

Tensors in Computations III

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recap from lecture II

recap: three definitions

- tensors capture three great ideas:
 - ① equivariance
 - ② multilinearity
 - ③ separability
- roughly correspond to three common definitions of a tensor
 - ① a multi-indexed object that satisfies tensor transformation rules
 - ② a multilinear map
 - ③ an element of a tensor product of vector spaces

recap: definition ②

- recall: is this

$$\begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 4 \\ 3 & 4 & 5 \end{bmatrix}$$

a tensor?

- makes no sense
- suppose it does represent a tensor, what kind of tensor is it?
- answer: can be
 - ▶ covariant 2-tensor $\beta : \mathbb{V} \times \mathbb{V} \rightarrow \mathbb{R}$
 - ▶ contravariant 2-tensor $\varphi : \mathbb{V}^* \times \mathbb{V}^* \rightarrow \mathbb{R}$
 - ▶ mixed 2-tensor $\Phi : \mathbb{V} \rightarrow \mathbb{V}$
 - ▶ contravariant 1-tensor $(\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3) \in \mathbb{V} \oplus \mathbb{V} \oplus \mathbb{V}$
 - ▶ covariant 1-tensor $(\varphi_1, \varphi_2, \varphi_3) \in \mathbb{V}^* \oplus \mathbb{V}^* \oplus \mathbb{V}^*$
 - ▶ or yet other possibilities

here \mathbb{V} is any vector space of dimension three

recap: definition ②

- say it is a mixed 2-tensor, which $\Phi : \mathbb{V} \rightarrow \mathbb{V}$ does it represent?
- answer: with probability one, **any** $\Phi : \mathbb{V} \rightarrow \mathbb{V}$ can be represented as

$$\begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 4 \\ 3 & 4 & 5 \end{bmatrix}$$

with respect to some choice of basis on \mathbb{V}

- moral: knowing

$$\begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 4 \\ 3 & 4 & 5 \end{bmatrix}$$

tells us almost completely nothing about the tensor

recap: why important

- saw two examples

higher derivatives: functions defined on spaces other than \mathbb{R}^n like

$$f, g : \mathbb{S}_{++}^n \rightarrow \mathbb{R}, \quad f(X) = \log \det(X), \quad g(X) = \text{tr}(X^{-1})$$

self-concordance: essential for defining this important notion

$$|\nabla^3 f(\mathbf{x})(\mathbf{h}, \mathbf{h}, \mathbf{h})| \leq 2\sigma |\nabla^2 f(\mathbf{x})(\mathbf{h}, \mathbf{h})|^{3/2}$$

$\nabla^3 f(\mathbf{x})$ is trilinear, $\nabla^2 f(\mathbf{x})$ is bilinear functional

- will say a bit more about these today

example: self-concordance

example: self-concordance

- log barrier for semidefinite programming

$$f : \mathbb{S}_{++}^n \rightarrow \mathbb{R}, \quad f(X) = -\log \det(X)$$

- inverse barrier for semidefinite programming

$$g : \mathbb{S}_{++}^n \rightarrow \mathbb{R}, \quad g(X) = \operatorname{tr}(X^{-1})$$

- why don't we ever see the latter?

example: self-concordance

- log barrier f

$$D^2f(X)(H, H) = \text{tr}(H^T[\nabla^2f(X)](H)) = \text{tr}(HX^{-1}HX^{-1})$$

$$D^3f(X)(H, H, H) = \text{tr}(H^T[\nabla^3f(X)](H, H)) = -2\text{tr}(HX^{-1}HX^{-1}HX^{-1})$$

