

Matrix Volume and its Applications

Adi Ben-Israel

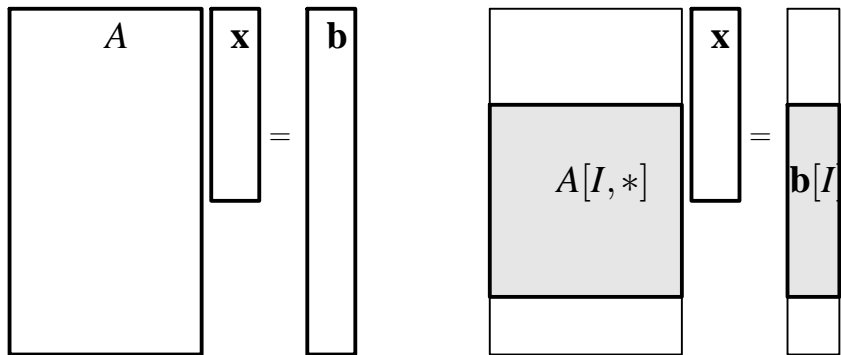
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- 2 Definitions
- 3 Factorizations
- 4 Angles
- 5 A multilinear setting
- 6 Surfaces
- 7 Integrals
- 8 Concentration of measure
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Least squares solution $\mathbf{x}^* := \arg \min \|A\mathbf{x} - \mathbf{b}\|$

I -basic solution $\mathbf{x}_I := A[I, *]^{-1} \mathbf{b}[I]$.

Consider a system of linear equations

$$A \mathbf{x} = \mathbf{b}$$

$A \in \mathbb{R}_r^{m \times r}$, $\mathbf{b} \in \mathbb{R}^m$, and its **least squares solution (LSS)**

$$\mathbf{x}^* := \arg \min \|A \mathbf{x} - \mathbf{b}\|.$$

For any $I = \{i_1, i_2, \dots, i_r\} \subset 1:m$, with $A[I, *]$ nonsingular, the I -**basic solution** is

$$\mathbf{x}_I := A[I, *]^{-1} \mathbf{b}[I].$$

Then LSS is a convex combination of the basic solutions

$$\mathbf{x}^* = \sum_I \lambda_I \mathbf{x}_I, \quad \lambda_I \propto \det^2 A[I, *]$$

$$\lambda_I = \frac{\det^2 A[I, *]}{\sum_J \det^2 A[J, *]}$$

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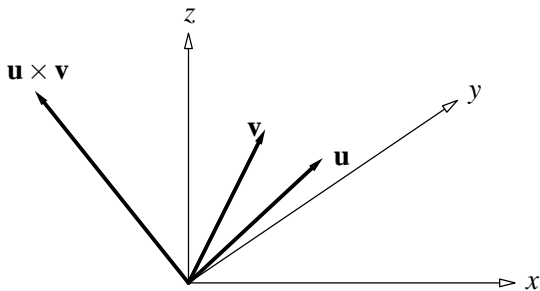
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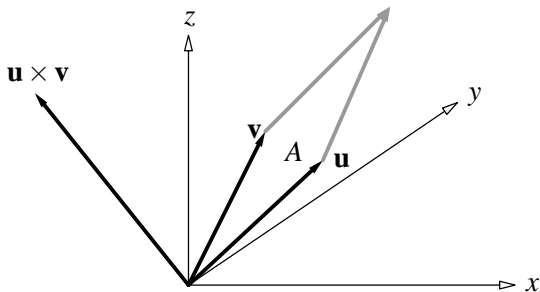
Why determinants? recall the cross product $\mathbf{u} \times \mathbf{v}$



Let $\mathbf{u} = (u_i)$, $\mathbf{v} = (v_i) \in \mathbb{R}^3$, and the **cross product**

$$\mathbf{u} \times \mathbf{v} = (u_2 v_3 - u_3 v_2) \mathbf{i} + (u_1 v_3 - u_3 v_1) \mathbf{j} + (u_1 v_2 - u_2 v_1) \mathbf{k}.$$

$\mathbf{u} \times \mathbf{v}$ is the (signed) area of $\diamond\{\mathbf{u}, \mathbf{v}\}$



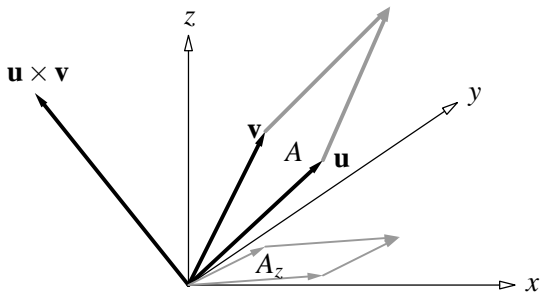
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The area A of $\diamond\{\mathbf{u}, \mathbf{v}\}$ is

$$A = \|\mathbf{u} \times \mathbf{v}\|$$

Why $\sum_J \det^2 A[J, *]$? A Pythagorean theorem for areas

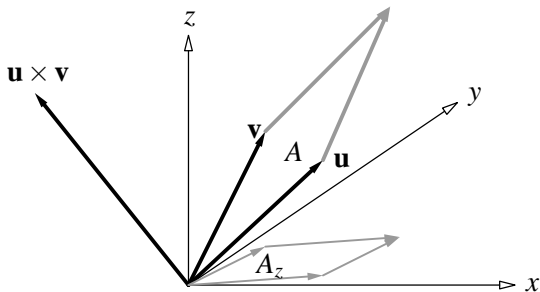


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$$A = \|\mathbf{u} \times \mathbf{v}\| = \sqrt{A_x^2 + A_y^2 + A_z^2}, \quad \text{where } A_z = |u_1 v_2 - u_2 v_1|$$

is the area of the projection of $\diamond\{\mathbf{u}, \mathbf{v}\}$ on the xy -plane, etc.

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Notation:

$$1:n := \{1, 2, \dots, n-1, n\}$$

$$\mathbf{Q}(r, n) = \{I = \{i_1, \dots, i_r\} \in 1:n \mid 1 \leq i_1 < i_2 < \dots < i_r \leq n\}$$

$$\mathbf{I}(A) = \{I \in \mathbf{Q}(r, m) \mid \text{rank } A[I, *] = r\}$$

$$\mathbf{J}(A) = \{J \in \mathbf{Q}(r, n) \mid \text{rank } A[* , J] = r\}$$

$$\mathbf{M}(A) = \{(I, J) \in \mathbf{Q}(r, m) \times \mathbf{Q}(r, n) \mid \text{rank } A[I, J] = r\}$$

Let $A \in \mathbb{R}_r^{m \times n}$, $\mathbf{b} \in \mathbb{R}^m$ and consider the **minimum norm least squares solution** (MNLSS) \mathbf{x}^* of

$$A\mathbf{x} = \mathbf{b}$$

For any $(I, J) \in \mathbf{M}(A)$, the solution \mathbf{x}_{IJ} of

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$$\mathbf{x}^* = \sum_{(I,J) \in \mathbf{M}(A)} \lambda_{IJ} \widehat{A[I,J]}^{-1} \mathbf{b}[I]$$

with convex weights proportional to $\det^2 A[I,J]$,

$$\lambda_{IJ} = \frac{\det^2 A[I,J]}{\sum_{(K,L) \in \mathbf{M}(A)} \det^2 A[K,L]}$$

