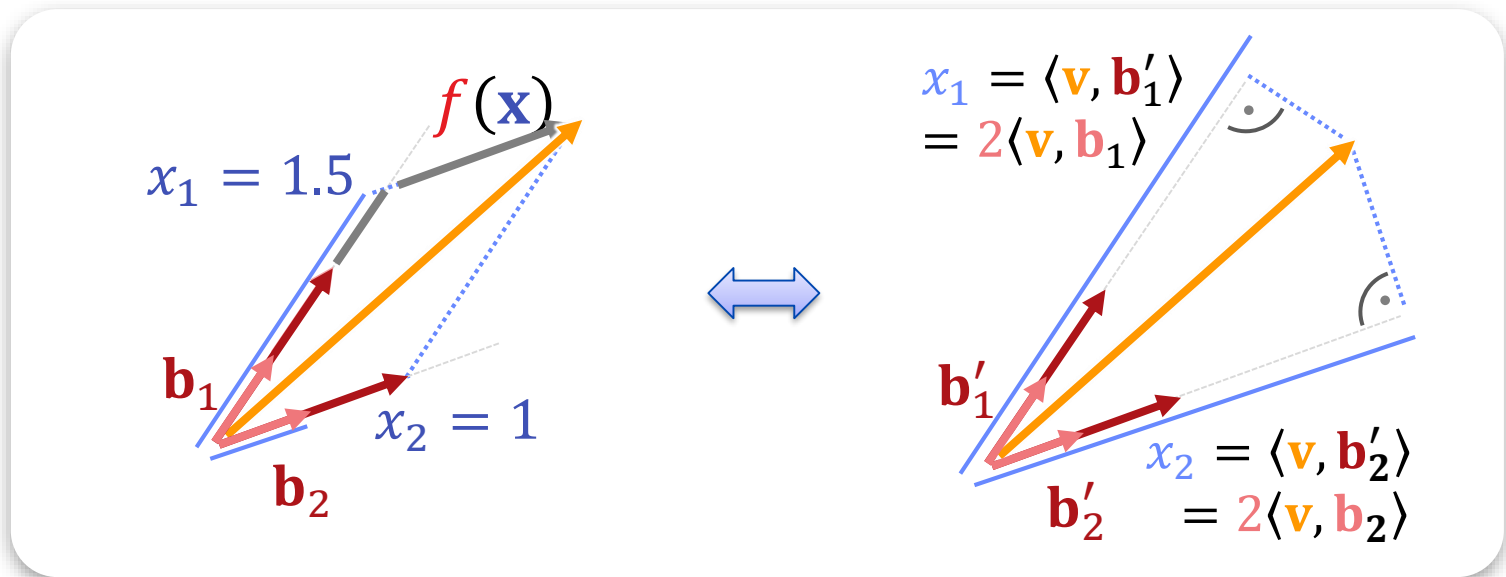


Modelling 1

SUMMER TERM 2020



ADDENDUM

Co- and Contravariance

Covariance & Contravariance

Representing Vectors

Two operations in linear algebra

- **Contravariant:**

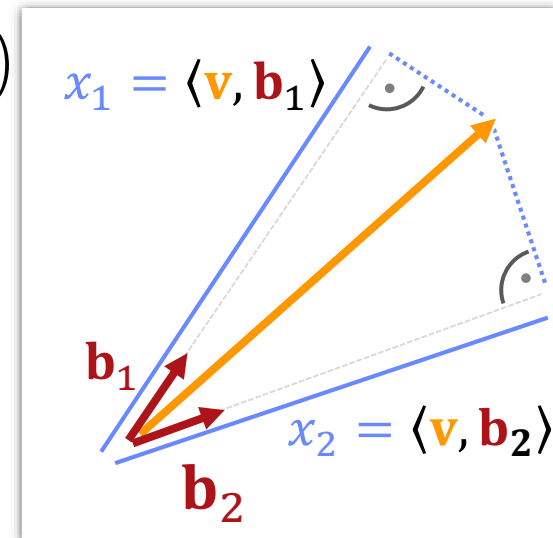
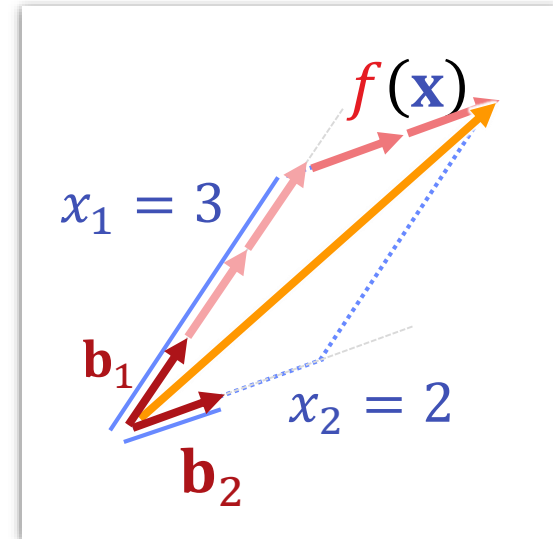
Linear combination of vectors

