

# Basics Concepts of Riemannian Manifolds

MLRG summer, 2021

# Outline

Linear algebra

Multivariate/vector calculus

Manifold

Chart/coordinate

Riemannian vector, dual vector, Riemannian metric

Geodesic, retraction

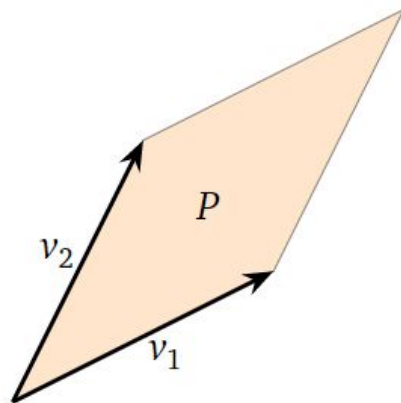
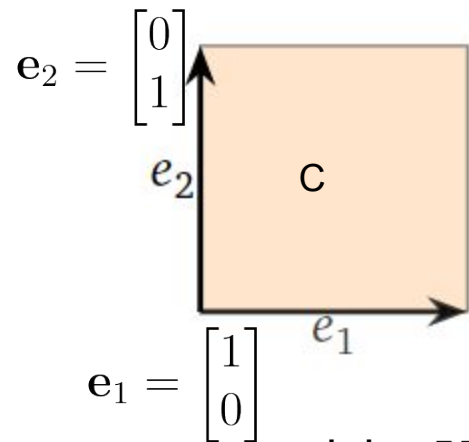
# Geometric meaning of the matrix determinant

Source: <https://textbooks.math.gatech.edu/ila/determinants-volumes.html>

An invertible matrix  $T$  can be viewed as a map

$$\mathbf{T} = \begin{bmatrix} \mathbf{v}_1 & \mathbf{v}_2 \end{bmatrix}$$

$$T : \mathcal{R}^n \rightarrow \mathcal{R}^n$$



$$\mathbf{v}_i = T(\mathbf{e}_i) = \mathbf{T}\mathbf{e}_i$$

$$\text{claim: } \text{vol}(\mathbf{P}) = |\det(T)| \text{vol}(\mathbf{C})$$

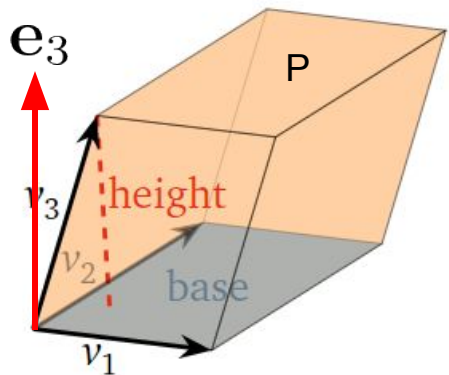
# An informal geometric proof $\text{vol}(\mathbf{P}) = |\det(T)|\text{vol}(\mathbf{C})$

We consider the  $n = 3$  case.

$$\mathbf{v}_i = T(\mathbf{e}_i) = \mathbf{T}\mathbf{e}_i$$

$$\text{vol}(\mathbf{C}) = 1$$

$$\mathbf{T} = \begin{bmatrix} \mathbf{v}_1 & \mathbf{v}_2 & \mathbf{v}_3 \end{bmatrix}$$



Cross product:

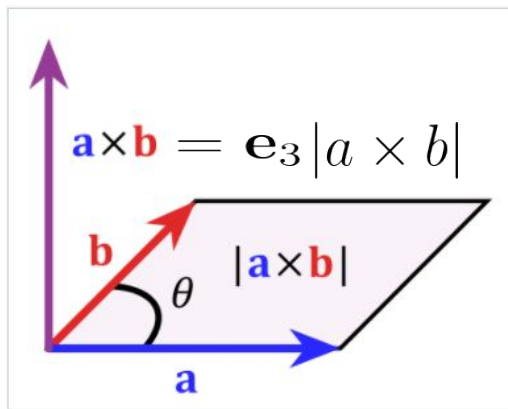
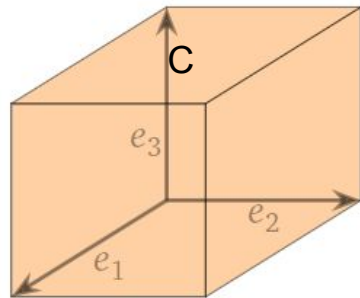
$$\mathbf{v}_1 \times \mathbf{v}_2 = \begin{bmatrix} \mathbf{e}_1 & v_{1,1} & v_{2,1} \\ \mathbf{e}_2 & v_{1,2} & v_{2,2} \\ \mathbf{e}_3 & v_{1,3} & v_{2,3} \end{bmatrix}$$