Theorem

If $A \in \mathbb{R}_r^{m \times n}$ then

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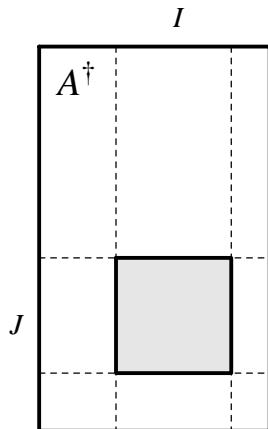
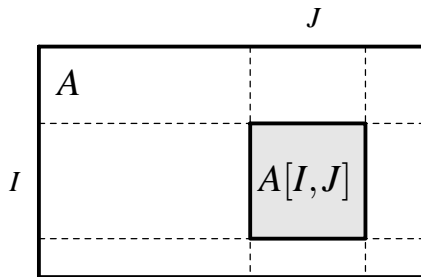
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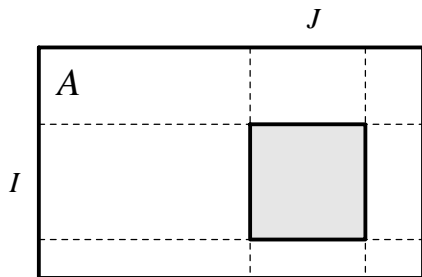
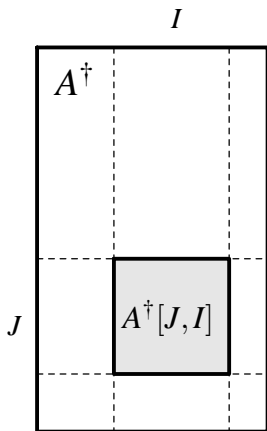
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$$A^\dagger = \sum_{(I,J) \in \widehat{\mathbf{M}}(A)} \lambda_{IJ} A[I,J]^{-1}, \quad \lambda_{IJ} \propto \det^2 A[I,J]$$



$$A = A^{\dagger\dagger} = \sum_{(J,I) \in \mathbf{M}(A^{\dagger})} \widehat{\lambda_{JI}} A^{\dagger}[J,I]^{-1}, \quad \lambda_{JI} \propto \det^2 A^{\dagger}[J,I]$$



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Definitions of $\text{vol}(A)$, $A \in \mathbb{R}_r^{m \times n}$

Let $A \in \mathbb{R}_r^{m \times n}$. The **volume** of A , $\text{vol}(A)$, is defined as

$$\text{vol}(A) := \begin{cases} 0, & r = 0; \\ \sqrt{\sum_{(I,J) \in \mathbf{M}(A)} \det^2 A[I,J]}, & r > 0. \end{cases}$$

Equivalently, if $r > 0$,

$$\text{vol}(A) := \prod_{i=1}^r \sigma_i$$

the product of the **singular values** of A .

Given $A \in \mathbb{R}_r^{m \times n}$, every **unit cube** in $\mathbf{R}(A^T)$ is mapped by A into a **parallelepiped** in $\mathbf{R}(A)$ of volume $\text{vol}(A)$

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If $\{\mathbf{w}_1, \dots, \mathbf{w}_n\} \subset \mathbb{R}^n$ are l.i., the (signed) volume of the parallelepiped $\diamond\{\mathbf{w}_1, \dots, \mathbf{w}_n\}$ is given by the determinant

$$\begin{aligned}\text{vol}(\diamond\{\mathbf{w}_1, \dots, \mathbf{w}_n\}) &= \det W, \quad W = (\mathbf{w}_1, \dots, \mathbf{w}_n), \\ \text{and } \text{vol}(W) &= |\det W|.\end{aligned}$$

If $\{\mathbf{w}_1, \dots, \mathbf{w}_k\} \subset \mathbb{R}^n$ are l.i., $k \leq n$, the volume of the parallelepiped $\diamond\{\mathbf{w}_1, \dots, \mathbf{w}_k\}$ is given by the Gram determinant,

$$\begin{aligned}\text{vol}^2(\diamond\{\mathbf{w}_1, \dots, \mathbf{w}_k\}) &= \det W^T W, \quad W = (\mathbf{w}_1, \dots, \mathbf{w}_k), \\ \text{and } \text{vol}(W) &= \sqrt{\det W^T W}.\end{aligned}$$

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Full rank factorizations

A full rank factorization (FRF) of $A \in \mathbb{R}^{m \times n}$ is

$$A = CR, \quad C \in \mathbb{R}^{m \times r}, \quad R \in \mathbb{R}^{r \times n}$$

If $A = CR$ is a FRF,

$$\mathbf{I}(A) = \mathbf{I}(C)$$

$$\mathbf{J}(A) = \mathbf{J}(R)$$

$$\mathbf{M}(A) = \mathbf{I}(A) \times \mathbf{J}(A)$$

$(I \in \mathbf{I}(A), J \in \mathbf{J}(A) \implies A[I, J] = C[I, *]R[*, J]$ nonsingular)

Examples: SVD, QR, CUR

The results below hold for any FRF.

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Volume of FRF

The **volume** of $A \in \mathbb{R}_r^{m \times n}$ is $\text{vol}(A) := \sqrt{\sum_{(I,J) \in \mathbf{M}(A)} \det^2 A[I,J]}$

Theorem

If $A \in \mathbb{R}_r^{m \times n}$, $r > 0$, and $A = CR$ is any FRF, then

$$\text{vol}(A) = \text{vol}(C) \text{vol}(R)$$

Proof.

$$\begin{aligned} \text{vol}^2(A) &= \sum_{(I,J) \in \mathbf{M}(A)} \det^2 A[I,J] = \sum_{(I,J) \in \mathbf{M}(A)} \det^2 C[I,*] R[*,J] \\ &= \sum_{(I,J) \in \mathbf{M}(A)} \det^2 C[I,*] \det^2 R[*,J] \\ &= \left(\sum_{I \in \mathbf{I}(A)} \det^2 C[I,*] \right) \left(\sum_{J \in \mathbf{J}(A)} \det^2 R[*,J] \right) \\ &= \text{vol}^2(C) \text{vol}^2(R). \end{aligned}$$

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$$A = U\Sigma V^T$$

with $\Sigma = \text{diag}(\sigma_i) \in \mathbb{R}_r^{r \times r}$, $U^T U = V^T V = I_r$

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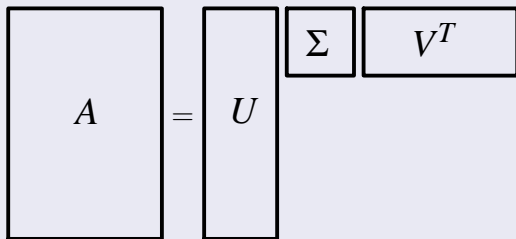
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$$A = U\Sigma V^T, \quad \Sigma = \text{diag}\{\sigma_i \mid i \in 1:r\}, \quad U^T U = V^T V = I_r$$



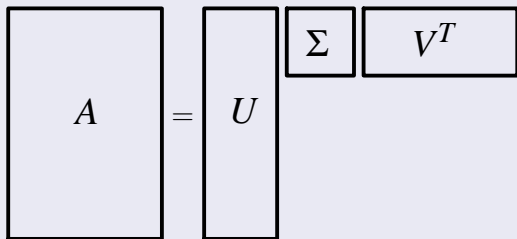
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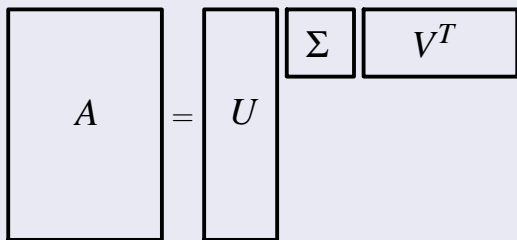
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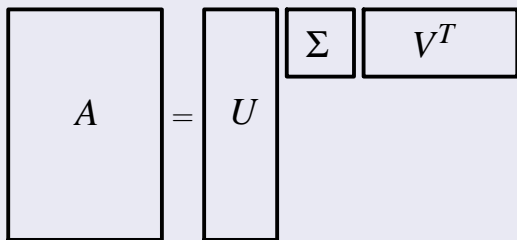
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Principal angles & vectors

Let L, M be subspaces in \mathbb{R}^n , $\dim L = \ell \leq \dim M = m$.