$$\mathbf{v} = \sum_{i=1}^n x_i \mathbf{b}_i \rightarrow \mathbf{v} \equiv \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$$

- **Covariant:**

Projection on vectors (w/scalar product)

$$\mathbf{v} \equiv \begin{pmatrix} \langle \mathbf{v}, \mathbf{b}_1 \rangle \\ \vdots \\ \langle \mathbf{v}, \mathbf{b}_n \rangle \end{pmatrix}$$



Where is the difference?

Change of basis

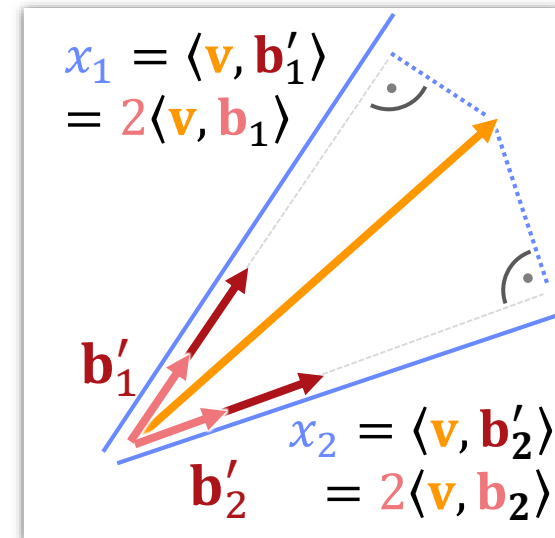
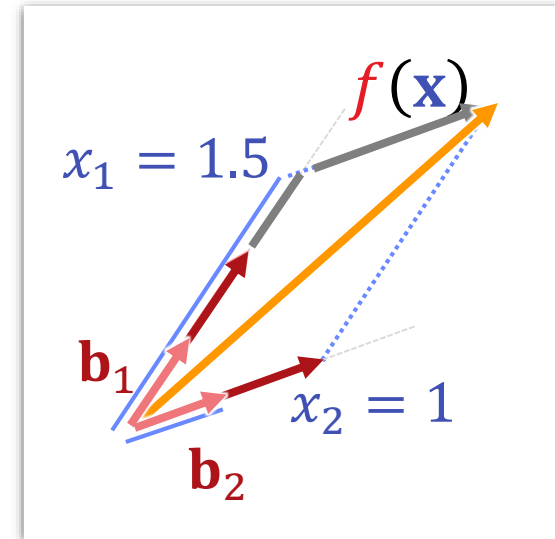
- **Contravariant:** $f(\mathbf{x}) = \sum_{i=1}^n x_i \mathbf{b}_i$

- Keep same output vector:
 $\mathbf{b}_i \rightarrow \mathbf{T}\mathbf{b}_i$ requires $\mathbf{x} \rightarrow \mathbf{T}^{-1}\mathbf{x}$

- **Covariant:**

$$f(\mathbf{x}) = \begin{pmatrix} \langle \mathbf{x}, \mathbf{b}_1 \rangle \\ \vdots \\ \langle \mathbf{x}, \mathbf{b}_n \rangle \end{pmatrix}$$

- Keep same output vector:
 $\mathbf{b}_i \rightarrow \mathbf{T}\mathbf{b}_i$ requires $\mathbf{x} \rightarrow \mathbf{T}\mathbf{x}$



