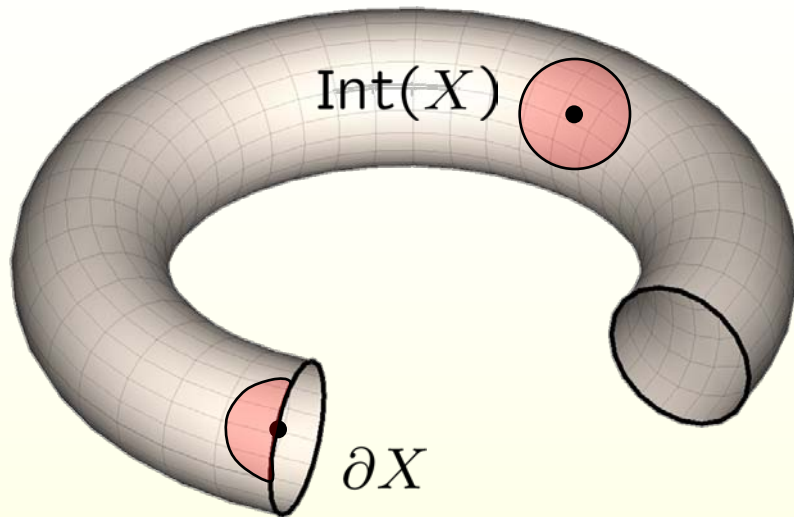
Given two charts $\alpha : U_\alpha \rightarrow \mathbb{R}^n$ and $\beta : U_\beta \rightarrow \mathbb{R}^n$ with overlapping domains, a change of coordinates is done by a transition function on $U_\alpha \cap U_\beta$

$$\beta \circ \alpha^{-1} : \alpha(U_\alpha \cap U_\beta) \rightarrow \mathbb{R}^n$$

If all transition functions are \mathcal{C}^r , the manifold is said to be \mathcal{C}^r

A \mathcal{C}^∞ manifold is called smooth

Manifolds with Boundary



A topological space in which every point has an open neighborhood homeomorphic to either

- topological disc \mathbb{R}^n ; or
- topological half-disc $[0, \infty) \times \mathbb{R}^{n-1}$

is called a manifold with boundary

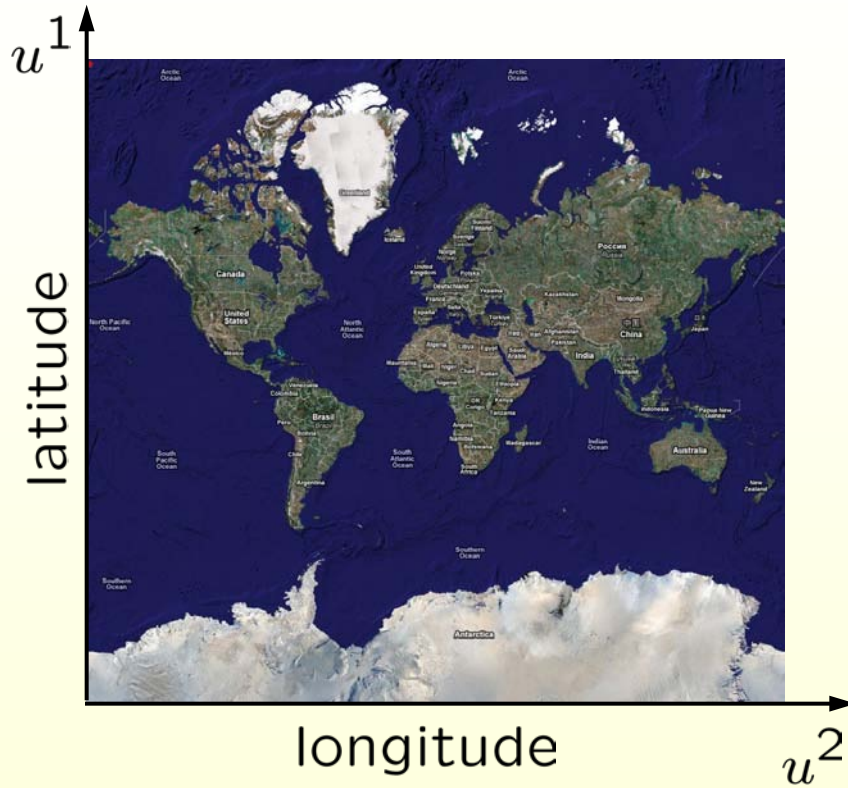
Points with disc-like neighborhood are called interior, denoted by $\text{Int}(X)$

Points with half-disc-like neighborhood are called boundary, denoted by ∂X

Embedded Surfaces

- Boundaries of tangible physical objects are two-dimensional manifolds.
- They reside in (are **embedded** into, are subspaces of) the ambient three-dimensional Euclidean space.
- Such manifolds are called embedded surfaces (or simply surfaces).
- Can often be described by the map $x : U \subset \mathbb{R}^2 \rightarrow X \subset \mathbb{R}^3$
 - $U \subset \mathbb{R}^2$ is a parametrization domain.
 - the map $x(u) = (x^1(u^1, u^2), x^2(u^1, u^2), x^3(u^1, u^2))$ is a global parametrization (embedding) of X .
- A smooth global parametrization does not always exist, nor is it easy to find.
- Sometimes it is more convenient to work with multiple charts.

Parametrization of the Earth



$$U = \left[-\frac{\pi}{2}, \frac{\pi}{2} \right] \times [-\pi, \pi]$$

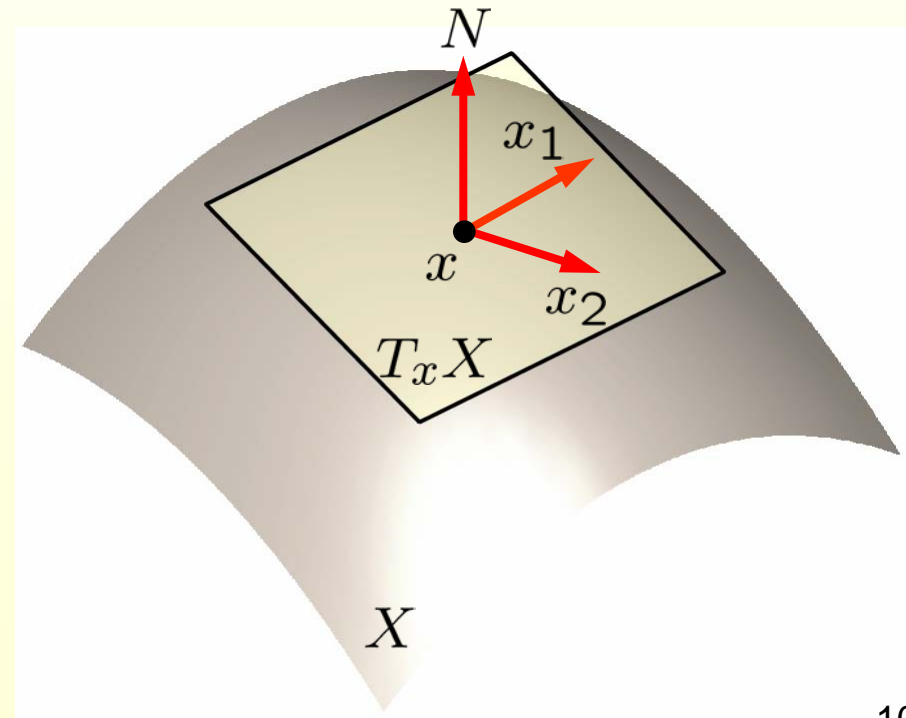
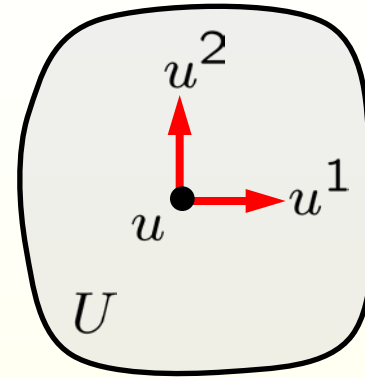
$$\begin{aligned}x^1 &= r \cos u^2 \cos u^1 \\x^2 &= r \sin u^2 \cos u^1 \\x^3 &= r \sin u^1\end{aligned}$$

Tangent Plane and Normal

- At each point $u \in U$, we define a local system of coordinates

$$x_1 = \frac{\partial x}{\partial u^1} \quad x_2 = \frac{\partial x}{\partial u^2}$$

- A parametrization is regular if x_1 and x_2 are linearly independent.
- The plane $T_x X = \text{span}\{x_1, x_2\}$ is the tangent plane at $x = x(u)$.
- Provides a local Euclidean approximation of the surface.
- $N \perp T_x X$ is the normal to surface.



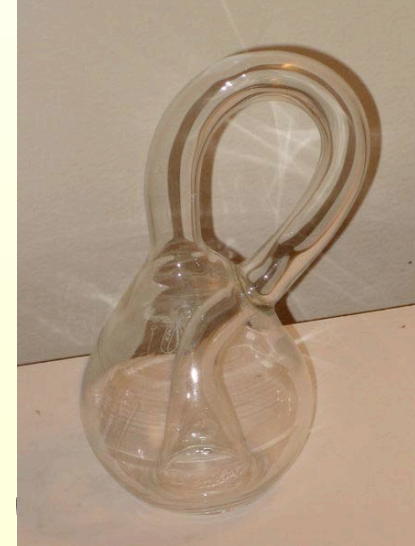
Orientability

- Normal is defined up to a sign.
- Partitions ambient space into inside and outside.
- A surface is orientable, if normal N depends smoothly on x .



Möbius stripe

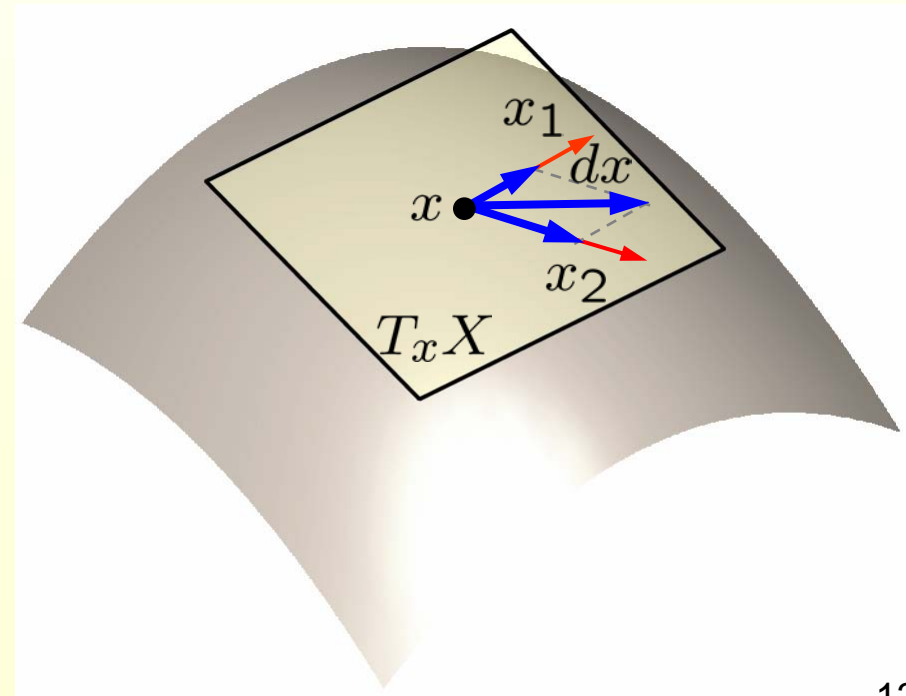
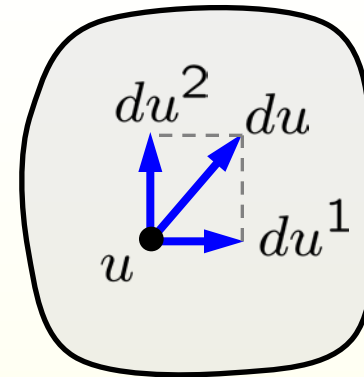
August Ferdinand Möbius



Felix Christian Klein
Klein bottle
(1849-1925)
(3D section)

First Fundamental Form

- Infinitesimal displacement on the chart du .
- Displaces x on the surface by $dx = x(u + du) - x(u)$
$$= x_1 du^1 + x_2 du^2$$
$$= J du$$
- J is the Jacobian matrix, whose columns are x_1 and x_2 .