The **principal angles** between L and M ,

$$0 \leq \theta_1 \leq \theta_2 \leq \dots \leq \theta_\ell \leq \frac{\pi}{2}$$

are computed recursively as follows

$$\cos \theta_i = \frac{\langle \mathbf{x}_i, \mathbf{y}_i \rangle}{\|\mathbf{x}_i\| \|\mathbf{y}_i\|} = \max \left\{ \frac{\langle \mathbf{x}, \mathbf{y} \rangle}{\|\mathbf{x}\| \|\mathbf{y}\|} \mid \begin{array}{l} \mathbf{x} \in L, \quad \mathbf{x} \perp \mathbf{x}_k, \\ \mathbf{y} \in M, \quad \mathbf{y} \perp \mathbf{y}_k, \end{array} \quad k \in 1:i-1 \right\}$$

where

$$(\mathbf{x}_i, \mathbf{y}_i) \in L \times M, \quad i \in 1:\ell$$

are the corresponding pairs of **principal vectors**. We also define

$$\sin\{L, M\} := \prod_{i=1}^{\ell} \sin \theta_i, \quad \cos\{L, M\} := \prod_{i=1}^{\ell} \cos \theta_i.$$

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The determinant of $A = (\mathbf{v}_1, \dots, \mathbf{v}_n)$ satisfies

$$|\det A| \leq \prod_{i=1}^n \|\mathbf{v}_i\|$$

equality \iff the vectors are orthogonal, or include zero.

Theorem

Let $A = (A_1, A_2)$, $A_1 \in \mathbb{R}_\ell^{n \times n_1}$, $A_2 \in \mathbb{R}_m^{n \times n_2}$, $\text{rank } A = \ell + m$. Then

$$\text{vol}_{\ell+m}(A) = \text{vol}_\ell(A_1) \text{vol}_m(A_2) \sin\{\mathbf{R}(A_1), \mathbf{R}(A_2)\}.$$

Corollary

Let $A = (A_1, A_2) \in \mathbb{R}^{n \times n}$, with $A_1 \in \mathbb{R}^{n \times \ell}$, $A_2 \in \mathbb{R}^{n \times m}$. Then

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Orthogonal projections

$V := \{\mathbf{v}_1, \dots, \mathbf{v}_k\}$ set of vectors in \mathbb{R}^n

$S := \text{span}\{V\}$, the subspace spanned by V

$\dim S = r$

Any $\mathbf{w} \in \mathbb{R}^n$ can be written as $\mathbf{w} = \mathbf{w}_S + \mathbf{w}_{S^\perp}$.

Theorem

Let V, S be as above. Then, for any $\mathbf{w} \in \mathbb{R}^n$,

$$\|\mathbf{w}_{S^\perp}\| = \frac{\text{vol}_{r+1}(\mathbf{v}_1, \dots, \mathbf{v}_k, \mathbf{w})}{\text{vol}_r(\mathbf{v}_1, \dots, \mathbf{v}_k)},$$

where $(\mathbf{v}_1, \dots, \mathbf{v}_k)$ is the matrix with \mathbf{v}_j as columns.

Proof.

If $\mathbf{w} \in S$, $0 = 0$. If $\mathbf{w} \notin S$ then

$$\text{vol}_{r+1}(\mathbf{v}_1, \dots, \mathbf{v}_k, \mathbf{w}) = \text{vol}_r(\mathbf{v}_1, \dots, \mathbf{v}_k) \text{vol}_1(\mathbf{w}) \sin\{S, \mathbf{w}\}$$



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For any two vectors $\mathbf{u}, \mathbf{v} \in \mathbb{R}^n$,

$$|\langle \mathbf{u}, \mathbf{v} \rangle| \leq \|\mathbf{u}\| \|\mathbf{v}\|,$$

with equality if and only if \mathbf{u}, \mathbf{v} are collinear.

The Cauchy–Schwarz equality:

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Exterior products

$V =$ finite-dimensional linear space over field F

An **exterior product** is an operation $\wedge : V \times V \rightarrow V$ that is

(a) anti-commutative, $\mathbf{u} \wedge \mathbf{v} = -\mathbf{v} \wedge \mathbf{u}$

(b) $(\lambda \cdot \mathbf{u}) \wedge \mathbf{v} = \lambda \cdot (\mathbf{u} \wedge \mathbf{v})$

(c) distributive in both variables:

$$(\mathbf{u} + \mathbf{v}) \wedge \mathbf{w} = \mathbf{u} \wedge \mathbf{w} + \mathbf{v} \wedge \mathbf{w}$$

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for all $\mathbf{u}, \mathbf{v}, \mathbf{w} \in V, \lambda \in F$.

$\wedge^k V =$ the k _{th}-**exterior space** over V , spanned by all exterior products $\mathbf{x}_1 \wedge \cdots \wedge \mathbf{x}_k$ of k elements in V

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Compound matrices

V, U = finite-dimensional linear spaces

$\mathbf{L}(V, U)$ = the linear transformations: $V \rightarrow U$

Linear transformations \longleftrightarrow their matrix representations.

For $V = \mathbb{R}^n$, $U = \mathbb{R}^m$,

$A \in \mathbb{R}_r^{m \times n}$, $r > 0$, $k \in 1:r$,

the k -**compound matrix** of A is the matrix representing the linear transformation $C_k(A) \in \mathbf{L}(\wedge^k V, \wedge^k U)$, defined by

$$C_k(A)(\mathbf{x}_1 \wedge \cdots \wedge \mathbf{x}_k) := A\mathbf{x}_1 \wedge \cdots \wedge A\mathbf{x}_k, \quad \forall \{\mathbf{x}_i\} \subset V,$$

The compound matrix $C_k(A)$ is $\binom{m}{k} \times \binom{n}{k}$ of rank $\binom{r}{k}$.

In particular, $C_r(A)$ is $\binom{m}{r} \times \binom{n}{r}$ of rank 1.

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If $A \in \mathbb{C}^{m \times n}$, $B \in \mathbb{C}^{n \times p}$, $X \in \mathbb{C}^{n \times n}$ then:

$$C_1(A) = A$$

$$\det C_k(X) = (\det X)^{\binom{n-1}{k-1}}, \quad \text{in particular } C_n(X) = \det X$$

$$C_k(AB) = C_k(A)C_k(B)$$

$$C_k(A^T) = (C_k(A))^T$$

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If X is diagonal [triangular] so is $C_k(X)$.

If A is unitary ($A^T A = I_n$), so is $C_k(A)$, in particular, $\|C_n(A)\|_2 = 1$.

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Maple program for $C_k(A)$

```
with(LinearAlgebra):with(combinat):

Compound:=proc(A,k)
local m,n,i,j,rr,cc,P,Q: global CO:
m:=RowDimension(A):n:=ColumnDimension(A)
P:=choose(m,k):Q:=choose(n,k):
rr:=numbcomb(m,k):cc:=numbcomb(n,k):
CO:=Matrix(rr,cc):
for i from 1 to rr do
convert(P[i],list):
for j from 1 to cc do
convert(Q[j],list):
CO(i,j):=evalf(Determinant(SubMatrix(A,P[i],Q[j])))
od:od:
print(CO):
end:
```

$$A \in \mathbb{R}_r^{m \times n}$$



$C_k(A)$ is $\binom{m}{k} \times \binom{n}{k}$ of rank $\binom{r}{k}$

Let $A \in \mathbb{R}^{m \times n}$. The k -compound $C_k(A)$ is defined by

$$A\mathbf{x}_1 \wedge \cdots \wedge A\mathbf{x}_k = C_k(A) (\mathbf{x}_1 \wedge \cdots \wedge \mathbf{x}_k),$$

for all $\{\mathbf{x}_1, \dots, \mathbf{x}_k\} \subset \mathbb{R}^n$.