- self-concordant by Cauchy–Schwarz

$$|D^3f(X)(H, H, H)| \leq 2\|HX^{-1}\|^3 = 2[D^2f(X)(H, H)]^{3/2}$$

- inverse barrier g

$$D^2g(X)(H, H) = 2\text{tr}(HX^{-1}HX^{-2})$$

$$D^3g(X)(H, H, H) = -6\text{tr}(HX^{-1}HX^{-1}HX^{-2})$$

- set $H = hI$, $X = xI$, then $6|h|^3/x^4 > 2(2h^2/x^3)^{3/2}$ as $x \rightarrow 0^+$, self-concordant condition fails when X is near singular

example: bilinear complexity

example: bilinear complexity

- given \mathbb{U} , \mathbb{V} , \mathbb{W} , how to construct a bilinear operator

$$B : \mathbb{U} \times \mathbb{V} \rightarrow \mathbb{W}?$$

- take linear functional $\varphi : \mathbb{U} \rightarrow \mathbb{R}$, linear functional $\psi : \mathbb{V} \rightarrow \mathbb{R}$, vector $\mathbf{w} \in \mathbb{W}$, define

$$B(\mathbf{u}, \mathbf{v}) = \varphi(\mathbf{u})\psi(\mathbf{v})\mathbf{w}$$

for any $\mathbf{u} \in \mathbb{U}$, $\mathbf{v} \in \mathbb{V}$

- evaluating B requires exactly **one** multiplication of variables
- call such a bilinear operator **rank-one**
- every bilinear operator is a sum of rank-one bilinear operators

example: bilinear complexity

- for example $U = V = W = \mathbb{R}^3$ with

$$\varphi(\mathbf{u}) = u_1 + 2u_2 + 3u_3$$

$$\psi(\mathbf{v}) = 2v_1 + 3v_2 + 4v_3$$

$$\mathbf{w} = (3, 4, 5)$$

then

$$B(\mathbf{u}, \mathbf{v}) = \begin{bmatrix} 3(u_1 + 2u_2 + 3u_3)(2v_1 + 3v_2 + 4v_3) \\ 4(u_1 + 2u_2 + 3u_3)(2v_1 + 3v_2 + 4v_3) \\ 5(u_1 + 2u_2 + 3u_3)(2v_1 + 3v_2 + 4v_3) \end{bmatrix}$$

- multiplications like $2u_2$ or $4v_3$ are all **scalar multiplications**, i.e., one of the factors is a constant
- only **variable multiplication** like $(u_1 + 2u_2 + 3u_3)(2v_1 + 3v_2 + 4v_3)$ counts

example: bilinear complexity

- this is the notion of **bilinear complexity** [Strassen, 1987]
- once we fixed φ, ψ, w , evaluation of these can be hardwired or hardcoded
- e.g., discrete Fourier transform

$$\begin{bmatrix} x'_0 \\ x'_1 \\ x'_2 \\ x'_3 \\ \vdots \\ x'_{n-1} \end{bmatrix} = \frac{1}{\sqrt{n}} \begin{bmatrix} 1 & 1 & 1 & 1 & \dots & 1 \\ 1 & \omega & \omega^2 & \omega^3 & \dots & \omega^{n-1} \\ 1 & \omega^2 & \omega^4 & \omega^6 & \dots & \omega^{2(n-1)} \\ 1 & \omega^3 & \omega^6 & \omega^9 & \dots & \omega^{3(n-1)} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \omega^{n-1} & \omega^{2(n-1)} & \omega^{3(n-1)} & \dots & \omega^{(n-1)(n-1)} \end{bmatrix} \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_{n-1} \end{bmatrix}$$

- may use FFT to evaluate DFT
- bilinear complexity of DFT or FFT all the same, namely, zero

example: bilinear complexity

- may often bound number of additions and scalar multiplications in terms of number of variable multiplications
- e.g., if an algorithm takes n^p variable multiplications, may show that it takes at most $10n^p$ additions and scalar multiplications
- so algorithm still $O(n^p)$ even if we count all arithmetic operations
- most importantly, **bilinear complexity = tensor rank**

$$\text{rank}(B) = \min \left\{ r : B(\mathbf{u}, \mathbf{v}) = \sum_{i=1}^r \varphi_i(\mathbf{u}) \psi_i(\mathbf{v}) \mathbf{w}_i \right\}$$