First Fundamental Form

- Length of the displacement

$$\begin{aligned} dl^2 &= \|dx\|^2 = du^\top J^\top J du \\ &= du^\top G du \end{aligned}$$

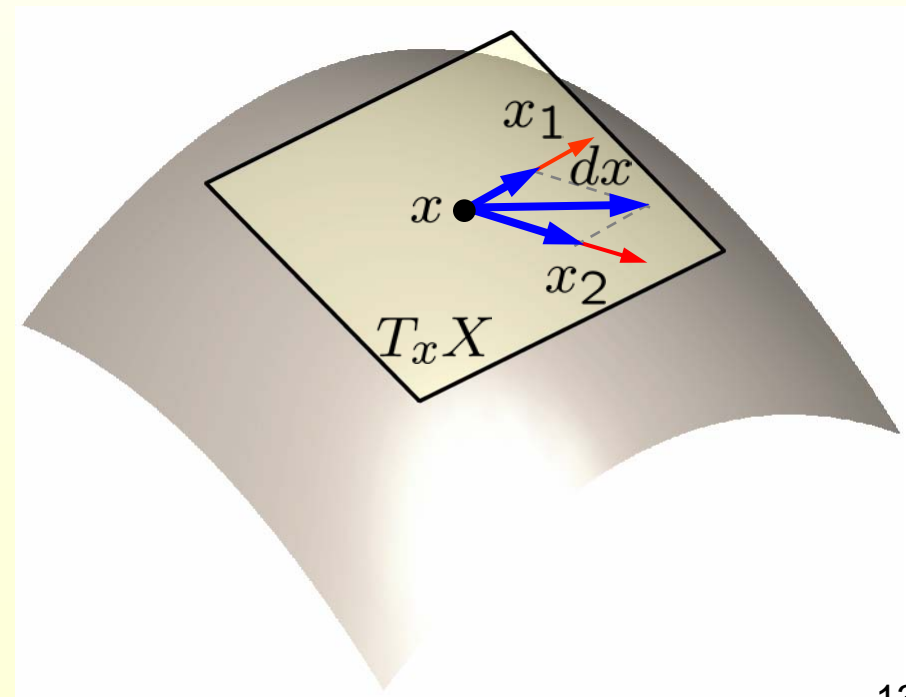
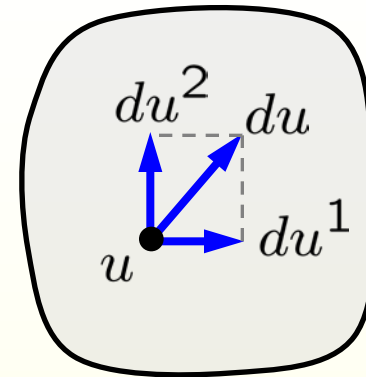
- G is a symmetric positive definite 2×2 matrix.
- Elements of G are inner products

$$g_{ij} = \langle x_i, x_j \rangle$$

- Quadratic form

$$dl^2 = du^\top G du$$

is the first fundamental form.



First Fundamental Form of the Earth

- Parametrization

$$x = (r \cos u^2 \cos u^1, r \sin u^2 \cos u^1, r \sin u^1)$$

- Jacobian

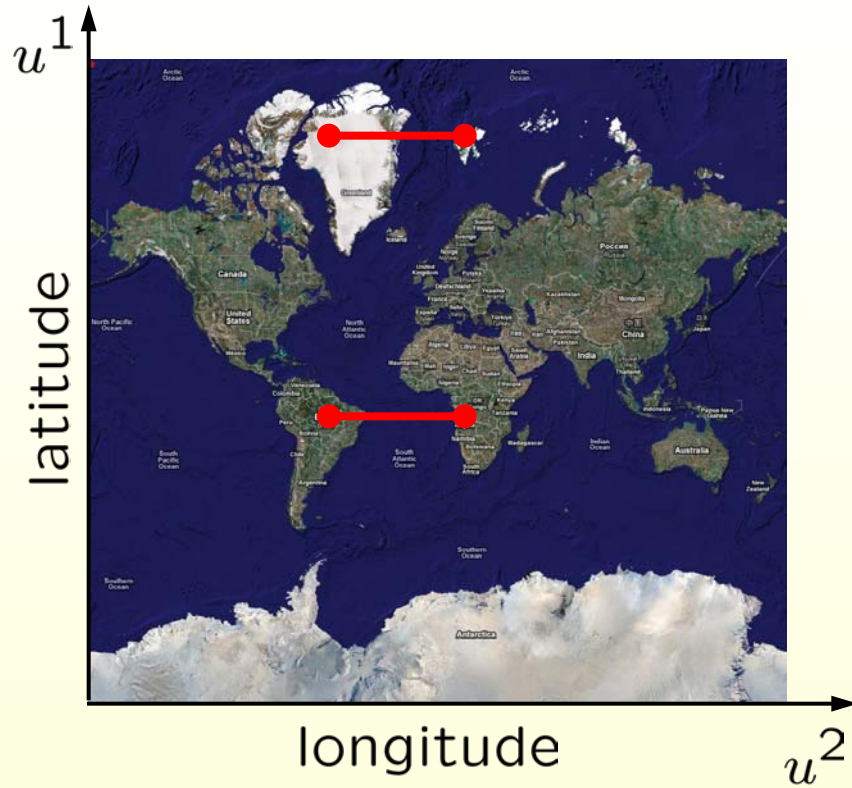
$$x_1 = (-r \cos u^2 \sin u^1, -r \sin u^2 \sin u^1, r \cos u^1)$$

$$x_2 = (-r \sin u^2 \cos u^1, r \cos u^2 \cos u^1, 0)$$

- First fundamental form

$$\begin{aligned} G &= \begin{pmatrix} \langle x_1, x_1 \rangle & \langle x_1, x_2 \rangle \\ \langle x_1, x_2 \rangle & \langle x_2, x_2 \rangle \end{pmatrix} \\ &= r \begin{pmatrix} 1 & 0 \\ 0 & \cos^2 u^1 \end{pmatrix} \end{aligned}$$

First Fundamental Form of the Earth



$$G = r \begin{pmatrix} 1 & 0 \\ 0 & \cos^2 u^1 \end{pmatrix}$$

First Fundamental Form

- Smooth curve on the chart:

$$\gamma : [a, b] \rightarrow U$$

- Its image on the surface:

$$\Gamma = x \circ \gamma$$

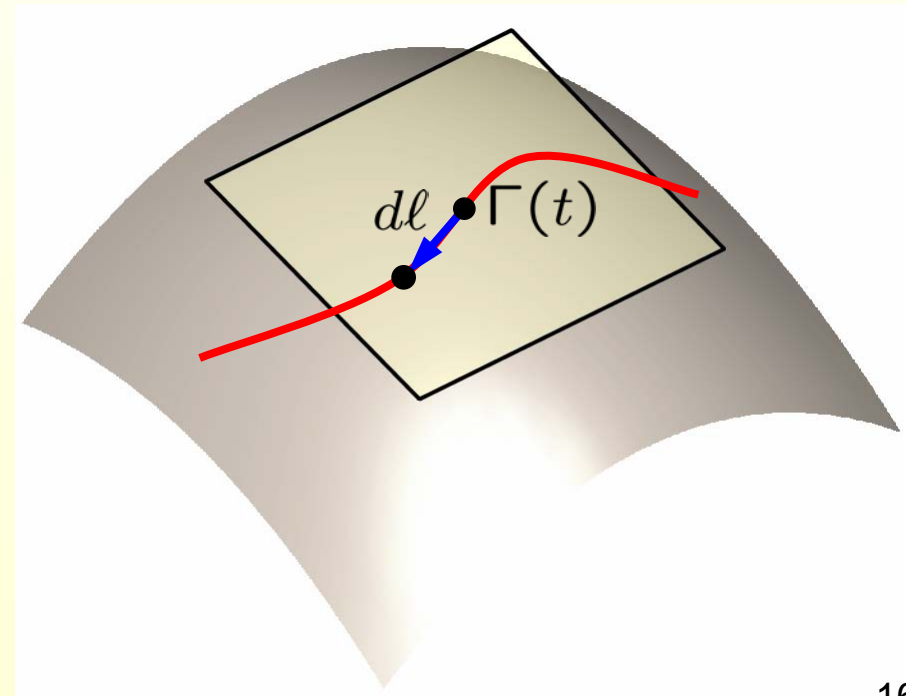
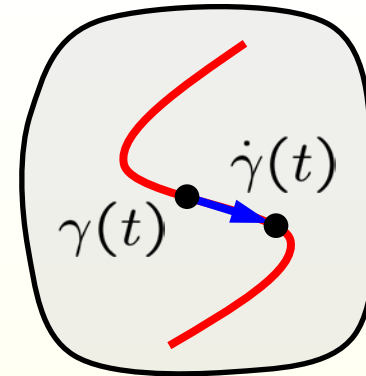
- Displacement on the curve: dt

- Displacement in the chart:

$$\begin{aligned} d\gamma &= \gamma(t + dt) - \gamma(t) \\ &= \dot{\gamma}(t)dt \end{aligned}$$

- Length of displacement on the surface:

$$d\ell = \sqrt{\dot{\gamma}(t)^T G(\gamma(t)) \dot{\gamma}(t)} dt$$



Length, Intrinsic Geometry

- Length of the curve

$$L(\Gamma) = \int_{\Gamma} dl = \int_a^b \sqrt{\dot{\gamma}(t)^{\top} G(\gamma(t)) \dot{\gamma}(t)} dt$$

- First fundamental form induces a length metric (intrinsic metric)

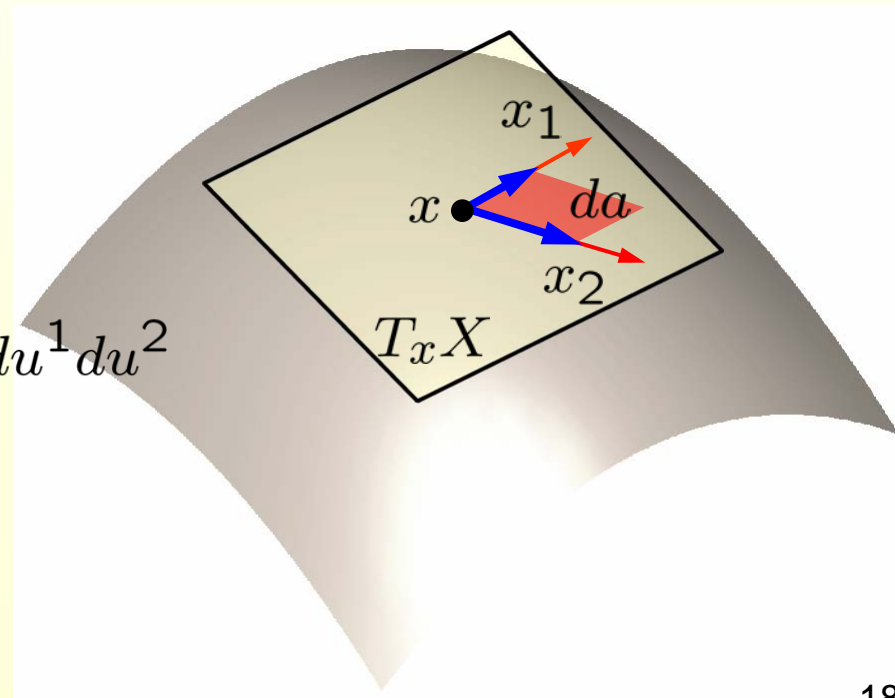
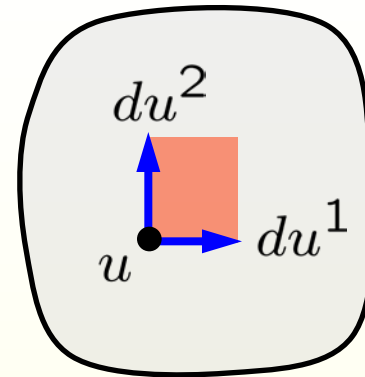
$$d_X(x_1, x_2) = \min_{\substack{\Gamma \\ \Gamma(0)=x_1, \Gamma(1)=x_2}} L(\Gamma)$$

- Intrinsic geometry of the shape is completely described by the first fundamental form.
- First fundamental form is invariant to isometries.