If A is $n \times n$ then $C_n(A) = \det(A)$, i.e.,

$$A\mathbf{x}_1 \wedge \cdots \wedge A\mathbf{x}_n = \det(A) (\mathbf{x}_1 \wedge \cdots \wedge \mathbf{x}_n),$$

for all $\{\mathbf{x}_1, \dots, \mathbf{x}_n\} \subset \mathbb{R}^n$.

Let $A \in \mathbb{R}_r^{m \times n}$. Then

$$A\mathbf{x}_1 \wedge \cdots \wedge A\mathbf{x}_r = \pm \text{vol}(A) (\mathbf{x}_1 \wedge \cdots \wedge \mathbf{x}_r),$$

for all $\{\mathbf{x}_1, \dots, \mathbf{x}_r\} \subset \mathbf{R}(A^T)$.

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Let $A \in \mathbb{R}^{m \times n}$. The k -compound $C_k(A)$ is defined by

$$A\mathbf{x}_1 \wedge \cdots \wedge A\mathbf{x}_k = C_k(A) (\mathbf{x}_1 \wedge \cdots \wedge \mathbf{x}_k),$$

for all $\{\mathbf{x}_1, \dots, \mathbf{x}_k\} \subset \mathbb{R}^n$.

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Plücker coordinates, [60]

To any subspace $W \subset \mathbb{R}^n$, $\dim W = r$, there corresponds a 1-dimensional subspace $\wedge^r W \subset \wedge^r \mathbb{R}^n$, spanned by

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where $\{\mathbf{w}_1, \dots, \mathbf{w}_r\}$ is any basis of W .

The $\binom{n}{r}$ components of \mathbf{w}^\wedge (determined up to a multiplicative constant) are the **Plücker coordinates** of W .

Let $A \in \mathbb{R}^{m \times n}$ and $A = U\Sigma V^T$ its SVD,

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Plücker coordinates of $\mathbf{R}(A)$ and $\mathbf{R}(A^T)$ are

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If A is square then

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Theorem

Let \mathbf{U}, \mathbf{V} be subspaces of \mathbb{R}^n , with the columns of

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Then

$$\cos\{\mathbf{U}, \mathbf{V}\} = \cos \angle\{\mathbf{u}^\wedge, \mathbf{v}^\wedge\}$$

WLOG assume columns o.n., angles $\leq \frac{\pi}{2}$. Then

$$\det(U^T V) = \cos\{\mathbf{U}, \mathbf{V}\}, \text{ also,}$$

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$$A = U \Sigma V^T$$

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SVD of $A \in \mathbb{R}_r^{m \times n}$ and $C_r(A)$

$$A = U \begin{bmatrix} \Sigma & \\ & V^T \end{bmatrix}$$

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$$C_r(A) = \text{vol}(A) \begin{bmatrix} \mathbf{u}^\wedge & (\mathbf{v}^\wedge)^T \end{bmatrix}$$

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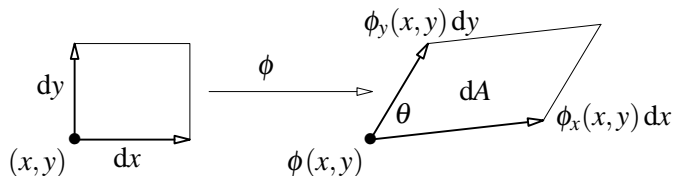
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- 1 Motivation
- 2 Definitions
- 3 Factorizations
- 4 Angles
- 5 A multilinear setting
- 6 Surfaces**
- 7 Integrals
- 8 Concentration of measure
- 9 Probability
- 10 Applications
- 11 References



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$$F := \phi_x \cdot \phi_y = \|\phi_x\| \|\phi_y\| \cos \theta$$

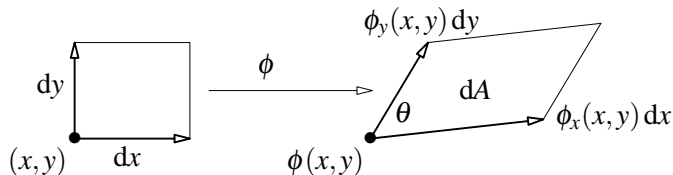
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$$ds^2 = E dx^2 + 2F dx dy + G dy^2 \quad (1\text{st fundamental form})$$

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$$= \sqrt{EG - F^2} dx dy$$

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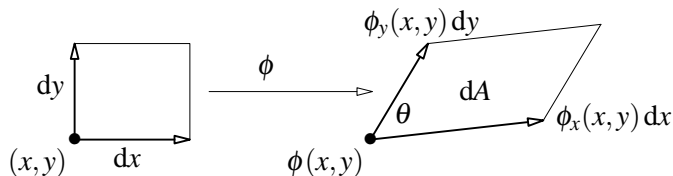
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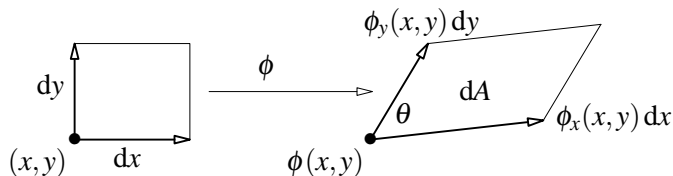
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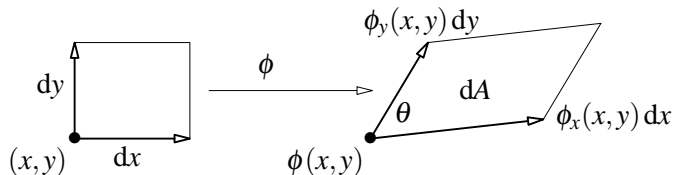
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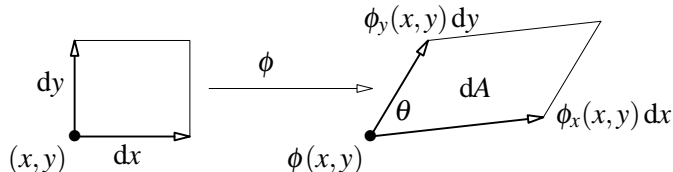
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Monge patch: Surface in \mathbb{R}^3 given by $z = f(x, y)$



$$\phi(x, y) = (x, y, f(x, y))$$

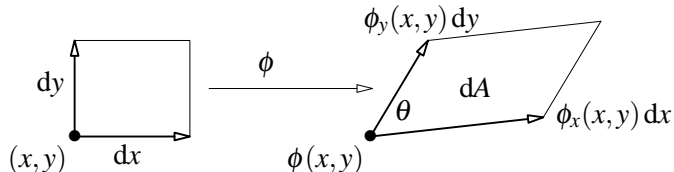
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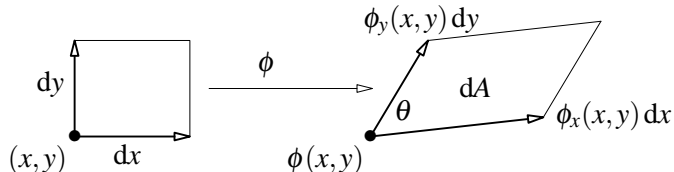
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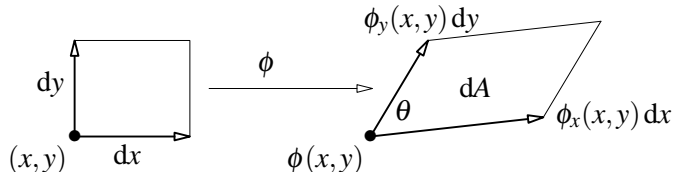
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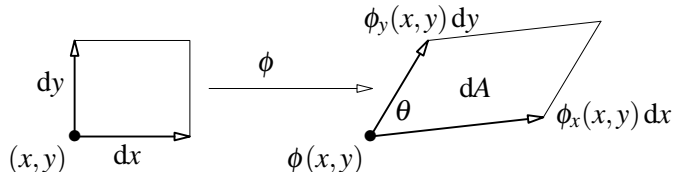
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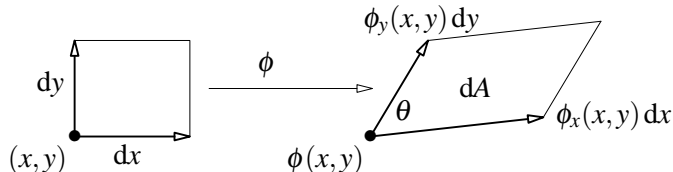
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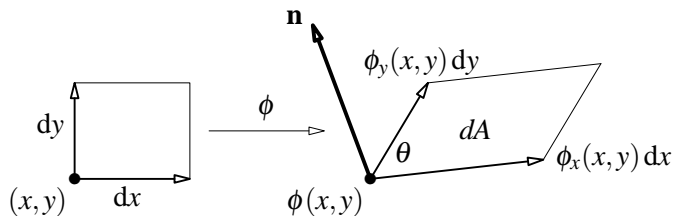
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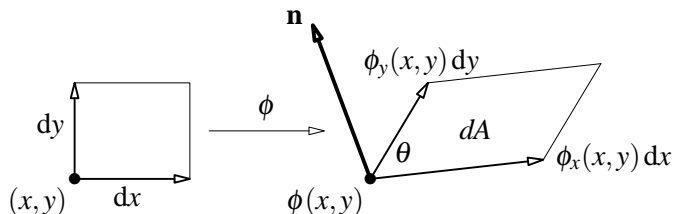