- if only need $B(\mathbf{u}, \mathbf{v})$ up to ε -accuracy, **border rank**

$$\overline{\text{rank}}(B) = \min \left\{ r : B(\mathbf{u}, \mathbf{v}) = \lim_{\varepsilon \rightarrow 0^+} \sum_{i=1}^r \varphi_i^\varepsilon(\mathbf{u}) \psi_i^\varepsilon(\mathbf{v}) \mathbf{w}_i^\varepsilon \right\}$$

- due to [Strassen, 1973] and [Bini–Lotti–Romani, 1980] respectively

example: Gauss's algorithm

- complex multiplication with three real multiplications

$$\begin{aligned}(a + bi)(c + di) &= (ac - bd) + i(bc + ad) \\ &= (ac - bd) + i[(a + b)(c + d) - ac - bd]\end{aligned}$$

- $B : \mathbb{C} \times \mathbb{C} \rightarrow \mathbb{C}$, $(z, w) \mapsto zw$ is \mathbb{R} -bilinear

$$B : \mathbb{R}^2 \times \mathbb{R}^2 \rightarrow \mathbb{R}^2, \quad B\left(\begin{bmatrix} a \\ b \end{bmatrix}, \begin{bmatrix} c \\ d \end{bmatrix}\right) = \begin{bmatrix} ac - bd \\ bc + ad \end{bmatrix}$$

- usual:

$$B(z, w) = [\mathbf{e}_1^*(z)\mathbf{e}_1^*(w) - \mathbf{e}_2^*(z)\mathbf{e}_2^*(w)]\mathbf{e}_1 + [\mathbf{e}_1^*(z)\mathbf{e}_2^*(w) + \mathbf{e}_2^*(z)\mathbf{e}_1^*(w)]\mathbf{e}_2$$

- Gauss:

$$\begin{aligned}B(z, w) &= [(\mathbf{e}_1^* + \mathbf{e}_2^*)(z)(\mathbf{e}_1^* + \mathbf{e}_2^*)(w)]\mathbf{e}_2 \\ &\quad + [\mathbf{e}_1^*(z)\mathbf{e}_1^*(w)](\mathbf{e}_1 - \mathbf{e}_2) - [\mathbf{e}_2^*(z)\mathbf{e}_2^*(w)](\mathbf{e}_1 + \mathbf{e}_2)\end{aligned}$$

example: Gauss's algorithm

- Gauss optimal in both exact and approximate sense:

$$\text{rank}(B) = 3 = \overline{\text{rank}}(B)$$

- why useful?
- complex matrix multiplication:

$$(A + iB)(C + iD) = (AC - BD) + i[(A + B)(C + D) - AC - BD]$$

for $A + iB, C + iD \in \mathbb{C}^{n \times n}$ with $A, B, C, D \in \mathbb{R}^{n \times n}$

- which is why we should allow for **modules**
 - ▶ \mathbb{C} two-dimensional vector space over \mathbb{R}
 - ▶ $\mathbb{C}^{n \times n}$ two-dimensional free module over $\mathbb{R}^{n \times n}$

other simple example?

- Gauss essentially the only one in two dimensions
- parallel evaluation of standard inner product and standard symplectic form on \mathbb{R}^2

$$g(x, y) = x_1y_1 + x_2y_2, \quad \omega(x, y) = x_1y_2 - x_2y_1$$

- algorithm similar to Gauss's gives result with $\text{rank}(B) = 3 = \overline{\text{rank}}(B)$
- three dimensions: skew-symmetric matrix-vector product

$$\begin{bmatrix} 0 & a & b \\ -a & 0 & c \\ -b & -c & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} ay + bz \\ -ax + cz \\ -bx - cy \end{bmatrix}$$