Awesome Video

Tensors, Co-/Contra-Variance

- „Tensors Explained Intuitively: Covariant, Contravariant, Rank“

Physics Videos by Eugene Khutoryansky

<https://www.youtube.com/watch?v=CliW7kSxxWU>

Covariance & Contravariance

Linear map

$$\mathbf{f}: V_1 \rightarrow V_2$$

Matrix representation (standard basis)

$$\mathbf{M} \in \mathbb{R}^{d_1 \times d_2}$$

Change of basis

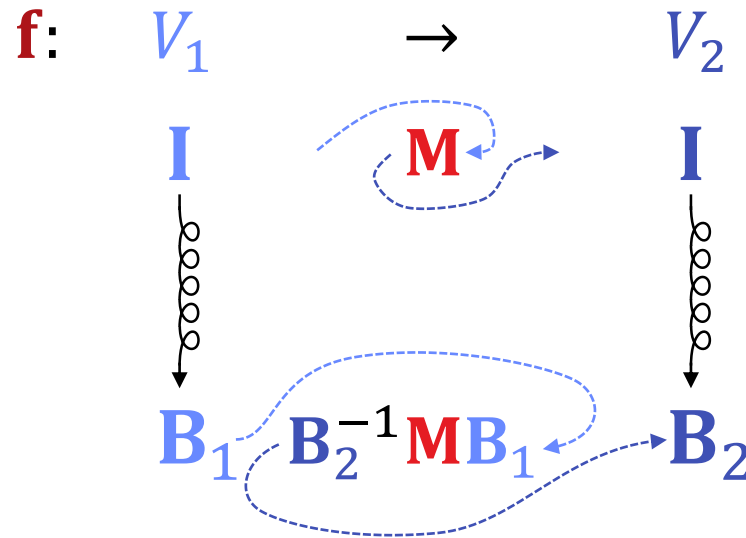
$$\mathbf{B}_1 = \left(\begin{array}{c|c|c} | & & | \\ \mathbf{b}_1^{(1)} & \dots & \mathbf{b}_{d_1}^{(1)} \\ | & & | \end{array} \right), \quad \mathbf{B}_2 = \left(\begin{array}{c|c|c} | & & | \\ \mathbf{b}_1^{(2)} & \dots & \mathbf{b}_{d_2}^{(2)} \\ | & & | \end{array} \right)$$

New matrix representation (bases $\mathbf{B}_1, \mathbf{B}_2$)

$$\mathbf{B}_2^{-1} \mathbf{M} \mathbf{B}_1 \in \mathbb{R}^{d_1 \times d_2}$$

Covariance & Contravariance

Situation

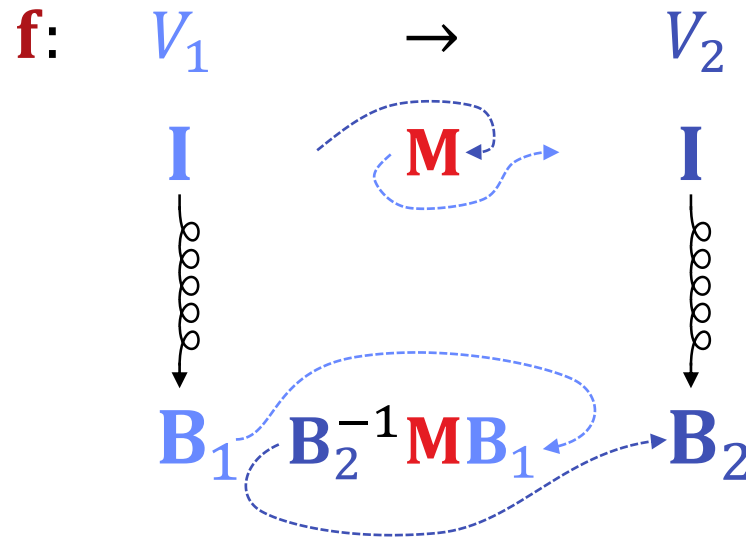


Transformation law

- Input vectors x (Mx): $x_{[B_1]} = B_1 x_{[I]}$ (covariant)
- Output vectors $y = Mx$: $y_{[B_2]} = B_2^{-1} y_{[I]}$ (contravariant)

Covariance & Contravariance

Situation



Transformation law

- Input vectors \mathbf{x} ($\mathbf{M}\mathbf{x}$): $\mathbf{x}_{[\mathbf{B}_1]} = \mathbf{B}_1 \mathbf{x}_{[\mathbf{I}]}$ (covariant)
- Output vectors $\mathbf{y} = \mathbf{M}\mathbf{x}$: $\mathbf{y}_{[\mathbf{B}_2]} = \mathbf{B}_2^{-1} \mathbf{y}_{[\mathbf{I}]}$ (contravariant)