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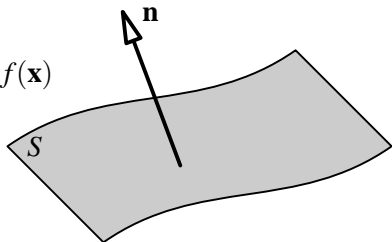
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n -dimensional surface, given by $\phi : \mathbb{R}^n \rightarrow \mathbb{R}^{n+1}$

$$x_{n+1} = f(x_1, x_2, \dots, x_n) = f(\mathbf{x})$$

$$S = \phi(U), \quad U \subset \mathbb{R}^n$$

$$\phi(\mathbf{x}) = \begin{pmatrix} \mathbf{x} \\ f(\mathbf{x}) \end{pmatrix}$$



$$J_\phi(\mathbf{x}) = \begin{pmatrix} I \\ \nabla f(\mathbf{x})^T \end{pmatrix}, \quad \text{vol}(J_\phi(\mathbf{x})) = \sqrt{1 + \|\nabla f(\mathbf{x})\|^2}, \quad [13]$$

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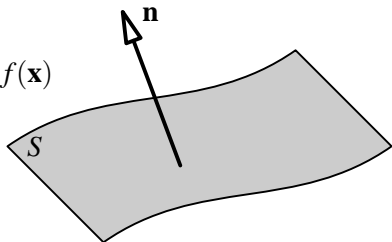
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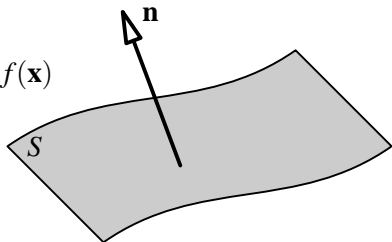
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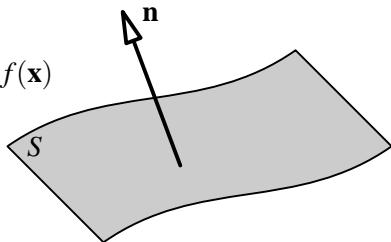
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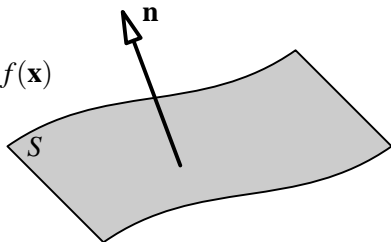
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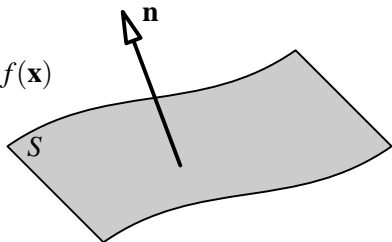
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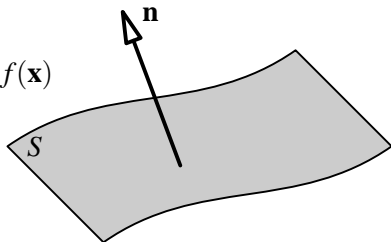
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- 2 Definitions
- 3 Factorizations
- 4 Angles
- 5 A multilinear setting
- 6 Surfaces
- 7 Integrals**
- 8 Concentration of measure
- 9 Probability
- 10 Applications
- 11 References

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$$\int_{\phi(U)} F(\mathbf{v}) \, d\mathbf{v} = \int_U (F \circ \phi)(\mathbf{u}) \, |\det J_\phi(\mathbf{u})| \, d\mathbf{u} \quad (\text{A})$$

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F is integrable on $\phi(U)$,

$d\mathbf{x}$ is the volume element $|dx_1 \wedge dx_2 \wedge \cdots \wedge dx_n|$, and

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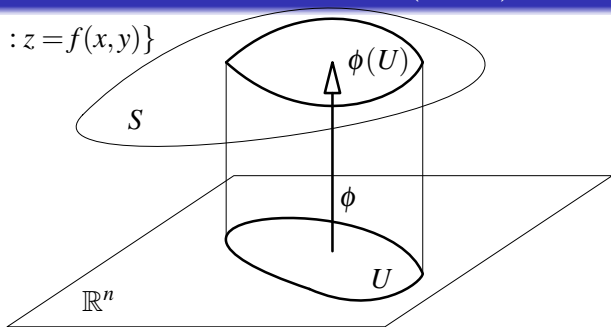
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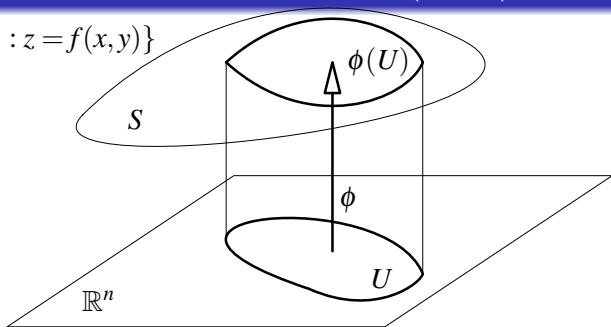
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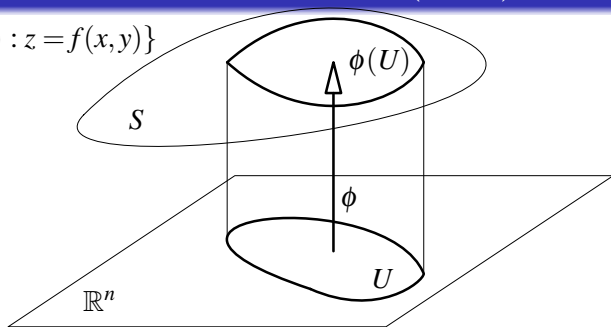
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Example: Cylindrical coordinates

Let S be a surface in \mathbb{R}^3 represented by $z = z(r, \theta)$ where $\{r, \theta\}$ are **polar coordinates**, or by the mapping

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Example: Regular simplex in \mathbb{R}^n