- in this case¹ $\text{rank}(B) = 5 = \overline{\text{rank}}(B)$

¹thanks to J. M. Landsberg (for \mathbb{C}) and Visu Makam (for \mathbb{R})

example: Strassen's algorithm

- 2×2 matrix multiplication with seven multiplications

$$\begin{bmatrix} a_1 & a_2 \\ a_3 & a_4 \end{bmatrix} \begin{bmatrix} b_1 & b_2 \\ b_3 & b_4 \end{bmatrix} = \begin{bmatrix} a_1 b_1 + a_2 b_2 & \beta + \gamma + (a_1 + a_2 - a_3 - a_4) b_4 \\ \alpha + \gamma + a_4 (b_2 + b_3 - b_1 - b_4) & \alpha + \beta + \gamma \end{bmatrix}$$

with

$$\alpha = (a_3 - a_1)(b_3 - b_4), \beta = (a_3 + a_4)(b_3 - b_1), \gamma = a_1 b_1 + (a_3 + a_4 - a_1)(b_1 + b_4 - b_3)$$

- consequence: inverting $n \times n$ matrix in $5.64n^{\log_2 7}$ arithmetic operations (both additions and multiplications) [Strassen, 1969]
- huge surprise as there were results showing $n^3/3$ required by Gaussian elimination cannot be improved
- such results assume **row** and **column** operations, Strassen used **block** operations
- $\text{rank}(B) = 7 = \overline{\text{rank}}(B)$ [Landsberg, 2006]

example: exponent of matrix multiplication

- bilinear operator

$$\mu_{m,n,p} : \mathbb{R}^{m \times n} \times \mathbb{R}^{n \times p} \rightarrow \mathbb{R}^{m \times p}, \quad (A, B) \mapsto AB$$

called **matrix multiplication tensor**

- exponent of matrix multiplication is

$$\omega := \inf \{ p \in \mathbb{R} : \text{rank}(\mu_{n,n,n}) = O(n^p) \}$$

- current bound $\omega < 2.3728596$ [Alman–Vassilevska Williams, 2021]
- ω underlies nearly every problem in numerical linear algebra

example: exponent of matrix multiplication

- **inversion:** given $A \in \text{GL}(n)$, find $A^{-1} \in \text{GL}(n)$
- **determinant:** given $A \in \text{GL}(n)$, find $\det(A) \in \mathbb{R}$
- **null basis:** given $A \in \mathbb{R}^{n \times n}$, find a basis $\mathbf{v}_1, \dots, \mathbf{v}_m \in \mathbb{R}^n$ of $\ker(A)$
- **linear system:** given $A \in \text{GL}(n)$ and $\mathbf{b} \in \mathbb{R}^n$, find $\mathbf{v} \in \mathbb{R}^n$ so that $A\mathbf{v} = \mathbf{b}$
- **LU decomposition:** given $A \in \mathbb{R}^{m \times n}$ of full rank, find permutation P , unit lower triangular $L \in \mathbb{R}^{m \times m}$, upper triangular $U \in \mathbb{R}^{m \times n}$ so that $PA = LU$
- **QR decomposition:** given $A \in \mathbb{R}^{n \times n}$, find orthogonal $Q \in \text{O}(n)$, upper triangular $U \in \mathbb{R}^{n \times n}$ so that $A = QR$

example: exponent of matrix multiplication

- **eigenvalue decomposition:** given $A \in \mathbb{S}^n$, find $Q \in O(n)$ and diagonal $\Lambda \in \mathbb{R}^{n \times n}$ so that $A = Q\Lambda Q^T$
- **Hessenberg decomposition:** given $A \in \mathbb{R}^{n \times n}$, find $Q \in O(n)$ and upper Hessenberg $H \in \mathbb{R}^{n \times n}$ so that $A = QHQ^T$
- **characteristic polynomial:** given $A \in \mathbb{R}^{n \times n}$, find $(a_0, \dots, a_{n-1}) \in \mathbb{R}^n$ so that $\det(xI - A) = x^n + a_{n-1}x^{n-1} + \dots + a_1x + a_0$
- **sparsification:** given $A \in \mathbb{R}^{n \times n}$ and $c \in [1, \infty)$, find $X, Y \in GL(n)$ so that $\text{nnz}(XAY^{-1}) \leq cn$