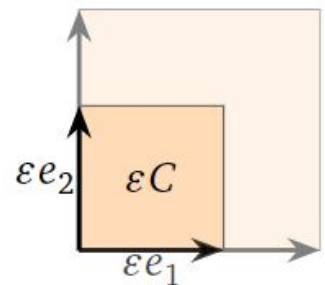
base:  $|\mathbf{v}_1 \times \mathbf{v}_2|$

height:  $\mathbf{e}_3 \cdot \mathbf{v}_3$

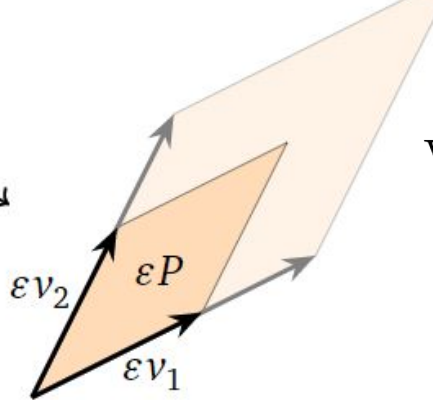
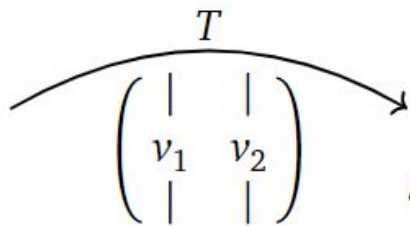
$$\text{vol}(\mathbf{P}) = |(\mathbf{v}_1 \times \mathbf{v}_2) \cdot \mathbf{v}_3|$$

$$(\mathbf{v}_1 \times \mathbf{v}_2) \cdot \mathbf{v}_3 = \det \begin{bmatrix} v_{1,1} & v_{2,1} & v_{3,1} \\ v_{1,2} & v_{2,2} & v_{3,2} \\ v_{1,3} & v_{2,3} & v_{3,3} \end{bmatrix}$$





$$\text{vol}(\epsilon\mathbf{C}) = \epsilon^2$$

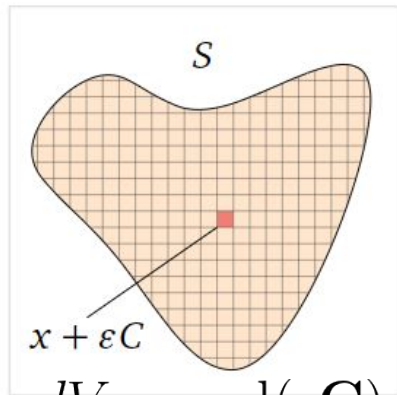


$$\text{vol}(\epsilon\mathbf{P}) = \epsilon^2 |\det(T)|$$

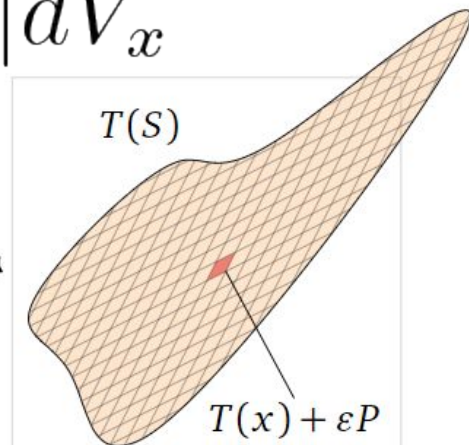
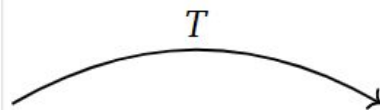
an invertible matrix  $T$

$$\text{vol}(\mathbf{P}) = |\det(T)| \text{vol}(\mathbf{C})$$

$$dV_y = |\det(T)| dV_x$$



$$dV_x = \text{vol}(\epsilon\mathbf{C})$$



$$dV_y = \text{vol}(\epsilon\mathbf{P}), y = T(x)$$

# Integration by substitution

$$\int_{\psi(\mathbf{S})} f(y) dV_y = \int_{\mathbf{S}} f \circ \psi(x) |\det(\nabla \psi)| dV_x$$

We approximate map  $\psi$  using its linearization  $T = \nabla \psi$

Classical examples: Work (line integral), Flux (surface integral)