Consider the **simplex**

$$\Delta_n = \{\mathbf{x} \in \mathbb{R}^n \mid \sum_{i=1}^n x_i \leq 1, \mathbf{x} \geq \mathbf{0}\}, \text{ with volume } V_n,$$

$$\text{face } F_0 = \{\mathbf{x} \in \Delta_n \mid \sum_{i=1}^n x_i = 1\}, \text{ with area } A_0,$$

and faces $F_j = \{\mathbf{x} \in \Delta_n \mid x_j = 0\}$, with area A_j , $j \in 1:n$

$$\text{Then } V_n = \frac{1}{n!}, \text{ by induction} \quad \therefore A_j = V_{n-1} = \frac{1}{(n-1)!}.$$

To calculate A_0 , let $\phi : F_j \rightarrow A_0$ be given by $x_n = 1 - \sum_{j \neq i=1}^{n-1} x_i$.

$$\therefore \text{vol}(J_\phi) = \sqrt{n}. \quad \therefore A_0 = \int_{F_j} \text{vol}(J_\phi) d\mathbf{x} = \sqrt{n} A_j.$$

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Then by similarity, the volume of $\Delta_n(\theta)$,

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Example: Radon transform

Let $\mathbf{H}(\mathbf{v}, p)$ be a (“non-vertical”) hyperplane in \mathbb{R}^n

$$\mathbf{H}(\mathbf{v}, p) := \{\mathbf{x} : \langle \mathbf{v}, \mathbf{x} \rangle = p\} = \left\{ \mathbf{x} \in \mathbb{R}^n \mid \sum_{i=1}^n v_i x_i = p \right\}, \quad (v_n \neq 0)$$

$$\mathbf{H}(\mathbf{v}, p) = \phi(\mathbb{R}^{n-1}), \quad x_n := \frac{p}{v_n} - \sum_{i=1}^{n-1} \frac{v_i}{v_n} x_i$$

$$\text{vol} J_\phi = \sqrt{1 + \sum_{i=1}^{n-1} \left(\frac{v_i}{v_n} \right)^2} = \frac{\|\mathbf{v}\|}{|v_n|}$$

The **Radon transform** $(\mathbf{R}F)(\mathbf{v}, p)$ of a function $F : \mathbb{R}^n \rightarrow \mathbb{R}$ is,

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\mathbb{R}^n is a union of (parallel) hyperplanes,

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Therefore an integral over \mathbb{R}^n ,

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Outline

- 1 Motivation
- 2 Definitions
- 3 Factorizations
- 4 Angles
- 5 A multilinear setting
- 6 Surfaces
- 7 Integrals
- 8 Concentration of measure**
- 9 Probability
- 10 Applications
- 11 References

The unit ball & sphere in \mathbb{R}^n

$\|\cdot\|$ the Euclidean norm,

$\mathbf{B}_n(r) := \{\mathbf{x} \in \mathbb{R}^n \mid \|\mathbf{x}\| \leq r\}$; $\mathbf{B}_n(1) = \mathbf{B}_n$, the **unit ball** in \mathbb{R}^n ,

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The **Jacobi matrix** and its **volume**,

$$\begin{aligned} J_\phi &= \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \\ -\frac{x_1}{x_n} & -\frac{x_2}{x_n} & \cdots & -\frac{x_{n-1}}{x_n} \end{pmatrix} \\ \text{vol } J_\phi &= \sqrt{1 + \sum_{i=1}^{n-1} \left(\frac{x_i}{x_n}\right)^2} = \frac{1}{|x_n|} = \frac{1}{\sqrt{1 - \sum_{i=1}^{n-1} x_i^2}}. \end{aligned}$$

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$$\text{vol } J_\phi = \sqrt{1 + \sum_{i=1}^{n-1} \left(\frac{x_i}{x_n}\right)^2} = \frac{1}{|x_n|} = \frac{1}{\sqrt{1 - \sum_{i=1}^{n-1} x_i^2}}.$$

The unit sphere in \mathbb{R}^n (cont'd)

The area A_n is twice the area of the “upper hemisphere”:

$$\begin{aligned} A_n &= 2 \int_{\mathbf{B}_{n-1}} \frac{dx_1 dx_2 \cdots dx_{n-1}}{\sqrt{1 - \sum_{i=1}^{n-1} x_i^2}} = 2 \int_{r=0}^1 \frac{dV_{n-1}(r)}{\sqrt{1 - r^2}} \\ &= 2 \int_{r=0}^1 \frac{A_{n-1}(r) dr}{\sqrt{1 - r^2}} = 2 \int_{r=0}^1 \frac{A_{n-1} r^{n-2} dr}{\sqrt{1 - r^2}} \\ \therefore \frac{A_n}{A_{n-1}} &= 2 \int_{r=0}^1 \frac{r^{n-2} dr}{\sqrt{1 - r^2}} \end{aligned}$$

$$\therefore A_n = \frac{2\pi^{\frac{n}{2}}}{\Gamma\left(\frac{n}{2}\right)}$$

using well-known properties of the [beta function](#),

$$B(p, q) := \int_0^1 (1-x)^{p-1} x^{q-1} dx$$

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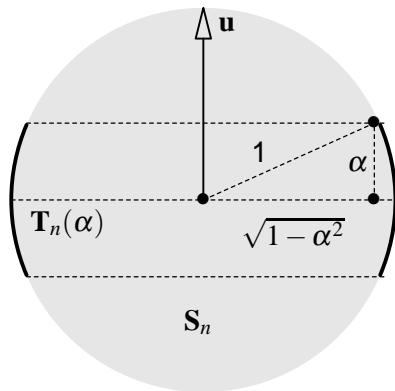
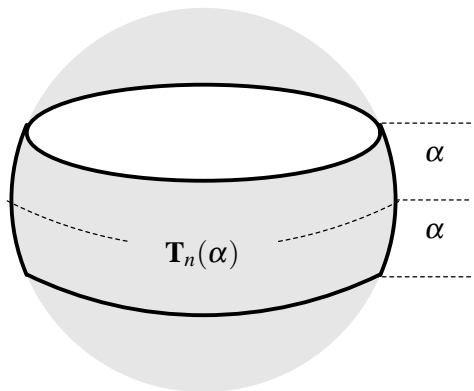
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The unit sphere \mathbf{S}_n and an equatorial belt $\mathbf{T}_n(\alpha)$, $\alpha > 0$

$$\mathbf{T}_n(\alpha) = \{\mathbf{x} \in \mathbf{S}_n : -\alpha \leq x_n \leq \alpha\}$$



$A(\mathbf{T}_n(\alpha)) := \text{area of } \mathbf{T}_n(\alpha)$

$$\text{Prob}\{\mathbf{X} \in \mathbf{T}_n(\alpha)\} = \frac{A(\mathbf{T}_n(\alpha))}{A_n}$$

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Prob $\{\mathbf{X} \in \mathbf{T}_n(\alpha)\}$, $\mathbf{X} \sim \mathbf{U}(S_n)$

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Prob $\{\mathbf{X} \in \mathbf{T}_n(\frac{k}{\sqrt{n}})\}$ for $\mathbf{X} \sim \mathbf{U}(S_n)$

n	$k = 1$	$k = 2$	$k = 3$
2	.5		
5	.6260990336	.9838699099	
10	.6565636037	.9632125020	.9999914613
100	.6802515257	.9550652747	.9976960345
1000	.6824473395	.9545539777	.9973400661

Values of Prob $\{\mathbf{X} \in \mathbf{T}_n(\frac{k}{\sqrt{n}})\}$ for some k, n

Theorem

Let $\mathbf{u} \in S_n$ be fixed, $\mathbf{x} \sim \mathbf{U}(S_n)$. Then, as $n \rightarrow \infty$,

$$\text{Prob} \left\{ |\langle \mathbf{u}, \mathbf{x} \rangle| \leq \frac{k}{\sqrt{n}} \right\} \longrightarrow \frac{1}{\sqrt{2\pi}} \int_{-k}^k e^{-x^2/2} dx.$$