Area

- Differential area element on the chart: rectangle $du^1 \times du^2$
- Copied by x to a parallelogram $du^1 x_1 \times du^2 x_2$ in tangent space.
- Differential area element on the surface:

$$\begin{aligned} da &= \|du^1 x_1 \times du^2 x_2\| \\ &= \|x_1 \times x_2\| du^1 du^2 \\ &= \sqrt{\|x_1\|^2 \|x_2\|^2 - \langle x_1, x_2 \rangle^2} du^1 du^2 \\ &= \sqrt{g_{11}g_{22} - g_{12}^2} du^1 du^2 \\ &= \sqrt{\det G} du^1 du^2 \end{aligned}$$



Area

- Area of a region $\Omega \subseteq X$ charted as $\Omega = x(\omega \subseteq U)$

$$\mu(\Omega) = \int_{\Omega} da = \int_{\omega} \sqrt{\det G} du^1 du^2$$

- Relative area

$$\nu(\Omega) = \frac{\mu(\Omega)}{\mu(X)}$$

- Probability of a point on X picked at random (with uniform distribution) to fall into Ω .

Formally $\mu(\Omega), \nu(\Omega)$

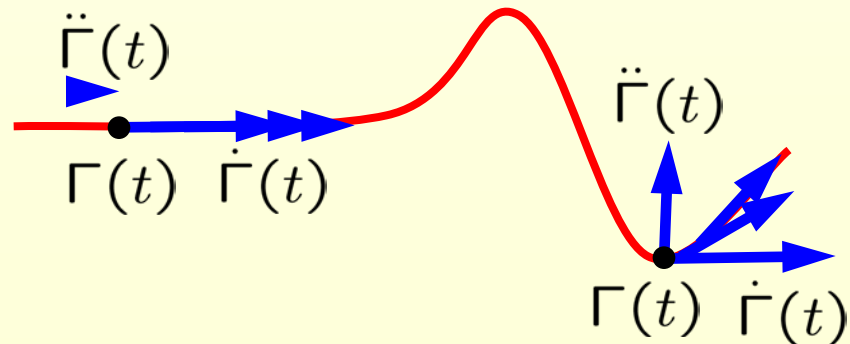
- are measures on X .

Curvature in the Plane

- Let $\Gamma : [0, L] \rightarrow \mathbb{R}^2$ be a smooth curve parameterized by arclength

$$\int_a^b \|\dot{\Gamma}(t)\| dt = |a - b|$$

- Γ trajectory of a race car driving at constant velocity.
- $\dot{\Gamma}$ velocity vector (rate of change of position), tangent to path.
- $\ddot{\Gamma}$ acceleration (curvature) vector, perpendicular to path.
- $\kappa = \|\ddot{\Gamma}\|_2$ curvature, measuring rate of rotation of velocity vector.

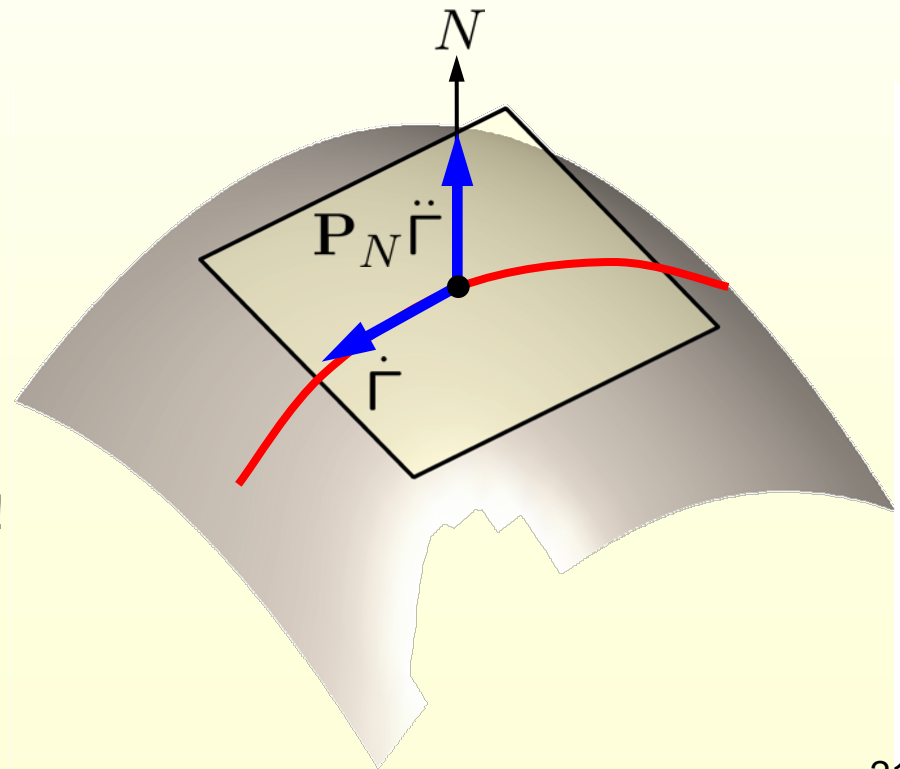


Curvature on the Surface

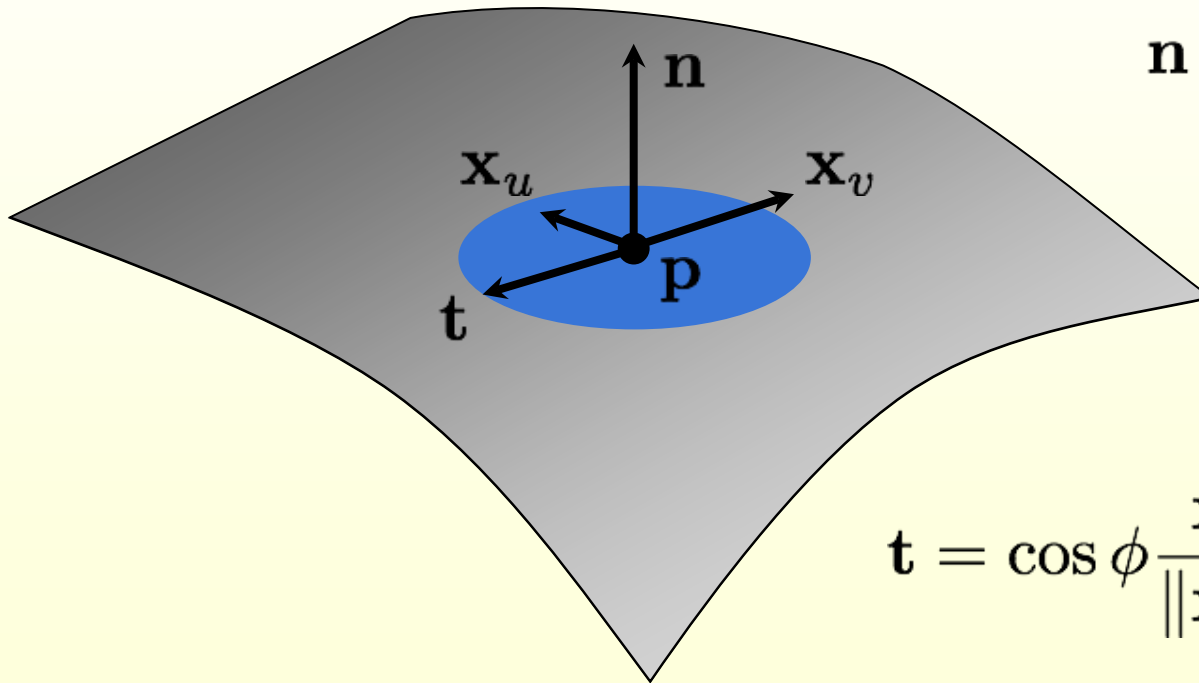
- Now the car drives on terrain X .
- Trajectory described by $\Gamma : [0, L] \rightarrow X$
- Curvature vector $\ddot{\Gamma}$ decomposes into
 - $\mathbf{P}_{T_{\Gamma}X} \ddot{\Gamma}$ geodesic curvature vector.
 - $\mathbf{P}_N \ddot{\Gamma}$ normal curvature vector.
- Normal curvature $\kappa_n = \langle N, \ddot{\Gamma} \rangle$
- Curves passing in different directions have different values of κ_n .

Said differently:

- A point $x \in X$ has multiple curvatures!



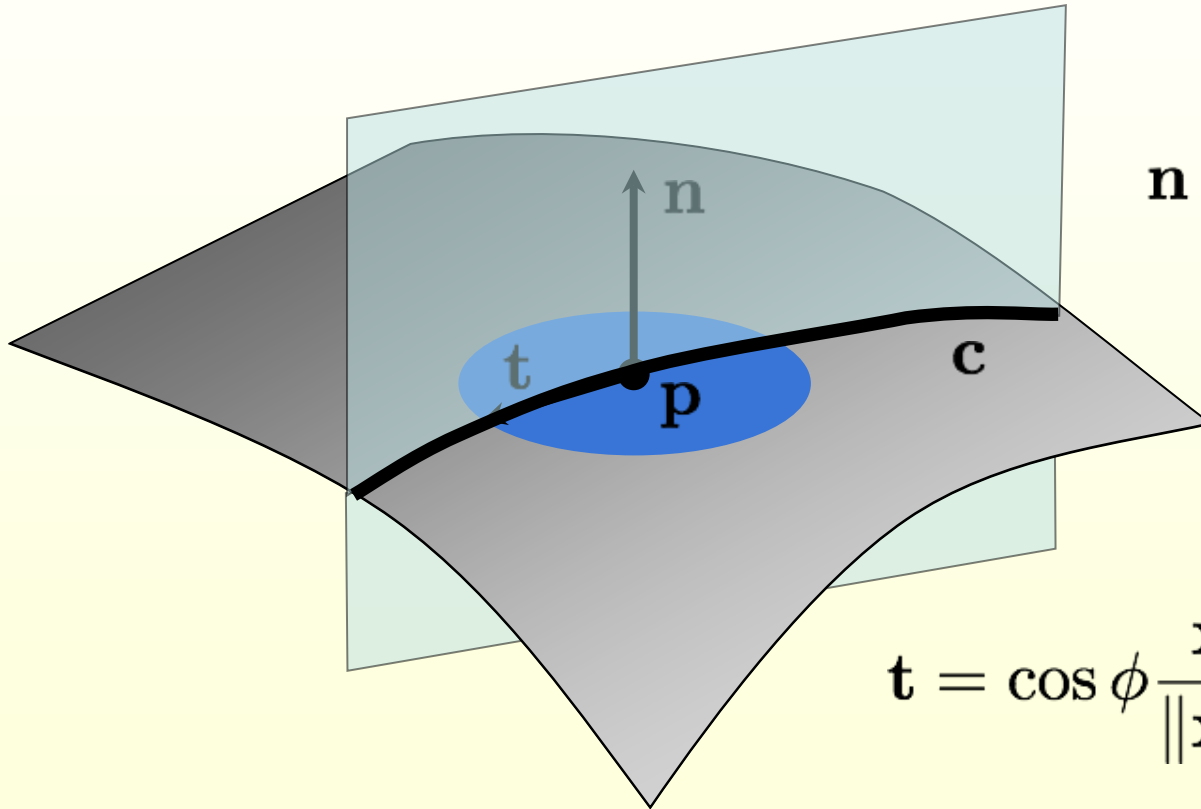
Normal Curvature



$$\mathbf{n} = \frac{\mathbf{x}_u \times \mathbf{x}_v}{\|\mathbf{x}_u \times \mathbf{x}_v\|}$$

$$\mathbf{t} = \cos \phi \frac{\mathbf{x}_u}{\|\mathbf{x}_u\|} + \sin \phi \frac{\mathbf{x}_v}{\|\mathbf{x}_v\|}$$

Normal Curvature



$$\mathbf{n} = \frac{\mathbf{x}_u \times \mathbf{x}_v}{\|\mathbf{x}_u \times \mathbf{x}_v\|}$$

$$\mathbf{t} = \cos \phi \frac{\mathbf{x}_u}{\|\mathbf{x}_u\|} + \sin \phi \frac{\mathbf{x}_v}{\|\mathbf{x}_v\|}$$

Principal Curvatures

- For each direction $v \in T_x X$, a curve Γ passing through $\Gamma(0) = x$ in the direction $\dot{\Gamma}(0) = v$ may have a different normal curvature κ_n .