ML example: normalizing flows  $y = \psi(x), x \sim p(x)$

$$1 = \int p_y(y) dy = \int p_y(\psi(x)) |\det(\nabla \psi)| dx$$

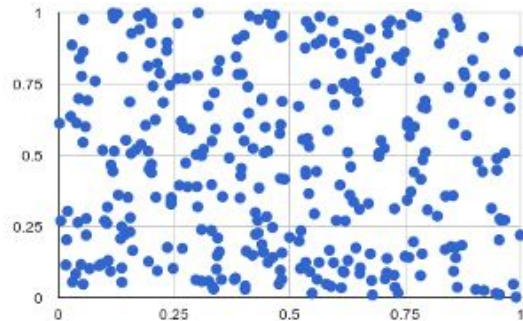
$$1 = \int p(x) dx$$

$$p_y(y) = p(x) |\det(\nabla \psi(x))|^{-1}, x = \psi^{-1}(y)$$

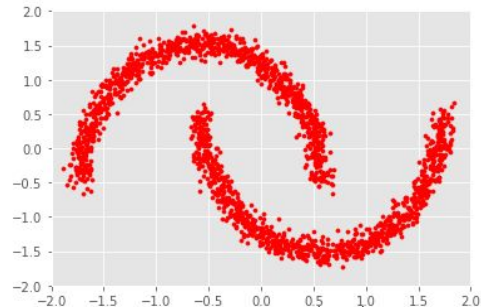
$$\psi : \mathcal{R}^n \rightarrow \mathcal{R}^n$$

$\psi$  deterministic, one-to-one map

continuously diff.

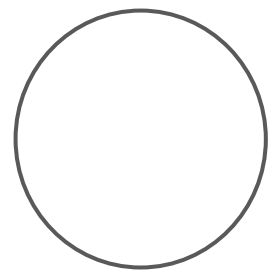
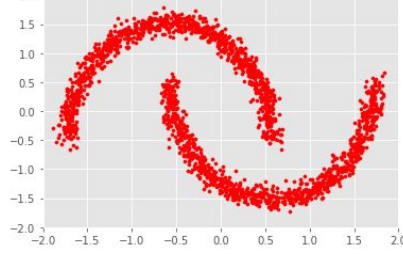


$x \in \mathbf{S}$



$y \in \psi(\mathbf{S})$

# Manifolds & charts



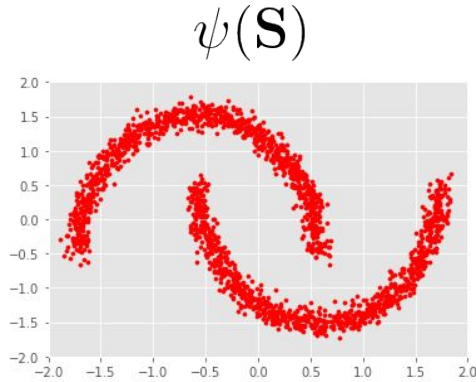
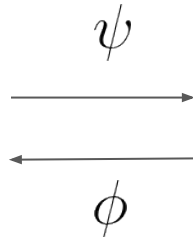
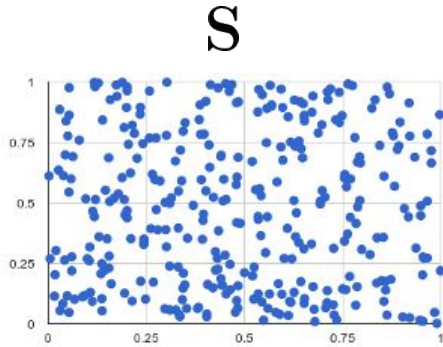
$$x^2 + y^2 = 1$$

A curved space locally looks like a flat/Euclidean space

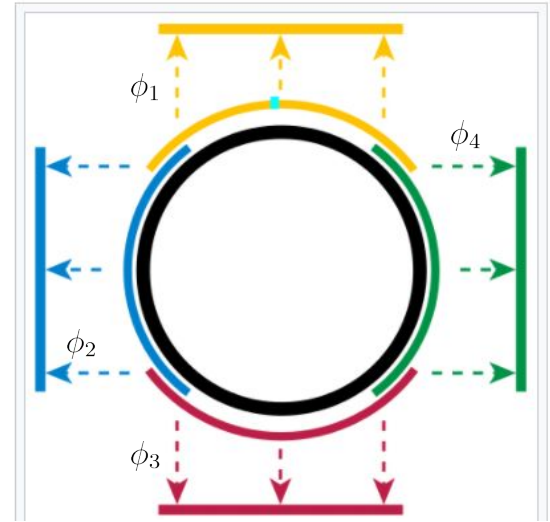
$\psi(\mathbf{S})$  An open subset of a manifold