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Outline

- 1 Motivation
- 2 Definitions
- 3 Factorizations
- 4 Angles
- 5 A multilinear setting
- 6 Surfaces
- 7 Integrals
- 8 Concentration of measure
- 9 Probability**
- 10 Applications
- 11 References

Probability density of a function of RV's

$(\mathbf{X}_1, \dots, \mathbf{X}_n)$ RV's with a given joint density $f_{\mathbf{X}}(x_1, \dots, x_n)$,

$h: \mathbb{R}^n \rightarrow \mathbb{R}$ well behaved, in particular $\frac{\partial h}{\partial x_n} \neq 0$,

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$$\mathbf{Y} = h(\mathbf{X}_1, \dots, \mathbf{X}_n).$$

Solve for x_n ,

$$x_n = h^{-1}(y|x_1, \dots, x_{n-1})$$

Change variables from $\{x_1, \dots, x_n\}$ to $\{x_1, \dots, x_{n-1}, y\}$, and use

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A surface integral on $\mathbf{V}(y)$

Let $\mathbf{V}(y)$ be the surface in \mathbb{R}^n given by

$$\begin{pmatrix} x_1 \\ \vdots \\ x_{n-1} \\ x_n \end{pmatrix} = \begin{pmatrix} x_1 \\ \vdots \\ x_{n-1} \\ h^{-1}(y|x_1, \dots, x_{n-1}) \end{pmatrix} = \phi \begin{pmatrix} x_1 \\ \vdots \\ x_{n-1} \end{pmatrix}$$

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If the ratio

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the ratio

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Functions $h : \mathbb{R}^n \rightarrow \mathbb{R}$ that satisfy (C):

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$$\mathbf{H}(\mathbf{v}, y) := \left\{ \mathbf{x} \in \mathbb{R}^n : \sum_{i=1}^n v_i x_i = y \right\}$$

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Check condition (C) for $h(x_1, \dots, x_n) := \sum_{i=1}^n x_i^2$

Two solutions of $y = h(x_1, \dots, x_n) := \sum_{i=1}^n x_i^2$ for x_n ,

$$x_n = h^{-1}(y|x_1, \dots, x_{n-1}) := \pm \sqrt{y - \sum_{i=1}^{n-1} x_i^2}$$

$$\text{with } \frac{\partial h^{-1}}{\partial y} = \pm \frac{1}{2\sqrt{y - \sum_{i=1}^{n-1} x_i^2}}$$

$$\sqrt{1 + \sum_{i=1}^{n-1} \left(\frac{\partial h^{-1}}{\partial x_i}\right)^2} = \frac{\sqrt{y}}{\sqrt{y - \sum_{i=1}^{n-1} x_i^2}}$$

Therefore the density of $\sum \mathbf{X}_i^2$ is expressed in terms of the integral of $f_{\mathbf{X}}$ on the sphere $\mathbf{S}_n(\sqrt{y})$ of radius \sqrt{y} .

Corollary

Let $(\mathbf{X}_1, \dots, \mathbf{X}_n)$ have joint density $f_{\mathbf{X}}(x_1, \dots, x_n)$. The density of

$$\mathbf{Y} = \sum_{i=1}^n \mathbf{X}_i^2 \quad \text{is} \quad f_{\mathbf{Y}}(y) = \frac{1}{2\sqrt{y}} \int_{\mathbf{S}_n(\sqrt{y})} f_{\mathbf{X}}$$

the integral is over the sphere $\mathbf{S}_n(\sqrt{y})$ of radius \sqrt{y} ,

$$\begin{aligned} \int_{\mathbf{S}_n(\sqrt{y})} f_{\mathbf{X}} = & \int_{\mathbf{B}_{n-1}(\sqrt{y})} \left[f_{\mathbf{X}} \left(x_1, \dots, x_{n-1}, \sqrt{y - \sum_{i=1}^{n-1} x_i^2} \right) + \right. \\ & \left. + f_{\mathbf{X}} \left(x_1, \dots, x_{n-1}, -\sqrt{y - \sum_{i=1}^{n-1} x_i^2} \right) \right] \frac{\sqrt{y} \, dx_1 \cdots dx_{n-1}}{\sqrt{y - \sum_{i=1}^{n-1} x_i^2}} \end{aligned}$$

The factor $1/2\sqrt{y}$ is the width of the spherical shell bounded by the two spheres $\mathbf{S}_n(\sqrt{y})$ and $\mathbf{S}_n(\sqrt{y+dy})$, i.e. the difference of radii $\sqrt{y+dy} - \sqrt{y} \approx \frac{dy}{2\sqrt{y}}$

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Let $(\mathbf{X}_1, \dots, \mathbf{X}_n)$ have joint density $f_{\mathbf{X}}(x_1, \dots, x_n)$. The density of

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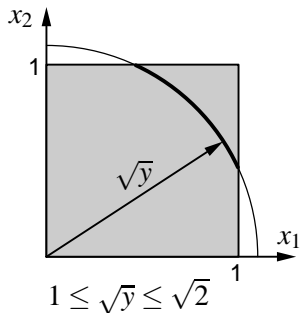
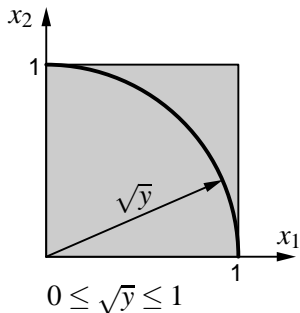
$$\begin{aligned} \int_{\mathbf{S}_n(\sqrt{y})} f_{\mathbf{X}} = & \int_{\mathbf{B}_{n-1}(\sqrt{y})} \left[f_{\mathbf{X}} \left(x_1, \dots, x_{n-1}, \sqrt{y - \sum_{i=1}^{n-1} x_i^2} \right) + \right. \\ & \left. + f_{\mathbf{X}} \left(x_1, \dots, x_{n-1}, -\sqrt{y - \sum_{i=1}^{n-1} x_i^2} \right) \right] \frac{\sqrt{y} \, dx_1 \cdots dx_{n-1}}{\sqrt{y - \sum_{i=1}^{n-1} x_i^2}} \end{aligned}$$

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$$X_i \text{ i.i.d.}, \mathbf{Y} = \sum_{i=1}^n \mathbf{X}_i^2 \implies f_{\mathbf{Y}}(y) = \frac{1}{2\sqrt{y}} \int_{\mathbf{S}_n(\sqrt{y})} f_{\mathbf{X}}$$

Example. Let $\mathbf{Y} = \mathbf{X}_1^2 + \mathbf{X}_2^2$, \mathbf{X}_i i.i.d., $\mathbf{X}_i \sim \mathbf{U}[0, 1]$. Then

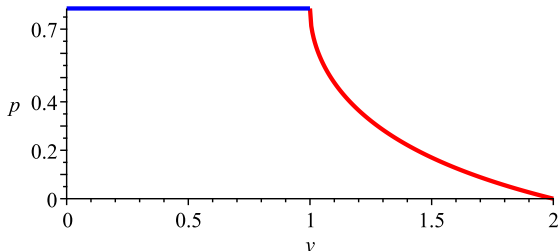
$$f_{\mathbf{Y}}(y) = \begin{cases} \frac{\pi}{4}, & 0 \leq y \leq 1; \\ \frac{\pi}{4} - \arccos\left(\frac{1}{\sqrt{y}}\right), & 1 \leq y \leq 2. \end{cases}$$



$$\mathbf{Y} = \mathbf{X}_1^2 + \mathbf{X}_2^2, \quad X_i \text{ i.i.d.}, \quad \mathbf{X}_i \sim \mathbf{U}[0, 1]$$

$$f_{\mathbf{Y}}(y) = \begin{cases} \frac{\pi}{4}, & 0 \leq y \leq 1; \\ \frac{\pi}{4} - \arccos\left(\frac{1}{\sqrt{y}}\right), & 1 \leq y \leq 2. \end{cases}$$