Covariance & Contravariance

$$f(\mathbf{x}) \leftarrow \mathbf{B}_2^{-1} \mathbf{M} \mathbf{B}_1 \leftarrow \mathbf{x}$$

$$\mathbf{B}_2^{-1} \underbrace{(\mathbf{M} \mathbf{B}_1)}$$

transforms row-vectors

$$\underbrace{(\mathbf{B}_2^{-1} \mathbf{M})} \mathbf{B}_1$$

transforms column-vectors

Scalar Product

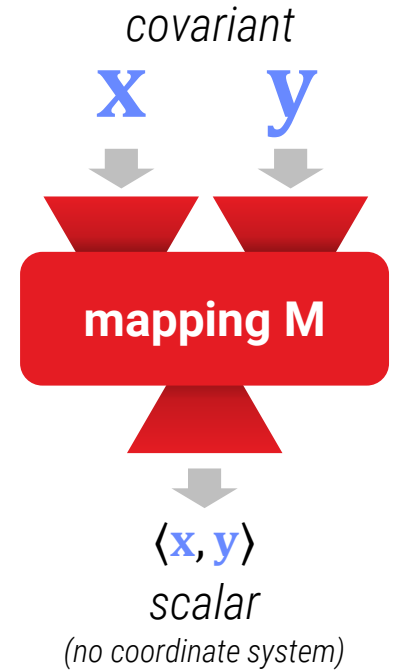
General scalar product

$$\begin{aligned} \mathbf{x}, \mathbf{y} &\in \mathbb{R}^d \\ \langle \mathbf{x}, \mathbf{y} \rangle &= \mathbf{x}^T \mathbf{Q} \mathbf{y}, \\ (\mathbf{Q} &= \mathbf{Q}^T, \mathbf{Q} > 0) \end{aligned}$$

Change of basis $\mathbf{I} \rightsquigarrow \mathbf{B}$

$$\langle \mathbf{x}, \mathbf{y} \rangle_{[\mathbf{I}]} = \mathbf{x}^T \mathbf{Q} \mathbf{y}$$

$$\langle \mathbf{x}, \mathbf{y} \rangle_{[\mathbf{B}]} = \mathbf{x}^T \cdot [\mathbf{B}^T \cdot \mathbf{Q} \cdot \mathbf{B}] \cdot \mathbf{y}$$

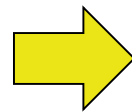
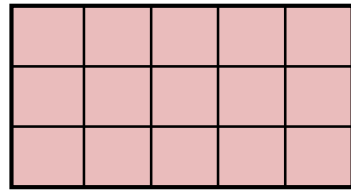
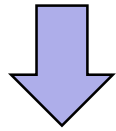


$$\begin{aligned} \mathbf{x} &\rightarrow \mathbf{B}\mathbf{x}, \\ \mathbf{y} &\rightarrow \mathbf{B}\mathbf{y} \end{aligned}$$