- Principal curvatures

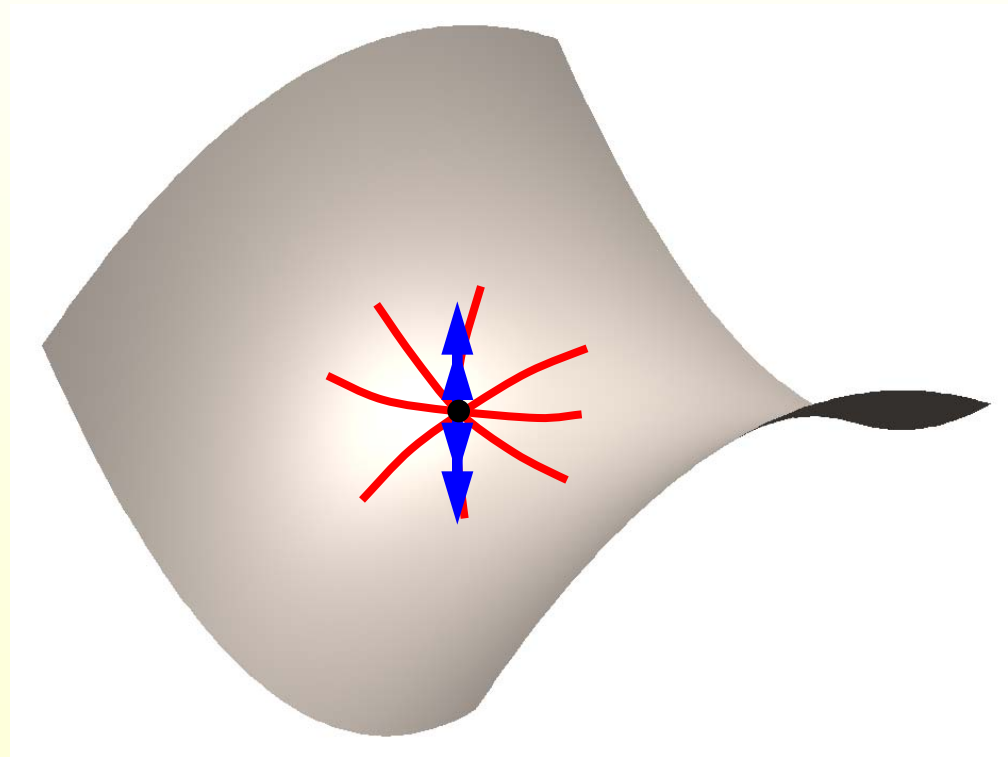
$$\kappa_1 = \min_{v \in T_x X} \langle N, \ddot{\Gamma} \rangle$$

$$\kappa_2 = \max_{v \in T_x X} \langle N, \ddot{\Gamma} \rangle$$

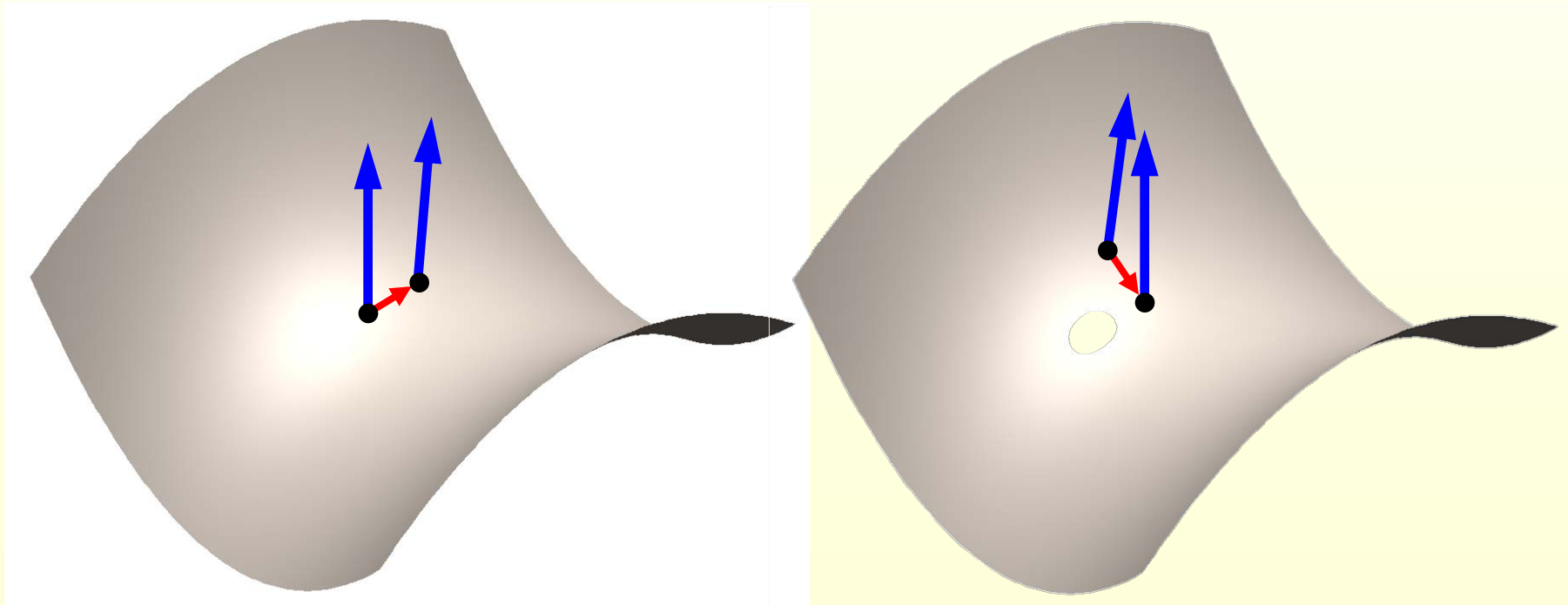
- Principal directions

$$T_1 = \arg \min_{v \in T_x X} \langle N, \ddot{\Gamma} \rangle$$

$$T_2 = \arg \max_{v \in T_x X} \langle N, \ddot{\Gamma} \rangle$$



- Sign of normal curvature = direction of rotation of normal to surface.
 - $\kappa_n > 0$ a step in direction $\dot{\Gamma}$ rotates N in same direction.
 - $\kappa_n < 0$ a step in direction $\dot{\Gamma}$ rotates N in opposite direction.



Curvature: A Different View

- A plane has a constant normal vector, e.g. $N = (0, 0, 1)$
- We want to quantify how a curved surface is different from a plane.
- Rate of change of N i.e., how fast the normal rotates.
- Directional derivative of N at point $x \in X$ in the direction $v \in T_x X$

$$D_v N = \lim_{t \rightarrow 0} \frac{1}{t} (N(\Gamma(t)) - N(x)) = \left. \frac{d}{dt} N(\Gamma(t)) \right|_{t=0}$$

$\Gamma : (-\epsilon, +\epsilon) \rightarrow X$ is an arbitrary smooth curve with $\Gamma(0) = x$
and $\dot{\Gamma}(0) = v$.

Curvature

- $D_v N$ is a vector in \mathbb{R}^3 measuring the change in N as we make differential steps in the direction v .
- Differentiate $1 = \langle N, N \rangle$ w.r.t. t
$$0 = \frac{d}{dt} \langle N, N \rangle = 2 \langle D_v N, N \rangle$$
- Hence $D_v N \perp N$ or $D_v N \in T_x X$.
- Shape operator (a.k.a. Weingarten map):
is the map $S : T_x X \rightarrow T_x X$ defined by

$$S(v) = -D_v N$$



Julius Weingarten
(1836-1910)

Shape Operator

- Can be expressed in parametrization coordinates as $S(v) = Sv$

S is a 2x2 matrix satisfying

$$\begin{pmatrix} S(x_1) \\ S(x_2) \end{pmatrix} = S \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

- Multiply by (x_1, x_2)

$$\begin{pmatrix} S(x_1) \\ S(x_2) \end{pmatrix} (x_1, x_2) = S \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} (x_1, x_2)$$

where

$$B = SG$$

$$B = \begin{pmatrix} \langle S(x_1), x_1 \rangle & \langle S(x_1), x_2 \rangle \\ \langle S(x_2), x_1 \rangle & \langle S(x_2), x_2 \rangle \end{pmatrix} = - \begin{pmatrix} \langle \partial_{u^1} N, x_1 \rangle & \langle \partial_{u^1} N, x_2 \rangle \\ \langle \partial_{u^2} N, x_1 \rangle & \langle \partial_{u^2} N, x_2 \rangle \end{pmatrix}$$

Shape Operator

- The shape operator is a 2 by 2 matrix defined at each point of S . At each point x it is a linear map from T_x to T_x .
- It defines the locally best quadratic approximation to the surface S at the point x , parametrized over the tangent plane T_x .
- Its eigenvalues are the principal curvatures, and its eigenvectors the principal curvature directions at x .

Second Fundamental Form

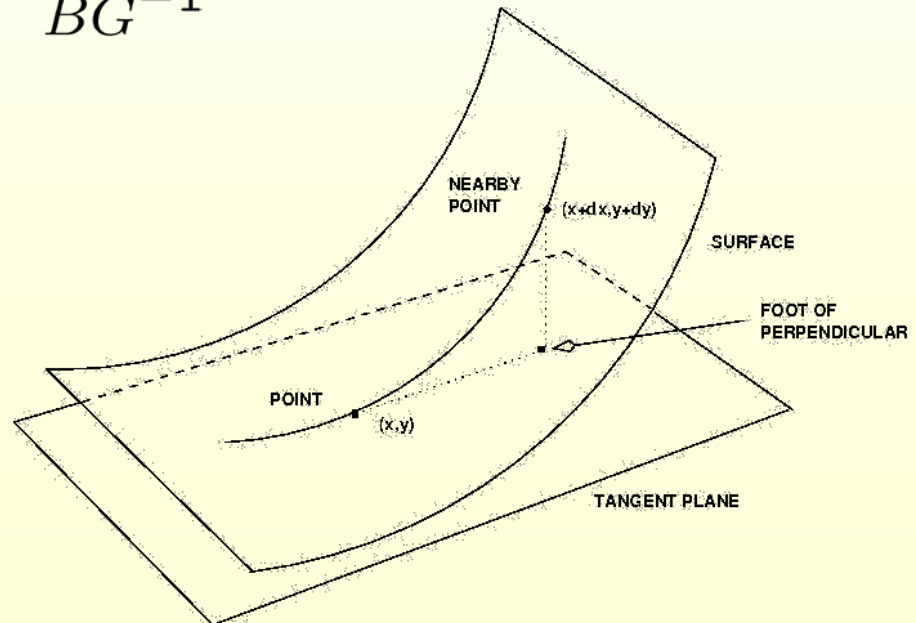
- The matrix B gives rise to the quadratic form

$$B(v, w) = \langle S(v), w \rangle = w^T B v$$

called the **second fundamental form**.