exponent of nearly all matrix computations

any $\varepsilon > 0$, there is an algorithm for each of these problems in $O(n^{\omega+\varepsilon})$ arithmetic operations (including additions and scalar multiplications)

example: integer multiplication

example: integer multiplication

- need to consider tensors over **modules**, i.e., replace field of scalars like \mathbb{R} or \mathbb{C} by a ring like \mathbb{Z}
- integer multiplication

$$B: \mathbb{Z} \times \mathbb{Z} \rightarrow \mathbb{Z}, \quad (a, b) \mapsto ab$$

bilinear map over the \mathbb{Z} -module \mathbb{Z}

- but this is not the relevant module structure in fast integer multiplication algorithms

example: integer multiplication

- unsigned integers represented as polynomials

$$a = \sum_{i=0}^{p-1} a_i \theta^i =: a(\theta), \quad b = \sum_{j=0}^{p-1} b_j \theta^j =: b(\theta)$$

for some number base θ

- product has coefficients given by convolutions

$$ab = \sum_{k=0}^{2p-2} c_k \theta^k =: c(\theta), \quad c_k = \sum_{i=0}^k a_i b_{k-i}$$

- set $n = 2p - 1$ and pad vectors of coefficients with enough zeros

$$(a_0, \dots, a_{n-1}), \quad (b_0, \dots, b_{n-1}), \quad (c_0, \dots, c_{n-1})$$

example: integer multiplication

- use DFT for some root of unity ω to perform convolution

$$\begin{bmatrix} a'_0 \\ a'_1 \\ a'_2 \\ \vdots \\ a'_{n-1} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ 1 & \omega & \omega^2 & \dots & \omega^{n-1} \\ 1 & \omega^2 & \omega^4 & \dots & \omega^{2(n-1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \omega^{n-1} & \omega^{2(n-1)} & \dots & \omega^{(n-1)(n-1)} \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ \vdots \\ a_{n-1} \end{bmatrix}$$

$$\begin{bmatrix} b'_0 \\ b'_1 \\ b'_2 \\ \vdots \\ b'_{n-1} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ 1 & \omega & \omega^2 & \dots & \omega^{n-1} \\ 1 & \omega^2 & \omega^4 & \dots & \omega^{2(n-1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \omega^{n-1} & \omega^{2(n-1)} & \dots & \omega^{(n-1)(n-1)} \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ b_2 \\ \vdots \\ b_{n-1} \end{bmatrix}$$

$$\begin{bmatrix} c_0 \\ c_1 \\ c_2 \\ \vdots \\ c_{n-1} \end{bmatrix} = \frac{1}{n} \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ 1 & \omega^{-1} & \omega^{-2} & \dots & \omega^{-(n-1)} \\ 1 & \omega^{-2} & \omega^{-4} & \dots & \omega^{-2(n-1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \omega^{-(n-1)} & \omega^{-2(n-1)} & \dots & \omega^{-(n-1)(n-1)} \end{bmatrix} \begin{bmatrix} a'_0 b'_0 \\ a'_1 b'_1 \\ a'_2 b'_2 \\ \vdots \\ a'_{n-1} b'_{n-1} \end{bmatrix}$$

example: integer multiplication

- Fourier transform turns convolution $*$ into pointwise product \cdot

$$\mathbf{a} * \mathbf{b} = \mathcal{F}^{-1}(\mathcal{F}(\mathbf{a}) \cdot \mathcal{F}(\mathbf{b}))$$

- key idea 1: convert integer multiplication to a bilinear operator

$$\begin{aligned} B_1: (\mathbb{Z}/2^s\mathbb{Z})[\theta] \times (\mathbb{Z}/2^s\mathbb{Z})[\theta] &\rightarrow (\mathbb{Z}/2^s\mathbb{Z})[\theta] \\ (a(\theta), b(\theta)) &\mapsto a(\theta)b(\theta) \end{aligned}$$