Three shades of dual PCA, SVD, MDS

Inputs and Outputs

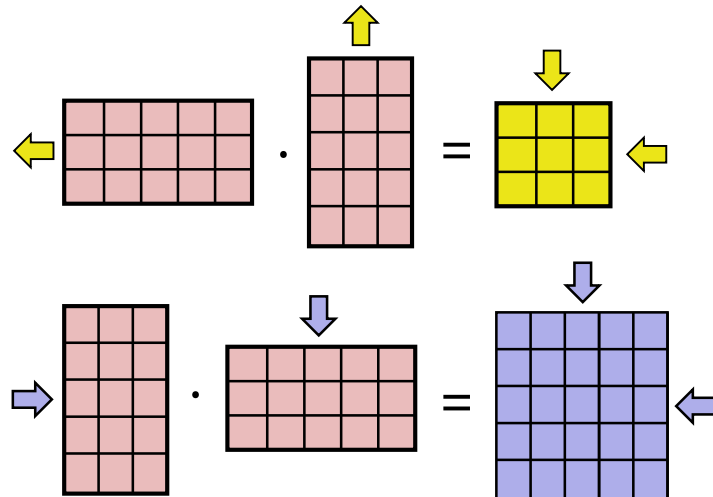
Input ("covariant") side
of the matrix



Output ("contravariant")
side of the matrix

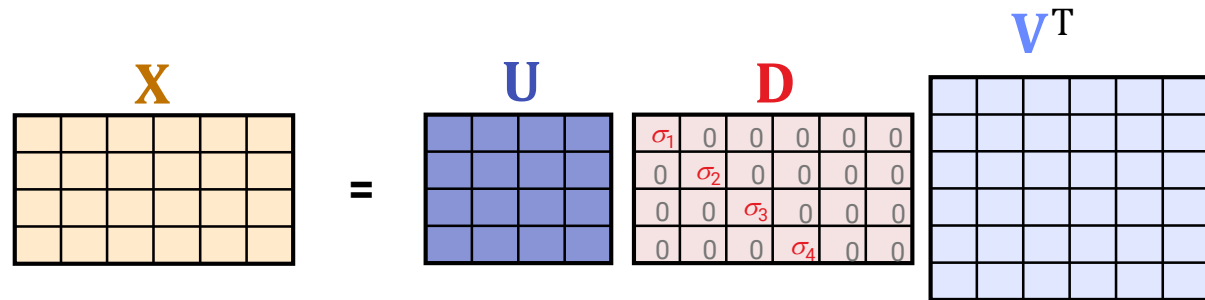
Squaring a Matrix

- Possibility 1: $\mathbf{A} \cdot \mathbf{A}^T$
- Possibility 2: $\mathbf{A}^T \cdot \mathbf{A}$



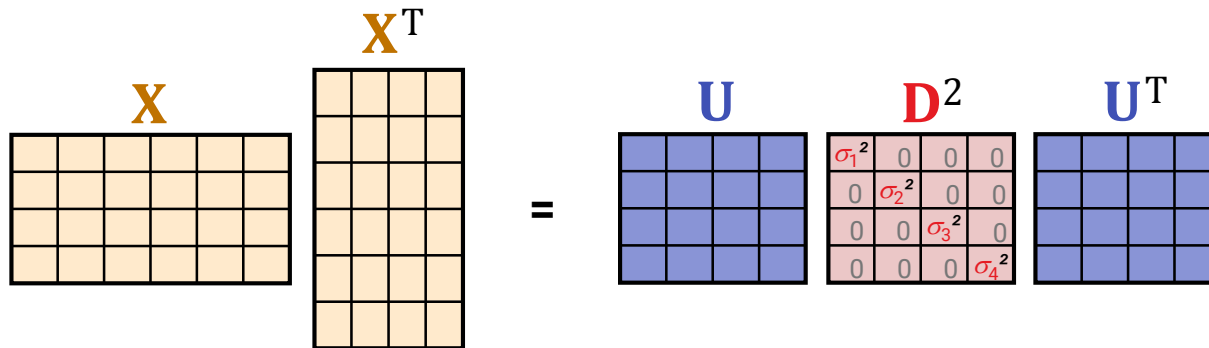
A Story about Dual Spaces

SVD

$$\mathbf{X} = \mathbf{U} \mathbf{D} \mathbf{V}^T$$


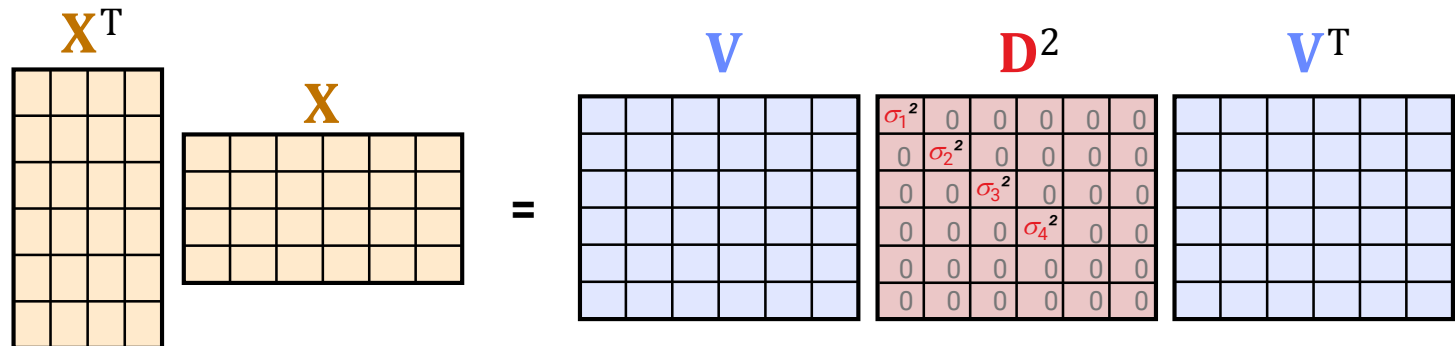
The diagram illustrates the SVD decomposition of a matrix \mathbf{X} . On the left is a 4x6 orange grid labeled \mathbf{X} . This is equal to the product of three matrices: a 4x4 blue grid labeled \mathbf{U} , a 4x6 pink grid labeled \mathbf{D} with diagonal elements $\sigma_1, \sigma_2, \sigma_3, \sigma_4$, and a 6x6 light blue grid labeled \mathbf{V}^T .