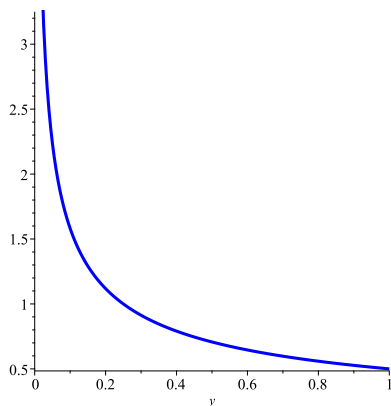
$$\mathbf{E}\{\mathbf{Y}\} = \frac{2}{3}, \quad \mathbf{Var}\{\mathbf{Y}\} = \frac{8}{45}$$



What makes this strange is that ...

the density of $\mathbf{Y} = \mathbf{X}^2$, $\mathbf{X} \sim \mathbf{U}[0, 1]$ is

$$f_{\mathbf{Y}}(y) = \frac{1}{2\sqrt{y}}, \quad 0 < y \leq 1.$$



Let $\mathbf{X} \sim \mathbf{U}(S_n)$. The probability of a surface element on S_n is,

$$\frac{dx_1 dx_2 \cdots dx_{n-1}}{A_n \sqrt{1 - \sum_{i=1}^{n-1} x_i^2}}$$

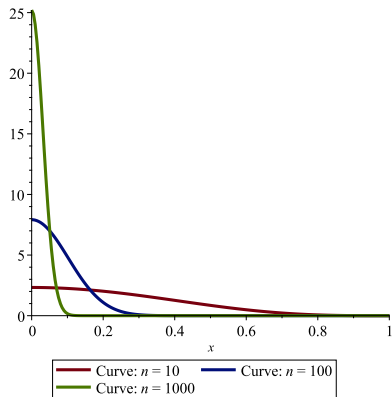
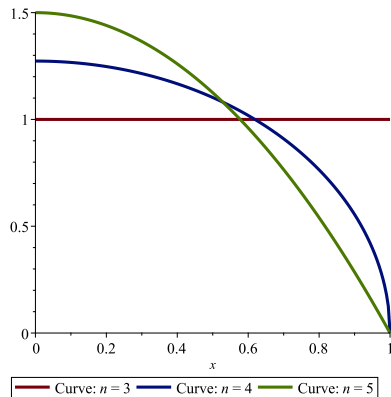
Let L_n be the length of the projection of \mathbf{X} on a fixed line through the origin, say the x_n axis. Then L_n has the density

$$f_{L_n}(x) = \frac{2}{B(\frac{1}{2}, \frac{n-1}{2})} (1 - x^2)^{\frac{n-3}{2}}$$

and expected value

$$\mathbf{E}\{L_n\} = \frac{\Gamma(\frac{n}{2})}{\Gamma(\frac{1}{2})\Gamma(\frac{n+1}{2})}$$

Probability densities of L_n for $n = 3, 4, 5, 10, 100, 1000$



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Face recognition [53], [83]

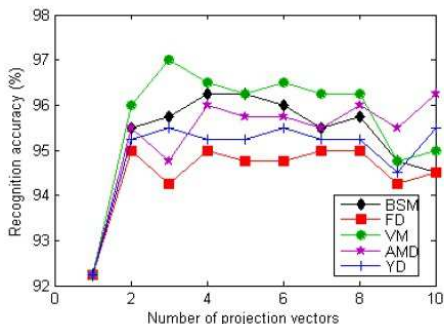
$\mathbf{Y} = \{Y_1, Y_2, \dots, Y_N\}$ a set of known faces;

$Y =$ a face.

Question: $Y \in \mathbf{Y}$?

Answer: Yes, if $\min_{i \in 1:N} \text{vol}(Y - Y_i) < \varepsilon$

No, otherwise.



VM = volume measure
FD = Frobenius distance
YD = Yang distance
AMD = assembled matrix distance
BSM = boosted similarity measure

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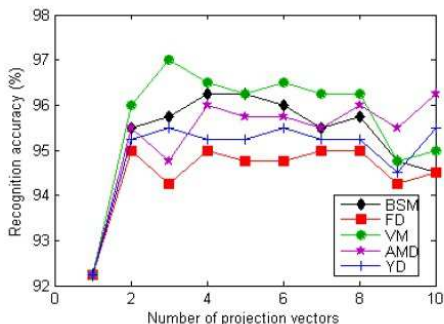
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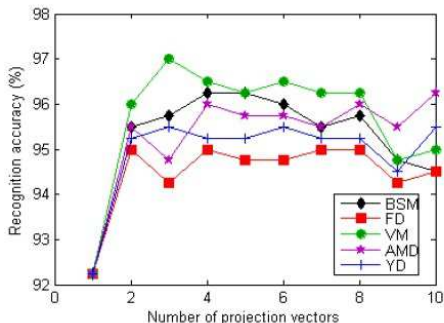
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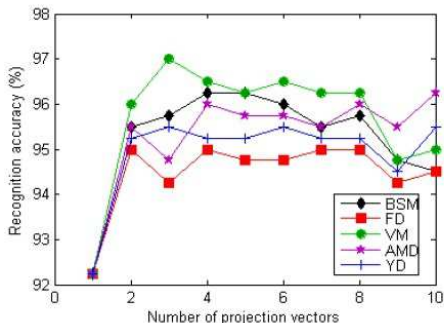
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Volume sampling [22]

Let $A \in \mathbb{R}^{m \times n}$,

S be a submatrix of k rows of A ,

$\Delta(S)$ the k -simplex in \mathbb{R}^n generated by S .

Theorem

If S is randomly chosen with probabilities

$$P_S = \frac{\text{vol}^2(\Delta(S))}{\sum_T \text{vol}^2(\Delta(T))}$$

then

$$\mathbf{E}_S \{ \|A - \widehat{A}(S)\|_F^2 \} \leq (k+1) \|A - A_k\|_F^2$$

*where A_k is the best k -rank approximation of A ,
 $\widehat{A}(S)$ is the projection of A to the span of S .*

$$\text{vol}(\Delta(S)) = \frac{1}{k!} \text{vol}(S)$$

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Applications to integration & integral operators

[2]: $\dots = \int (1 + z_{x_1}^2 + \dots + z_{x_n}^2)^{1/2} dx_1 \dots dx_n$ (Theorem 2)

[7]: Rectangular Jacobian J_ϕ , replace $|\det(J_\phi)|$ by $\text{vol}(J_\phi)$

[9]: Probability densities of $\sum v_i \mathbf{X}_i$ and $\sum \mathbf{X}_i^2$ for $\{\mathbf{X}_i\}$ i.i.d.

[13]: $\text{vol}(J_\phi(\mathbf{x})) = \sqrt{1 + \|\nabla f(\mathbf{x})\|^2}$, etc. (P. 5105, bottom)

[14]: $L(S) \geq \iint \sqrt{J_1^2(u, v) + J_2^2(u, v) + J_3^2(u, v)} du dv$ (3)

[21]: Fourier integral operators of Schrödinger type

[31]: Bayesian learning of kernel embeddings

[32]: Kernel embeddings & associated probability measures

[52]: $L(S) = \iint (X^2 + Y^2 + Z^2) du dv = \iint (1 + p^2 + q^2) du dv$ (17.3)

[57]: Integrals on n -sphere.

[68]: $L(S) = \iint \left\{ \left[\frac{\partial(y,z)}{\partial(u,v)} \right]^2 + \left[\frac{\partial(x,z)}{\partial(u,v)} \right]^2 + \left[\frac{\partial(x,y)}{\partial(u,v)} \right]^2 \right\}^{1/2} du dv$ (p. 76)

[71],[72]: Singular Jacobians in statistics

[74]: Rectangular Jacobian, $3N \times 6$, p. 401, section 2

[75]: Rectangular Jacobians, §A.1, Lemma 1

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