- key idea 2: a Fourier conversion into another bilinear operator

$$\begin{aligned} B_2: (\mathbb{Z}/m\mathbb{Z})^n \times (\mathbb{Z}/m\mathbb{Z})^n &\rightarrow (\mathbb{Z}/m\mathbb{Z})^n \\ ((a_0, \dots, a_{n-1}), (b_0, \dots, b_{n-1})) &\mapsto (a_0b_0, \dots, a_{n-1}b_{n-1}) \end{aligned}$$

- $(\mathbb{Z}/2^s\mathbb{Z})[\theta]$ is a $\mathbb{Z}/2^s\mathbb{Z}$ -module
- $(\mathbb{Z}/m\mathbb{Z})^n$ is a $\mathbb{Z}/m\mathbb{Z}$ -module

example: integer multiplication

- all fast integer multiplication algorithms based on variation of these ideas: [Karatsuba–Ofman, 1962], [Cook–Aanderaa, 1969], [Toom, 1963], [Schönhage–Strassen, 1971], [Fürer, 2009]
- sensational breakthrough by [Harvey–van der Hoeven, 2021]:
 $O(n \log n)$ -algorithm for n -bit integer multiplication
- clever idea: use multidimensional DFT

$$a'(\phi_1, \phi_2, \dots, \phi_d) = \sum_{\theta_1=0}^{n_1} \cdots \sum_{\theta_d=0}^{n_d} \omega_1^{\phi_1 \theta_1} \omega_2^{\phi_2 \theta_2} \cdots \omega_d^{\phi_d \theta_d} a(\theta_1, \theta_2, \dots, \theta_d),$$

- replace bilinear operator with d -linear operator

example: cryptography

example: Diffie–Hellman key exchange

- Alice and Bob want to generate (secure) common password over (insecure) internet
- pick large prime p and primitive root of unity $g \in (\mathbb{Z}/p\mathbb{Z})^\times$
- any non-zero $x \in \mathbb{Z}/p\mathbb{Z}$ may be expressed as

$$x \equiv g^a \pmod{p}$$

henceforth write $x = g^a$

- Alice picks secret $a \in \mathbb{Z}$ and sends g^a publicly to Bob
- Bob picks secret $b \in \mathbb{Z}$ and sends g^b publicly to Alice
- Alice computes $g^{ab} = (g^b)^a$ from the g^b she received from Bob
- Bob computes $g^{ab} = (g^a)^b$ from the g^a he received from Alice
- they now share the secure password g^{ab}

example: multilinear cryptography

- security based on intractability of computing $a = \log_g(g^a)$
- observation 1: $(\mathbb{Z}/p\mathbb{Z})^\times$ is \mathbb{Z} -module
- observation 2: Diffie–Hellman is \mathbb{Z} -bilinear map

$$B: (\mathbb{Z}/p\mathbb{Z})^\times \times (\mathbb{Z}/p\mathbb{Z})^\times \rightarrow (\mathbb{Z}/p\mathbb{Z})^\times, \quad (g^a, g^b) \mapsto g^{ab}$$

- for any $\lambda, \lambda' \in \mathbb{Z}$ and $g^a, g^b \in (\mathbb{Z}/p\mathbb{Z})^\times$

$$B(g^{\lambda a + \lambda' a'}, g^b) = B(g^a, g^b)^\lambda B(g^{a'}, g^b)^{\lambda'}$$

- what if not two parties but 1000 parties, e.g., on Zoom or Teams?
- $d + 1$ parties require each party doing $d + 1$ exponentiations
- solution: cryptographic multilinear map [Boneh–Silverberg, 2003]

example: multilinear cryptography

- **cryptographic** d -linear map $\Phi : G \times \dots \times G \rightarrow G$
- assumptions: discrete log in G **hard**, evaluating Φ **easy**
- i th party pick password a_i , perform one exponentiation to get g^{a_i}
- broadcast g^{a_i} to other parties, who will each do likewise
- every party now has $g^{a_1}, \dots, g^{a_{d+1}}$
- i th party will now compute

$$\Phi(g^{a_1}, \dots, g^{a_{i-1}}, g^{a_{i+1}}, \dots, g^{a_{d+1}})^{a_i} = \Phi(g, \dots, g)^{a_1 \dots a_{d+1}}$$