- Related to shape operator and first fundamental form by identity

$$S = B G^{-1}$$



Principal Curvatures Encore

- Let $\Gamma : [0, L] \rightarrow X$ be a curve on the surface.
- Since $\dot{\Gamma} \in T_x X$, $\langle \dot{\Gamma}, N \rangle = 0$.
- Differentiate w.r.t. to t

$$0 = \frac{d}{dt} \langle \dot{\Gamma}, N \rangle = \langle \ddot{\Gamma}, N \rangle + \langle \dot{\Gamma}, \frac{d}{dt} N \rangle$$

$$\kappa_n = \langle \ddot{\Gamma}, N \rangle = \langle \dot{\Gamma}, -D_{\dot{\Gamma}} N \rangle = B(\dot{\Gamma}, \dot{\Gamma}) = \dot{\Gamma}^T B \dot{\Gamma}$$

- $\kappa_1 \leq \dot{\Gamma}^T B \dot{\Gamma} \leq \kappa_2$
- κ_1 is the smallest eigenvalue of S .
- κ_2 is the largest eigenvalue of S .
- T_1, T_2 are the corresponding eigenvectors.

Second Fundamental Form of the Earth

■ Parametrization $x = (r \cos u^2 \cos u^1, r \sin u^2 \cos u^1, r \sin u^1)$

■ Normal

$$N = (\cos u^2 \cos u^1, \sin u^2 \cos u^1, \sin u^1)$$

$$\partial_{u^1} N = (-\cos u^2 \sin u^1, -\sin u^2 \sin u^1, \cos u^1)$$

$$\partial_{u^2} N = (-\sin u^2 \cos u^1, \cos u^2 \cos u^1, 0)$$

■ Second fundamental form

$$B = - \begin{pmatrix} \langle \partial_{u^1} N, x_1 \rangle & \langle \partial_{u^1} N, x_2 \rangle \\ \langle \partial_{u^2} N, x_1 \rangle & \langle \partial_{u^2} N, x_2 \rangle \end{pmatrix} = -\frac{1}{r} G = \begin{pmatrix} -1 & 0 \\ 0 & -\cos^2 u^1 \end{pmatrix}$$

Shape Operator of the Earth

- First fundamental form

$$G = r \begin{pmatrix} 1 & 0 \\ 0 & \cos^2 u^1 \end{pmatrix}$$

- Second fundamental form

$$B = \begin{pmatrix} -1 & 0 \\ 0 & -\cos^2 u^1 \end{pmatrix}$$

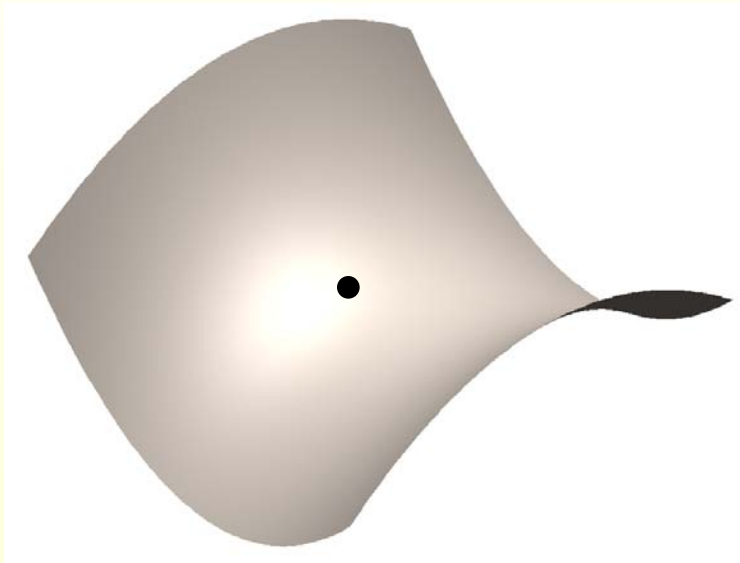
- Shape operator $S = BG^{-1} = -\frac{1}{r}I$

- Constant at every point.

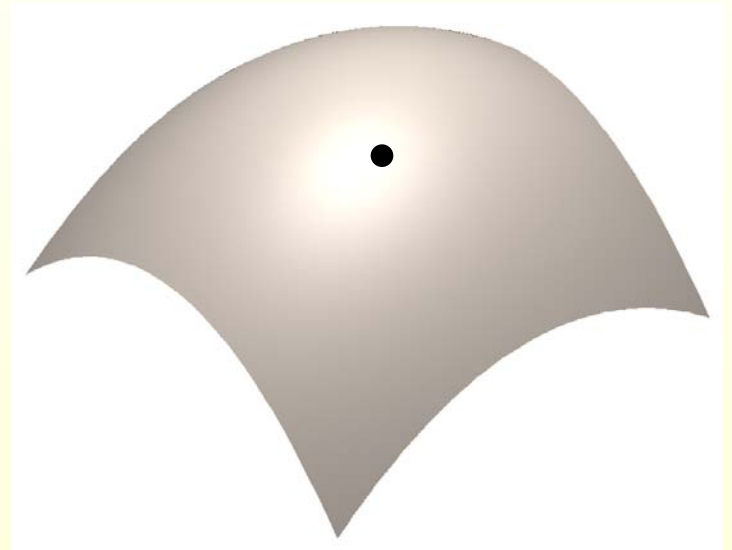
- Is there connection between algebraic invariants of the shape operator S (trace, determinant) with geometric invariants of the shape?

Mean and Gaussian Curvatures

- Mean curvature $H = \frac{1}{2}(\kappa_1 + \kappa_2) = \frac{1}{2}\text{trace } S$
- Gaussian curvature $K = \kappa_1\kappa_2 = \det S$ isometric invariant!



hyperbolic point $K < 0$

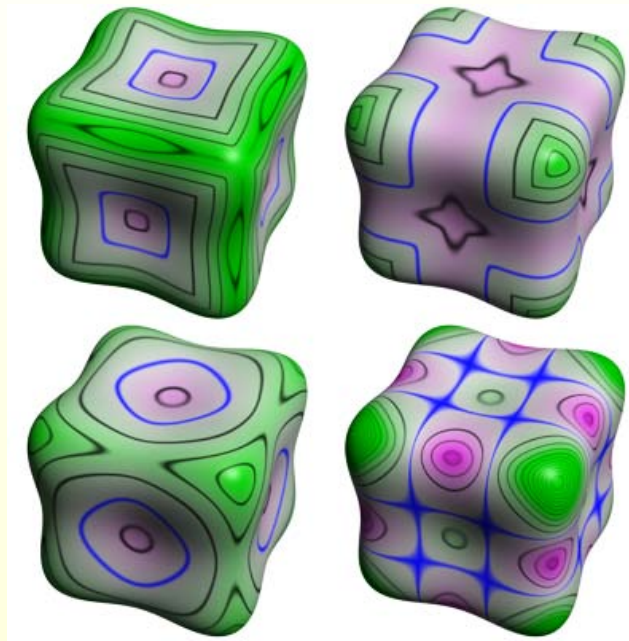


elliptic point $K > 0$

Mean and Gaussian Curvatures

$$\kappa_1 = \max_{\phi} \kappa_n(\phi)$$

$$H = \frac{1}{2}(\kappa_1 + \kappa_2)$$



$$\kappa_2 = \min_{\phi} \kappa_n(\phi)$$

$$K = \kappa_1 \cdot \kappa_2$$

Extrinsic v.s. Intrinsic Geometry

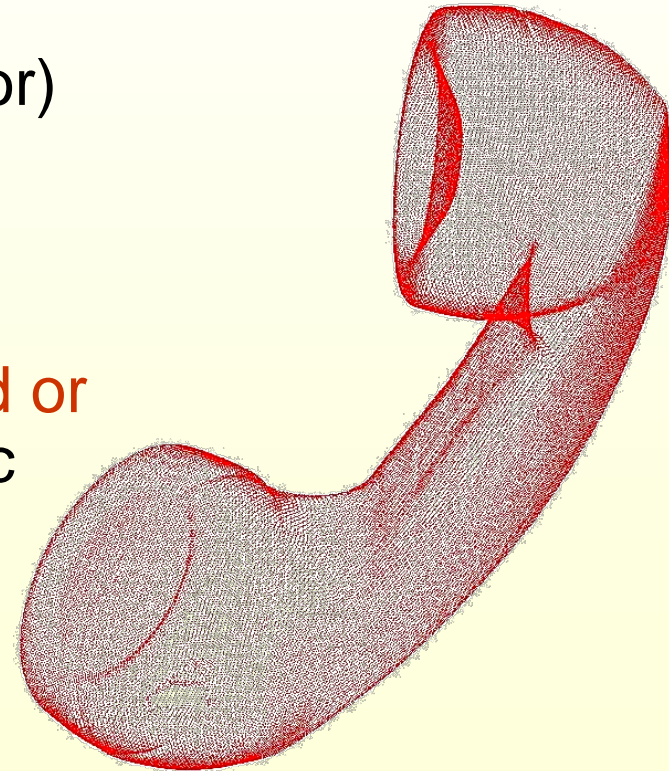
- First fundamental form describes completely the intrinsic geometry.
- Second fundamental form describes completely the extrinsic geometry – the “layout” of the shape in ambient space.
- First fundamental form is invariant to isometry.
- Second fundamental form is invariant to rigid motion (congruence).
- If X and $f(X)$ are congruent (i.e., $f \in \text{Iso}(\mathbb{R}^3)$), then they have identical intrinsic and extrinsic geometries.
- Fundamental theorem: a map preserving the first and the second fundamental forms is a congruence.

Said differently: an isometry preserving the second fundamental form is a restriction of Euclidean isometry.

Differential Quantities on a Point Cloud

Goal: PCD as First-Class Geometric Models

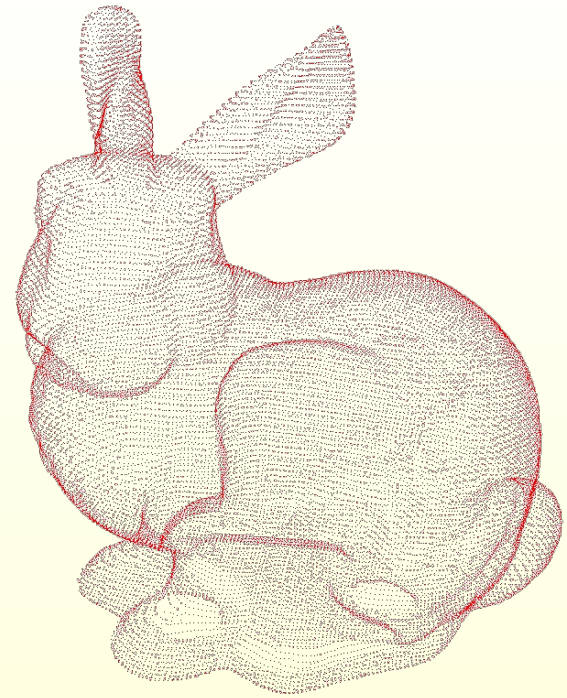
- PCD = “point cloud data”
 - unorganized collection of points sampled from the surface (or interior) of an object, with noise added
 - typical output of a 3-D scanning process
- **no connectivity information or manifold or mesh structure** □ hard to use geometric methods
- **no regular sampling**
□ hard to use signal processing tools