$\mathbf{S}$  An open subset in a Euclidean space

$\phi := \psi^{-1}$  a (local) chart/coordinate



$$U := \psi(\mathbf{S})$$



# Free parameters in a chart

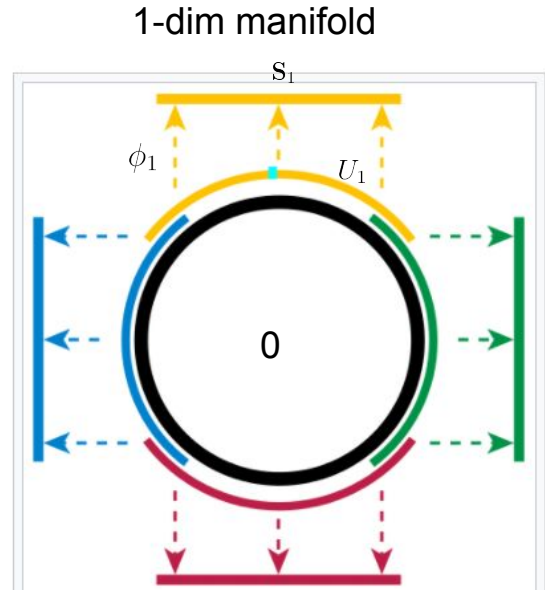
We will assume  $\phi_1$  and  $U_1$  are known.

$$U_1 = \{(x, y) | x^2 + y^2 = 1, y > 0, -1 < x < 1\}$$

$$\mathbf{S}_1 = \{x | -1 < x < 1\} \subset \mathcal{R}^1 \subset \mathcal{R}^2$$

$$\phi_1((x, y)) = x \in \mathbf{S}_1$$

$$\psi_1(t) := \phi_1^{-1}(t) = (t, \sqrt{1 - t^2}) \in U_1, t \in \mathbf{S}_1 \quad x^2 + y^2 = 1$$



In set  $U_1$ ,  $y$  is fully determined by  $x$ . Therefore, we only consider  $x$  is the single free parameter

# of free parameters implicitly defines the dimension of a manifold

We ONLY use free parameters to represent a vector in the manifold

We only compute gradients w.r.t. free parameters. There are some exceptions for matrix manifolds

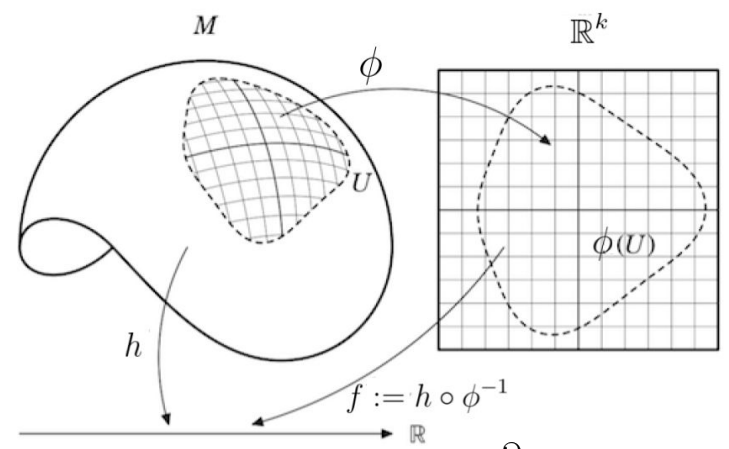


# Riemannian vectors and metric

Given a chart,  $x=[x_1, \dots, x_k]$  represents a set of free variables.

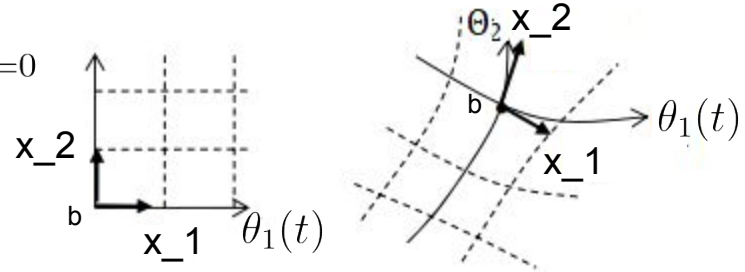
A basis of a tangent vector space at point  $b=[b_1, \dots, b_k]$  is denoted by  $\left\{ \frac{\partial}{\partial x_i} \right\}_{i=1}^k$