- result is common password for the $d + 1$ parties

- tensor nuclear norm and numerical stability
- bilinear Hilbert transform and Calderon conjecture
- tensor fields: multilinear operators over $C^\infty(M)$ -modules
- metric, Ricci, and Riemann curvature tensors
- Grothendieck inequality

classifying multilinear maps

problem with definition ②

- many more multilinear maps than there are types of tensors
- $d = 2$:

- ▶ linear operators

$$\phi : U^* \rightarrow V, \quad \phi : U \rightarrow V^*, \quad \phi : U^* \rightarrow V^*$$

- ▶ bilinear functionals

$$\beta : U^* \times V \rightarrow \mathbb{R}, \quad \beta : U \times V^* \rightarrow \mathbb{R}, \quad \beta : U^* \times V^* \rightarrow \mathbb{R}$$

- $d = 3$:

- ▶ bilinear operators

$$B : U^* \times V \rightarrow W, \quad B : U \times V^* \rightarrow W, \dots, B : U^* \times V^* \rightarrow W^*$$

- ▶ trilinear functionals

$$\tau : U^* \times V \times W \rightarrow \mathbb{R}, \quad \tau : U \times V^* \times W \rightarrow \mathbb{R}, \dots, \tau : U^* \times V^* \times W^* \rightarrow \mathbb{R}$$

- ▶ more complicated maps

$$\begin{aligned} \Phi_1 : U \rightarrow L(V; W), \quad \Phi_2 : L(U; V) \rightarrow W, \\ \beta_1 : U \times L(V; W) \rightarrow \mathbb{R}, \quad \beta_2 : L(U; V) \times W \rightarrow \mathbb{R} \end{aligned}$$

problem with definition ②

- possibilities increase exponentially with order d
- ought to be only as many as types of transformation rules

covariant 2-tensor: $\Phi : \mathbb{U} \rightarrow \mathbb{V}^*$, $\beta : \mathbb{U} \times \mathbb{V} \rightarrow \mathbb{R}$

contravariant 2-tensor: $\Phi : \mathbb{U}^* \rightarrow \mathbb{V}$, $\beta : \mathbb{U}^* \times \mathbb{V}^* \rightarrow \mathbb{R}$

mixed 2-tensor: $\Phi : \mathbb{U} \rightarrow \mathbb{V}$, $\beta : \mathbb{U} \times \mathbb{V}^* \rightarrow \mathbb{R}$,

$\Phi : \mathbb{U}^* \rightarrow \mathbb{V}^*$, $\beta : \mathbb{U}^* \times \mathbb{V} \rightarrow \mathbb{R}$

- definition ③ accomplishes this without reference to the transformation rules

imperfect fix

- only allow $\mathbb{W} = \mathbb{R}$
- d -tensor of contravariant order p and covariant order $d - p$ is multilinear functional

$$\varphi : \mathbb{V}_1^* \times \cdots \times \mathbb{V}_p^* \times \mathbb{V}_{p+1} \times \cdots \times \mathbb{V}_d \rightarrow \mathbb{R}$$

- excludes vectors, by far the most common 1-tensor
- excludes linear operators, by far the most common 2-tensor
- excludes bilinear operators, by far the most common 3-tensor
- e.g., instead of talking about $\mathbf{v} \in \mathbb{V}$, need to talk about linear functionals $f : \mathbb{V}^* \rightarrow \mathbb{R}$
- ultimately need definition ③

- Simons Foundation Award no. 663281 granted to the Institute of Mathematics of the Polish Academy of Sciences for 2021–2023
- L.-H. Lim, “Tensors in computations,” *Acta Numer.*, **30** (2021), pp. 555–764