The Normal Estimation Problem

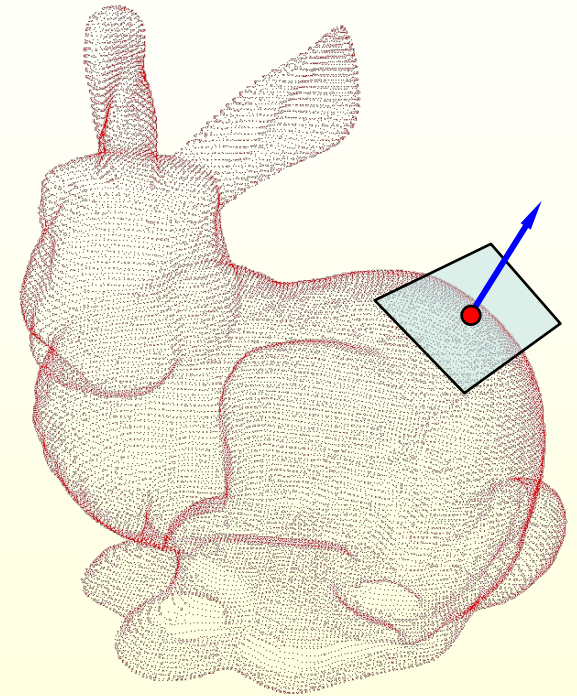
- Given

Noisy PCD sampled from
a curve/surface



The Normal Estimation Problem

- **Given**
Noisy PCD sampled from
a curve/surface
- **Goal**
Compute surface normals
at each point p

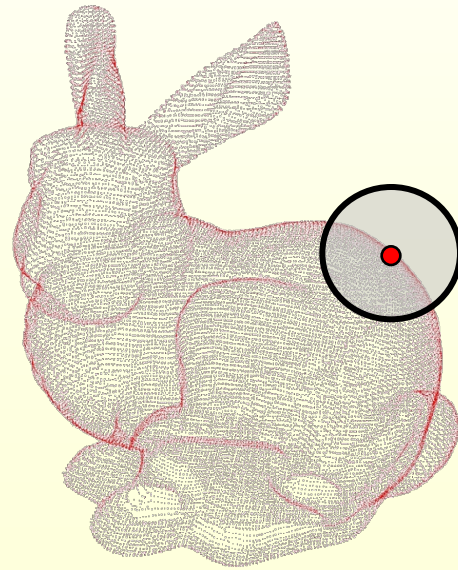
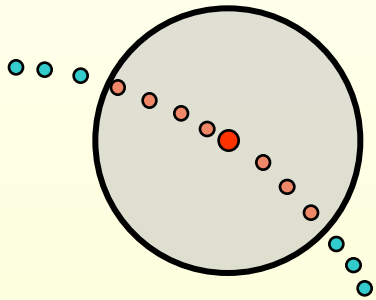


Error bound the normal estimates

Without first computing a mesh

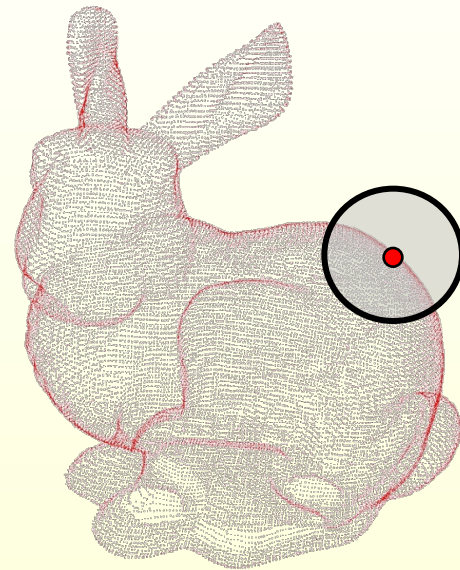
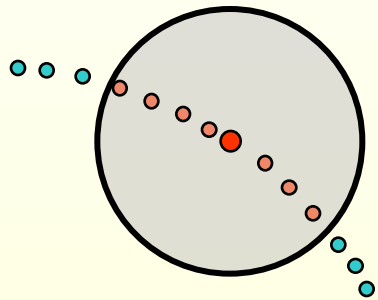
A Standard Solution

Use *least square fit* to a neighborhood of radius r around point p



A Standard Solution

Use *least square fit* to a neighborhood of radius r around point p



PROBLEM !!

what neighborhood size to choose?

Least Square Fit

- Assume

best fit hyperplane: $a^T p = c$

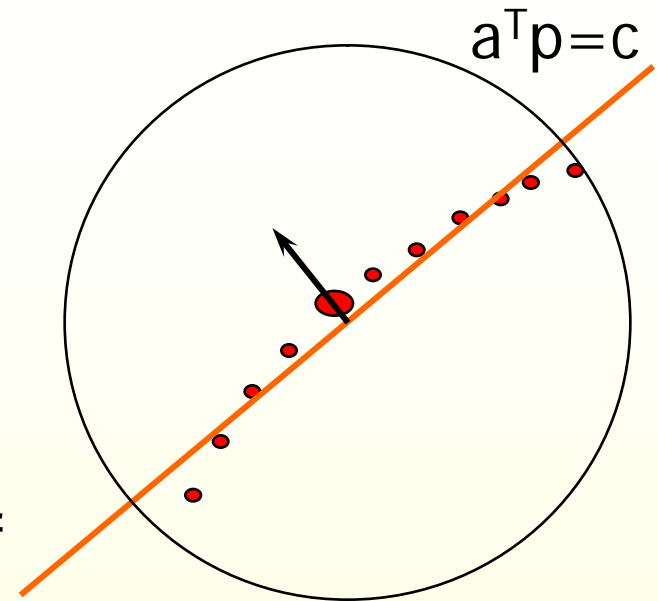
- Minimize

$$\frac{1}{k} \sum_{i=1}^k (a^T p_i - c)^2$$

- Reduces to the eigen-analysis of the **covariance matrix** of the p_i

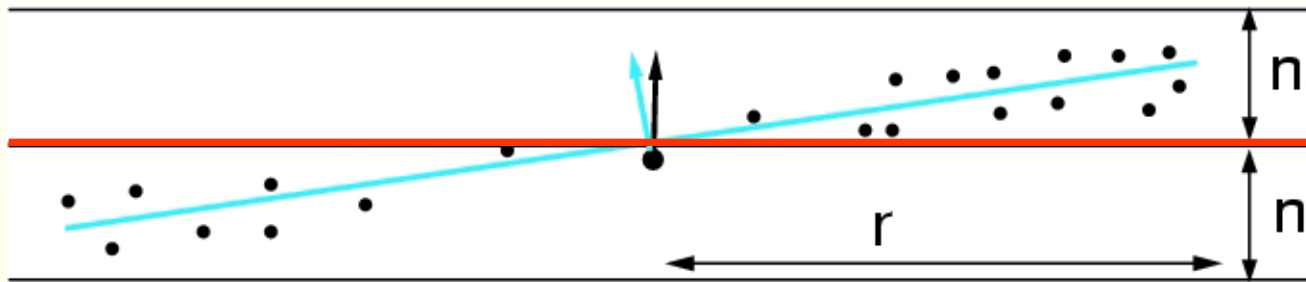
- Smallest eigenvector of M is the estimate of the normal

$$M = \frac{1}{k} \sum_{i=1}^k (p_i - \bar{p})(p_i - \bar{p})^T$$



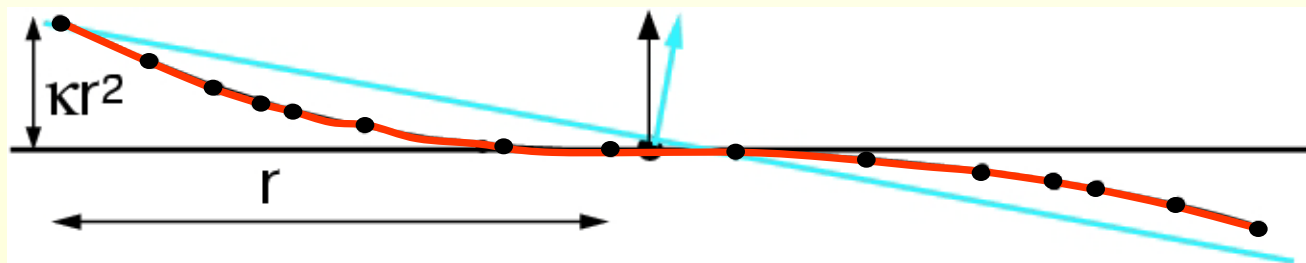
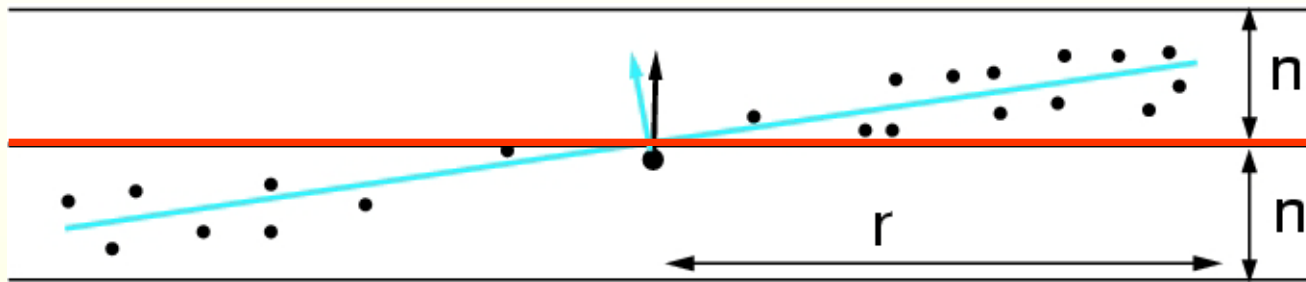
Deceptive Case

Collusive noise



Deceptive Cases

Collusive noise



Curvature effect

Important Issue

- Study the effects on normal computation of
 - *curvature*
 - *sampling density*
 - *noise*
 - *neighborhood size*
- Use this insight to choose an optimal neighborhood size
- Compute bound on the estimation error
- Direction of normal?

Assumptions

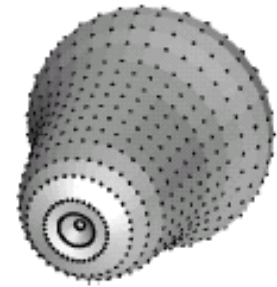
● Noise

- Independent of measurement
- Zero mean
- Variance is known (noise need not be bounded)

● Data

- Sampling criterion satisfied
- *Evenly distributed* data
 - To prevent biased estimates
- Curvature is bounded

Sampling Criteria (2D)



Sampling density

- lower bound (like Nyquist rate)
- upper bound (to prevent biased fits)

Evenly distributed

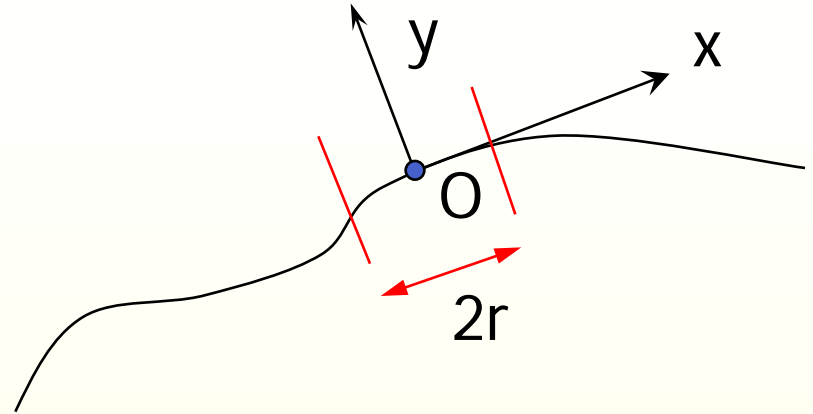
Number of points in a disc of radius r bounded *above* and *below* by $\Theta(1)r\rho$

ρ is the sampling density

(ε, δ) sampling condition [Dey et. al.] implies evenly distributed.