PCA

$$\mathbf{X} \mathbf{X}^T = \mathbf{U} \mathbf{D}^2 \mathbf{U}^T$$


The diagram illustrates the PCA decomposition of the matrix $\mathbf{X} \mathbf{X}^T$. On the left is a 4x4 orange grid labeled $\mathbf{X} \mathbf{X}^T$. This is equal to the product of three matrices: a 4x4 blue grid labeled \mathbf{U} , a 4x4 pink grid labeled \mathbf{D}^2 with diagonal elements $\sigma_1^2, \sigma_2^2, \sigma_3^2, \sigma_4^2$, and a 4x4 blue grid labeled \mathbf{U}^T .

MDS

$$\mathbf{X}^T \mathbf{X} = \mathbf{V} \mathbf{D}^2 \mathbf{V}^T$$


The diagram illustrates the MDS decomposition of the matrix $\mathbf{X}^T \mathbf{X}$. On the left is a 6x6 orange grid labeled $\mathbf{X}^T \mathbf{X}$. This is equal to the product of three matrices: a 6x6 light blue grid labeled \mathbf{V} , a 6x6 pink grid labeled \mathbf{D}^2 with diagonal elements $\sigma_1^2, \sigma_2^2, \sigma_3^2, \sigma_4^2$, and a 6x6 light blue grid labeled \mathbf{V}^T .

Tensors: Multi-Linear Maps

Tensors

General notion: Tensor

- Tensor: multi-linear form^{*)} with $r \in \mathbb{N}$ input vectors
 - $\mathbf{T}: V_1, \dots, V_n, V_{n+1}, \dots, V_r \rightarrow F$ (usually: field $F = \mathbb{R}$)
 - “Rank r ” tensor
 - Linear in each input (when keeping the rest constant)
- Each input can be covariant or contravariant
 - (n, m) tensor
 - $r = n + m$
 - n – contravariant inputs
 - m – covariant inputs

^{*)} i.e.: multi-linear mapping / function

Tensors

Representation

- Represented as r-dimensional array

$$t_{j_1, j_2, \dots, j_m}^{i_1, i_2, \dots, i_n}$$

- n – contravariant inputs (“indices”)
 - m – covariant inputs (“indices”)
- Mapping rule

$$\mathbf{T}(\mathbf{v}^{(1)}, \dots, \mathbf{v}^{(n)}, \mathbf{w}^{(1)}, \dots, \mathbf{w}^{(m)}) := \sum_{i_1=0, \dots, n_{i_1}} \dots \sum_{i_n=0, \dots, n_{i_n}} \sum_{j_1=0, \dots, n_{j_1}} \dots \sum_{j_m=0, \dots, n_{j_m}} v_{i_1}^{(1)} \dots v_{i_n}^{(n)} w_{j_1}^{(1)} \dots w_{j_m}^{(m)} t_{j_1, j_2, \dots, j_m}^{i_1, i_2, \dots, i_n}$$

(Note: writing the application of \mathbf{T} as multi-linear mapping here)

Tensors

Remarks

- No difference between co-/contravariant dimensions in terms of numerical representation
- Generalization of matrix

Example

$$\mathbf{T} \left(\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}, \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}, \begin{pmatrix} z_1 \\ z_2 \\ z_3 \end{pmatrix} \right) = 42x_1y_1z_1 + 23x_1y_1z_2 + \dots + 16x_2y_2z_3$$

- Purely linear polynomial in each input parameter when all others remain constant.
- 3D array - $2 \times 2 \times 3$ combinations of coefficients

Einstein Notation

Example: Quadratic polynomial $\mathbb{R}^3 \rightarrow \mathbb{R}^3$

$$p^j(\mathbf{x}) = \mathbf{x}^T \mathbf{A} \mathbf{x} + \mathbf{b} \mathbf{x} + \mathbf{c}$$

$$p^j = \left[\sum_{k=1}^3 \sum_{l=1}^3 x_k x_l a_{kl}^j \right] + \left[\sum_{k=1}^3 x_k b_k^j \right] + c^j$$

Tensor notation

- Input: $x_i, i = 1..3$
- Output: $p^j, j = 1..3$
- Quadratic form (Matrix) $\mathbf{A}: a_{kl}$
- Linear form (Co-Vector) $\mathbf{b}: b_k$
- Constant c