A basis vector  $\frac{\partial}{\partial x_1}$  can be viewed as the tangent vector of the coordinate curve/direction  $\theta_1(t)$



$$\frac{\partial}{\partial x_1} := \nabla_t \theta_1(t) \Big|_{t=0} = \nabla_t [b_1 + t, b_2, \dots, b_k] \Big|_{t=0}$$

$$\left\langle \frac{\partial}{\partial x_1}, v \right\rangle_{\mathbf{F}} := \mathbf{e}_1^T \mathbf{F} \mathbf{v} \quad \text{Metric } \mathbf{F}$$



**Cartesian**

**Curvilinear**

In the Euclidean case,  $\mathbf{F}$  is the identity matrix

# Gradients of a scalar function h

$$\frac{\partial}{\partial x_1} := \nabla_t [b_1 + t, b_2, \dots, b_k] \Big|_{t=0}$$

Directional derivative

$$\frac{\partial}{\partial x_1}(f) := \nabla_t f([b_1 + t, b_2, \dots, b_k]) \Big|_{t=0}$$

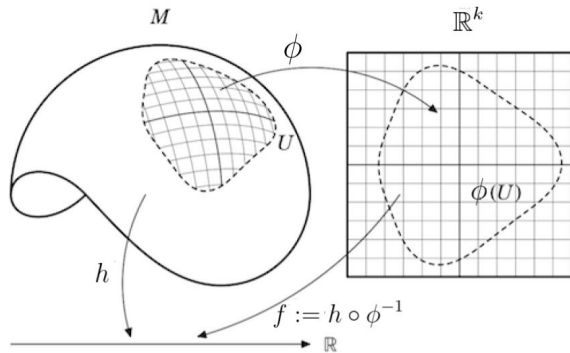
A scalar function h defined on a k-dim manifold can be expressed as f(x) given a chart, where  $x=[x_1, \dots, x_k]$  are free variables.

$$\left\langle \frac{\partial}{\partial x_1}, \hat{\mathbf{g}}_f \right\rangle_{\mathbf{F}} := \frac{\partial}{\partial x_1}(f) = \frac{\partial}{\partial x_1} f(x)$$

$$\left\langle \frac{\partial}{\partial x_1}, \hat{\mathbf{g}}_f \right\rangle_F := e_1^T \mathbf{F} \hat{\mathbf{g}}_f$$

$$\hat{\mathbf{g}}_f = \mathbf{F}^{-1} \mathbf{g}_f$$

$$\mathbf{g}_f := \left[ \frac{\partial}{\partial x_1} f(x), \dots, \frac{\partial}{\partial x_k} f(x) \right]$$



Riemannian metric

$\mathbf{F}$

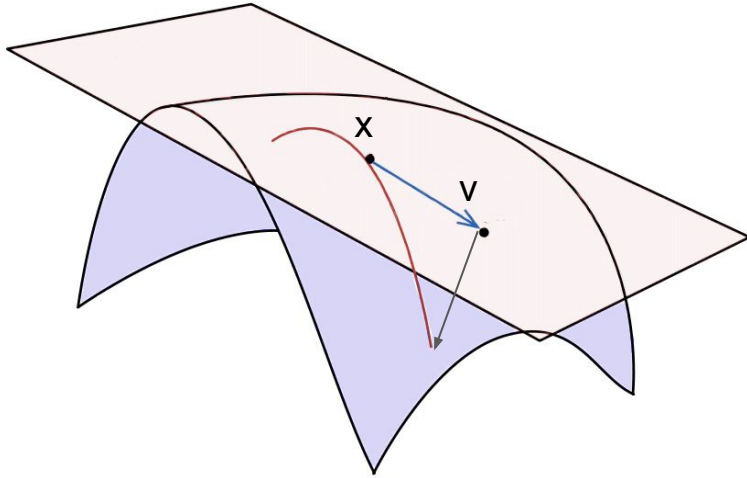
Riemannian gradient (vector)

$\hat{\mathbf{g}}_f$

Euclidean gradient (dual vector)

$\mathbf{g}_f$

# Geodesic & Manifold Exponential Map & Retraction Maps



Given a starting point  $x$  and a Riemannian direction/gradient  $v$ ,  
A geodesic: a “straight line” on the manifold.  
Input:  $t$ ; Output: a point on the manifold

$$L(t) = \mathbf{x} + t\mathbf{v} \quad \text{a straight line in the Euclidean case}$$

Given a starting point  $x$  and step-size  $t=1$   
The exponential map:  
Input:  $v$ ; Output: a point on the manifold

Retraction: an approximation of the exponential map