Modeling (2D)

- At a point O



- Points of PCD inside a disc of radius r comes from a segment of the curve
- $y = g(x)$ define the curve for all $x \in [-r, r]$
- Bounded curvature: $|g''(x)| < \kappa$ for all x
- Additive Noise(n) in y -direction $(x, g(x) + n)$
- $\kappa r, \sigma_n/r$ assumed to be small

Proof Idea

- Eigen-analysis of covariance matrix

$$M = \begin{bmatrix} m_{11} & m_{12} \\ m_{21} & m_{22} \end{bmatrix}$$

Proof Idea

- covariance matrix
- let,

$$M = \begin{bmatrix} m_{11} & m_{12} \\ m_{21} & m_{22} \end{bmatrix}$$

$$\alpha = (|m_{12}| + m_{22}) / m_{11}$$

Proof Idea

$$M = \begin{bmatrix} m_{11} & m_{12} \\ m_{21} & m_{22} \end{bmatrix}$$

- covariance matrix
- let, $\alpha = (|m_{12}| + m_{22}) / m_{11}$
- error angle bounded by,

$$\tan^{-1} \left(\frac{\alpha(1+\alpha)}{(1-\alpha)^2} \right) \approx \alpha$$

- to bound estimation error,
need to bound α

Final Result in 2D

$$\alpha \leq \Theta(1)\kappa r + \Theta(1)\frac{\sigma_n}{\sqrt{\varepsilon\rho r^3}} + \Theta(1)\frac{\sigma_n^2}{r^2}$$

- $\kappa = 0$,

take as large a neighborhood as possible

Final Result in 2D

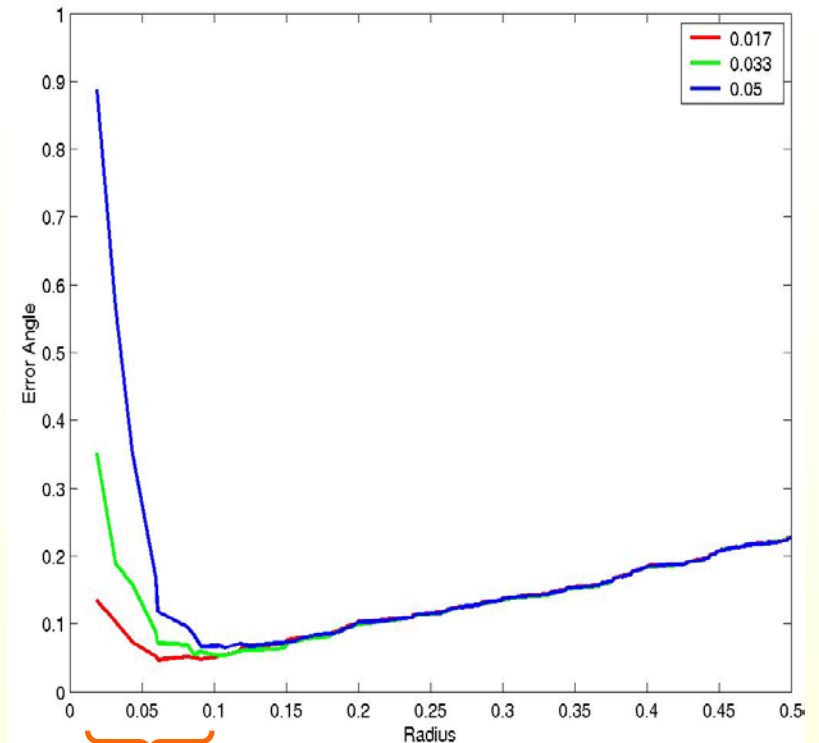
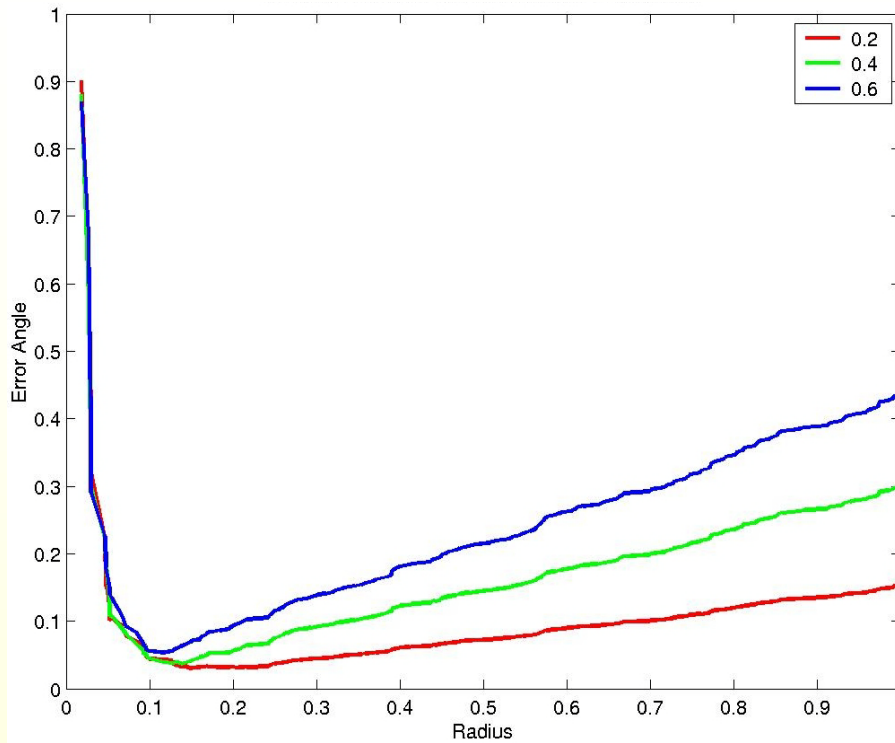
$$\alpha \leq \Theta(1)\kappa r + \Theta(1)\frac{\sigma_n}{\sqrt{\varepsilon\rho r^3}} + \Theta(1)\frac{\sigma_n^2}{r^2}$$

- $\kappa = 0$, take as large a neighborhood as possible
- $\sigma_n = 0$

take as small a neighborhood as possible

Experiments in 2D

κ



$$error \leq \Theta(1)\kappa r + \Theta(1) \frac{\sigma_n}{\sqrt{\epsilon p r^3}} + \Theta(1) \frac{\sigma_n^2}{r^2}$$

Result for 3D

A similar but involved analysis results in,

$$\text{error} \leq \Theta(1)\kappa r + \Theta(1)\sigma_n / (r^2 \sqrt{\varepsilon\rho}) + \Theta(1)\sigma_n^2 / r^2$$

A good choice of r is,

$$r = \left(\frac{1}{\kappa} \left(c_1 \frac{\sigma_n}{\sqrt{\varepsilon\rho}} + c_2 \sigma_n^2 \right) \right)^{1/3}$$

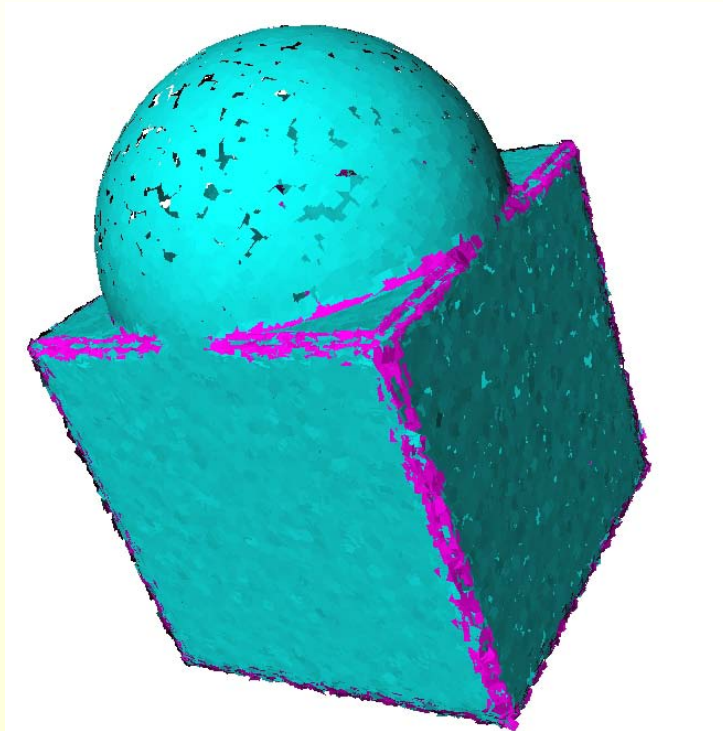
How can we use this result?

$$r = \left(\frac{1}{\kappa} \left(c_1 \frac{\sigma_n}{\sqrt{\epsilon \rho}} + c_2 \sigma_n^2 \right) \right)^{1/3}$$

- Need to
 - know ϵ , σ_n
 - estimate suitable values for c_1 , c_2
 - estimate ρ , κ locally

Estimating c_1, c_2

Exact normals known at *almost* all points



$$r = \left(\frac{1}{K} \left(c_1 \frac{\sigma_n}{\sqrt{\epsilon\rho}} + c_2 \sigma_n^2 \right) \right)^{1/3}$$

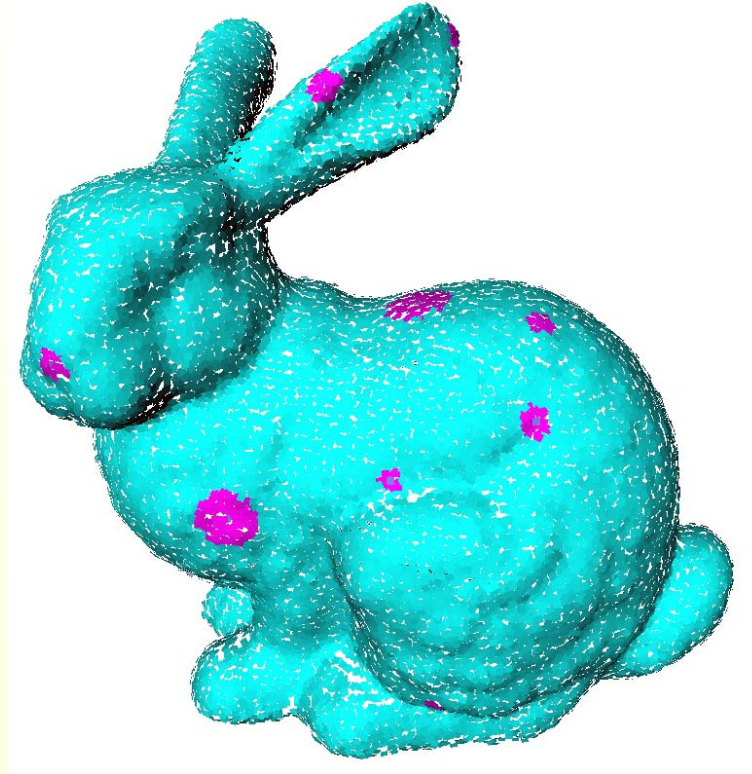
$$c_1=1, c_2=4$$

- same constants used for following results

Algorithm

- For each point, start with $k = 15$
- Iterate and refine (maximum of 10 steps)
 - Compute r, ρ, κ [Gumhold et al.] locally
 - Use them to compute r_{new}
 - $k_{new} = \pi r_{new}^2 \rho_{old}$
 - Stop if
 - $k > threshold$
 - k saturates