Einstein Notation

Example: Quadratic polynomial $\mathbb{R}^3 \rightarrow \mathbb{R}^3$

$$p^j(\mathbf{x}) = \mathbf{x}^T \mathbf{A} \mathbf{x} + \mathbf{b} \mathbf{x} + \mathbf{c}$$

Einstein notation (implicit sums over common indices)

$$p^j = x_k x_l a_{kl}^j + x_k b_k^j + c^j$$

Tensor notation

- Input: $x_i, i = 1..3$
- Output: $p^j, j = 1..3$
- Quadratic form (Matrix) \mathbf{A} : a_{kl}
- Linear form (Co-Vector) \mathbf{b} : b_k
- Constant c

Further Examples

Examples

- (n, m) -tensor
 - n contravariant “indices”
 - m covariant “indices”
- Matrix: $(1, 1)$ -tensor
- Scalar product: $(0, 2)$ -tensor
- Vector: $(1, 0)$ -tensor
- Co-vector: $(0, 1)$ -tensor
- Geometric vectors: $(1, 0)$ -tensors

Covariant Derivatives?

Examples

- Geometric vectors: $(1,0)$ tensors
- Derivatives^{*)} / gradients / normal vectors: $(0,1)$ tensors

^{*)} to be precise:

- Spatial derivatives co-vary for changes of the basis of the space
 - $f: \mathbb{R}^n \rightarrow \mathbb{R}, f(\mathbf{x}) = y, \Rightarrow \nabla f$ is covariant $(0,1)$.
 - Examples: Gradient vector
- Derivatives of vector functions by unrelated dimensions remain contravariant
 - $f: \mathbb{R} \rightarrow \mathbb{R}^n, f(t) = \mathbf{y}, \Rightarrow \frac{d}{dt} f$ remains contravariant $(1,0)$.
 - Examples: velocity, acceleration
- Mixed case: $f: \mathbb{R}^n \rightarrow \mathbb{R}^m, \nabla f = J_f$ is a $(1,1)$ -tensor $(1,1)$

Example: Plane Equation

Plane equation(s)

- Parametric:

$$\mathbf{x} = \lambda_1 \mathbf{r}_1 + \lambda_2 \mathbf{r}_2 + \mathbf{o}$$

- Implicit:

$$\langle \mathbf{n}, \mathbf{x} \rangle - d = 0$$

Transformation $\mathbf{x} \rightarrow \mathbf{T}\mathbf{x}$

- Parametric:

$$\mathbf{T}\mathbf{x} = \mathbf{T}(\lambda_1 \mathbf{r}_1 + \lambda_2 \mathbf{r}_2 + \mathbf{o}) = \lambda_1 \mathbf{T}\mathbf{r}_1 + \lambda_2 \mathbf{T}\mathbf{r}_2 + \mathbf{T}\mathbf{o}$$

- Implicit:

$$\langle \mathbf{n}, \mathbf{T}\mathbf{x} \rangle - d = (\mathbf{n}^T \mathbf{T})\mathbf{x} - d_0$$

More Structure?

Connecting

- Integrals
- Derivatives
- In higher dimensions
- And their transformation rules

“Exterior Calculus”

- Unified framework
- Beyond this lecture (take a real math course :-)

Vectors & Covectors in Function Spaces

Remark: Function Spaces

Discrete vector spaces

- Picking entries by index is a linear operation
- Can be represented by projection to vector (multiplication with “co-vector”)

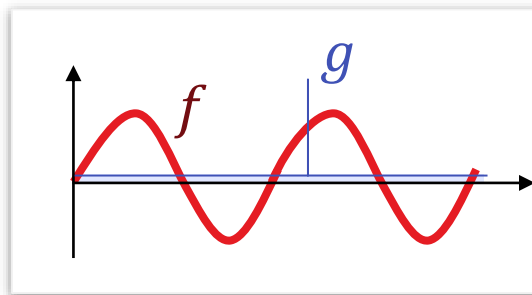
Example

- $\mathbf{x} = (x_1, x_2, x_3, x_4, x_5)$
- $\mathbf{x} \mapsto x_4$ is a linear maps
- Represented by $\langle (0, 0, 0, 1, 0), \mathbf{x} \rangle$
- “Linear form”: $\mathbf{x} \mapsto \langle (0, 0, 0, 1, 0), \mathbf{x} \rangle$,
in short, $\langle \cdot, (0, 0, 0, 1, 0) \rangle$, shorter: $(0, 0, 0, 1, 0) = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{pmatrix}^T$