Effect of Curvature on Neighborhood Size



1x noise

Effect of Noise on Neighborhood Size



1x noise

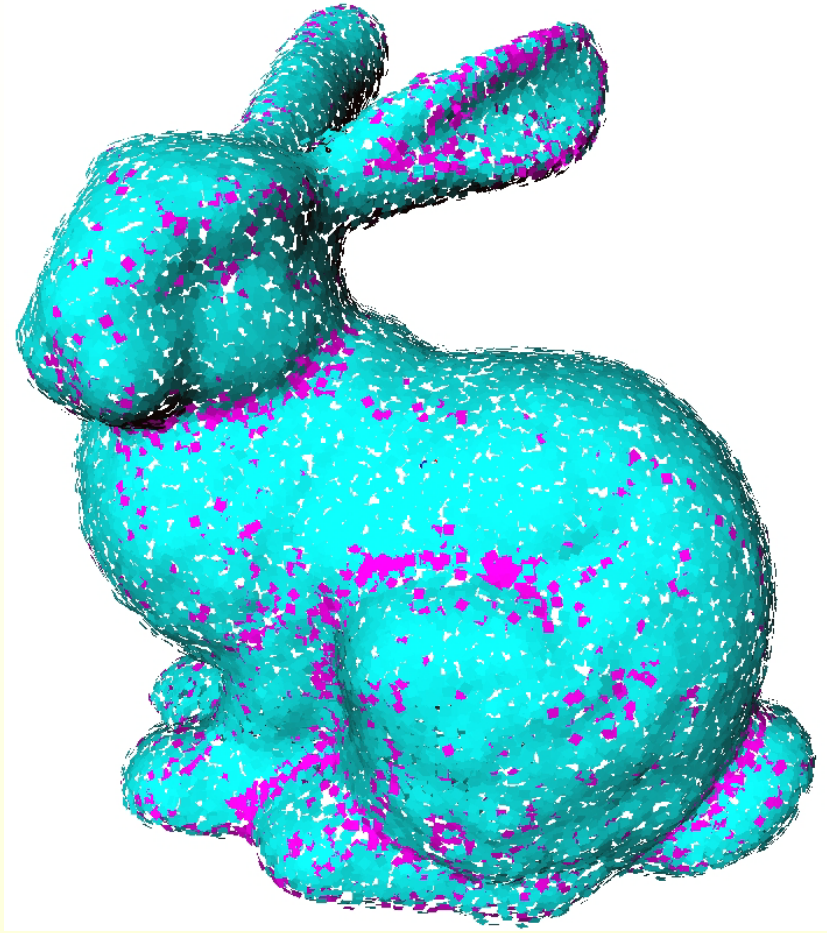


2x noise

Estimation Error > 5



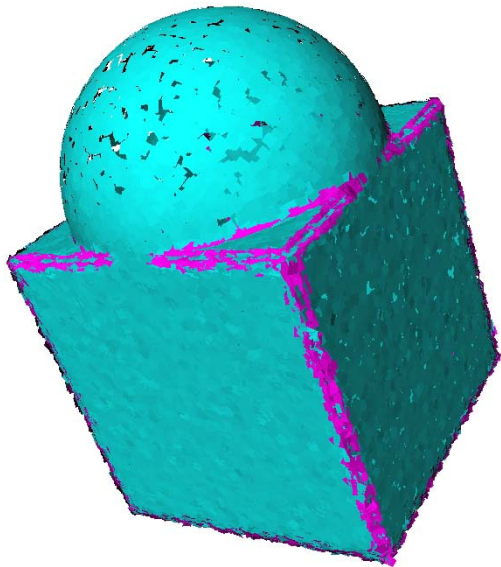
1x noise



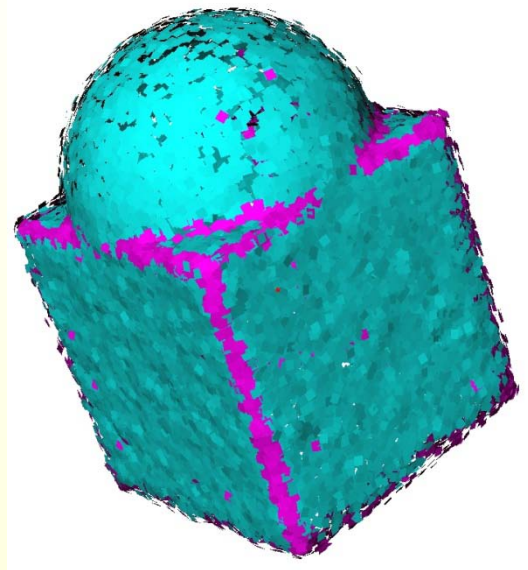
2x noise

Increasing Noise

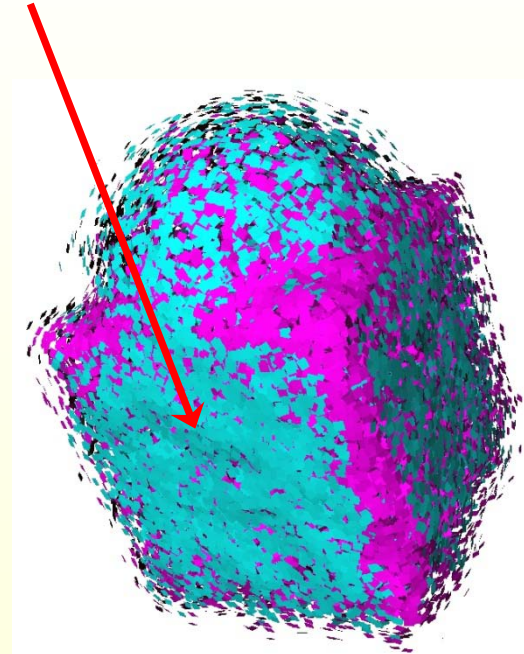
Can still get good estimates in flat areas



1x noise



2x noise

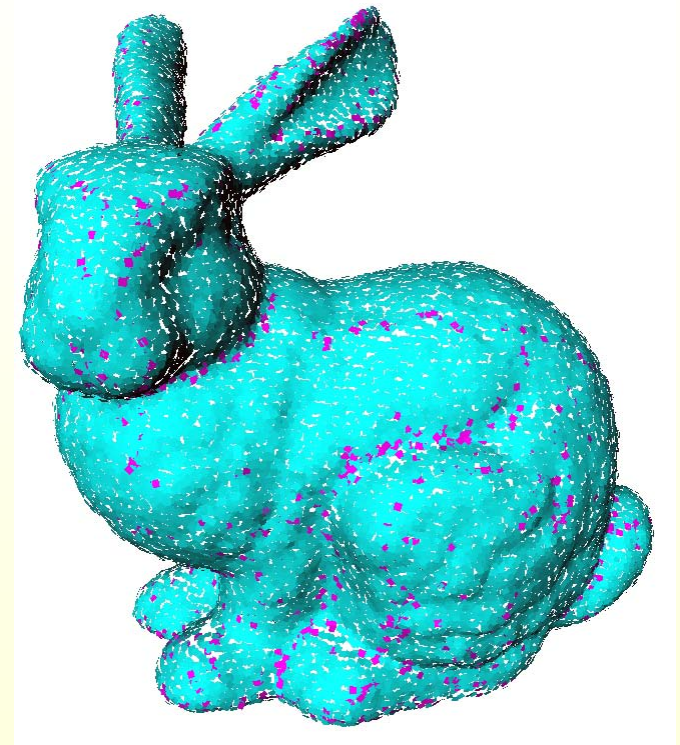


4x noise

Different Noise Distribution (same variance)

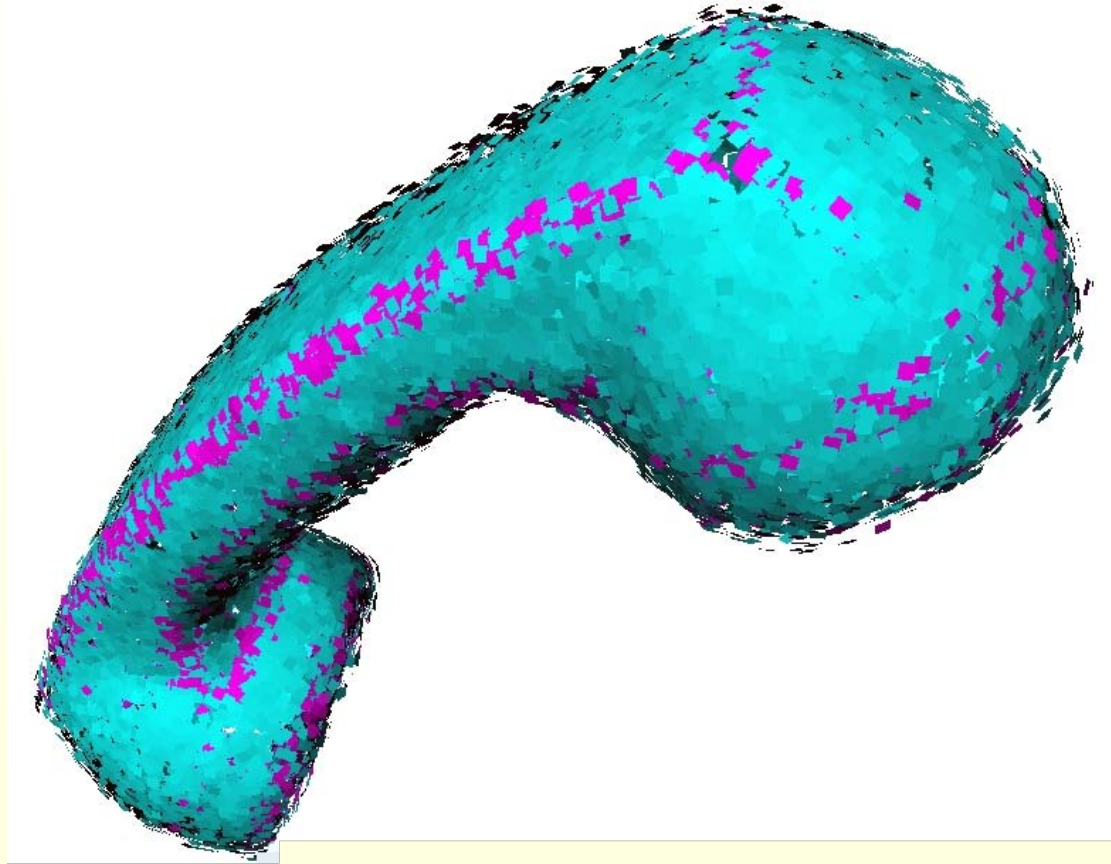


uniform



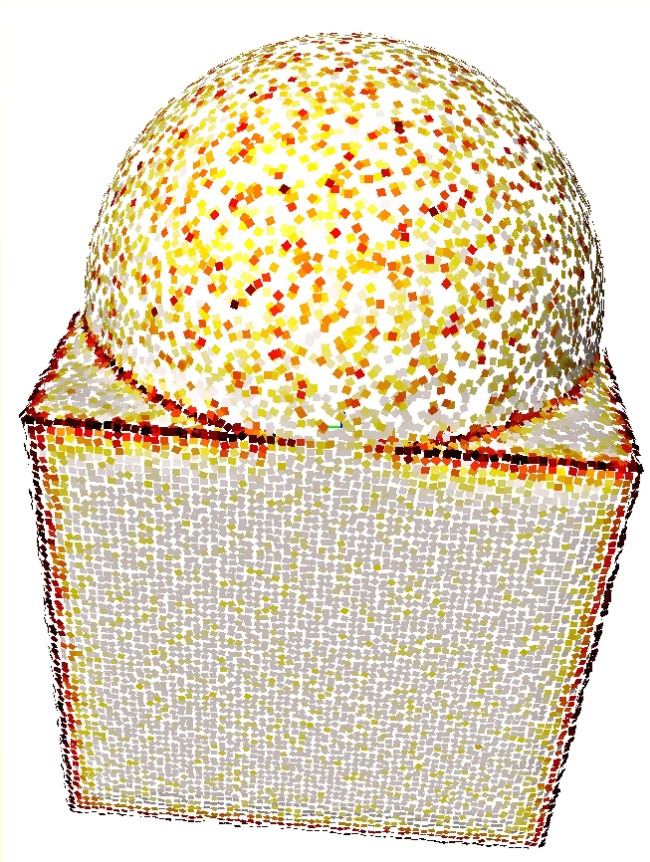
gaussian

Result: Phone



1x noise

Varying Neighborhood Size



Neighborhood size at all points being shown using color-coding. Purple denotes the smallest neighborhood and turns blue as the neighborhood size increases

The End