Linear Forms in Function Spaces

In function spaces

- Picking entries by x-axis is a linear operation
- *Cannot* be represented by projection to another function (multiplication with “co-vector”)



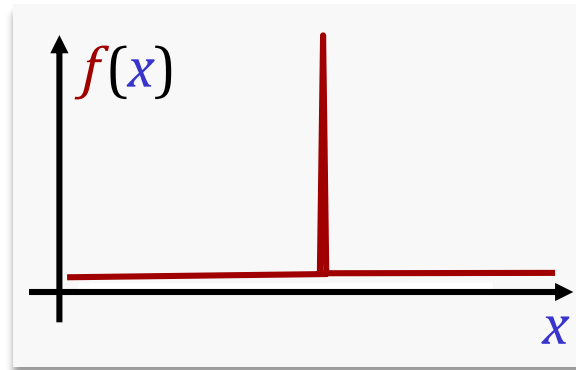
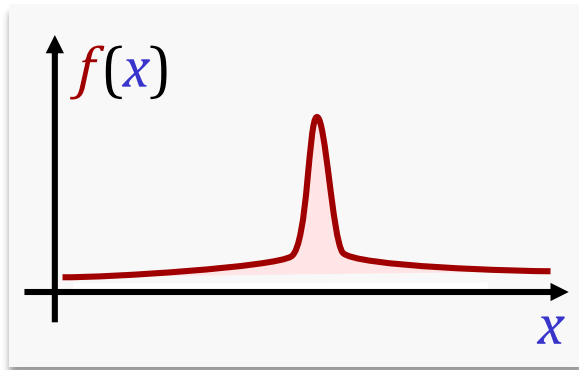
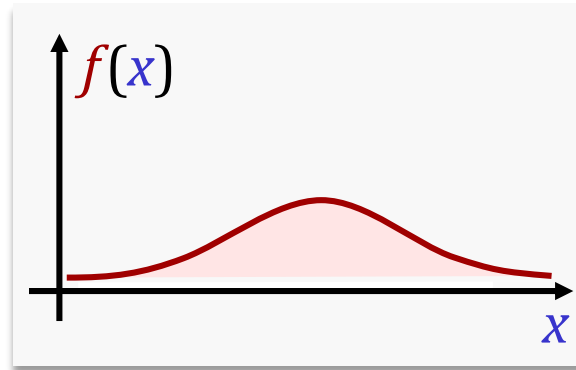
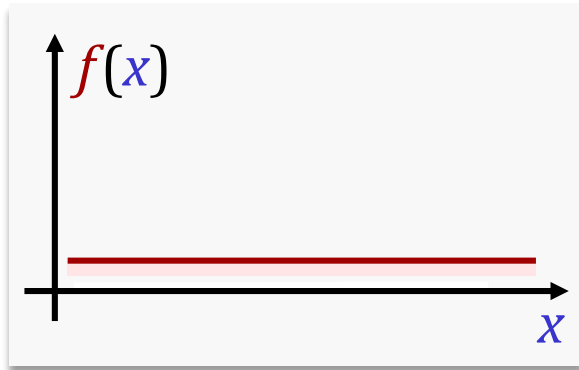
$$g(x) = \begin{cases} 1, & \text{if } x = 4 \\ 0, & \text{elsewhere} \end{cases}$$

$$\int_{\mathbb{R}} f(x)g(x)dx = 0$$

Example

- $f: \mathbb{R} \rightarrow \mathbb{R}$, $f(x) = \sin(x)$
- $L: (\mathbb{R} \rightarrow \mathbb{R}) \rightarrow \mathbb{R}$, $L: f \mapsto f(4.0)$ is a linear map
- A function g with $\langle g, f \rangle = f(4.0)$ does not exist

Dirac's "Delta Function"



$$\int_{\Omega} f(x) dx = 1$$

Dirac Delta "Function"

- $\int_{\mathbb{R}} \delta(x) dx = 1$, zero everywhere but at $x = 0$
- Idealization ("distribution") – think of very sharp peak

Distributions

Distributions

- Adding all linear forms to the vector space
 - All linear mappings from the function space to \mathbb{R}
- This makes the situation symmetric
- δ is a distribution, not a (traditional) function

Formalization

- Different approaches (details beyond our course)
 - Limits of “bumps”
 - Space of linear-forms (“co-vectors”, “dual functions”)
 - Difference of complex functions on Riemann sphere (exotic)