

The Quest for Unification

- Intersecting Mathematics, Physics and AI -

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Mathematics Colloquium

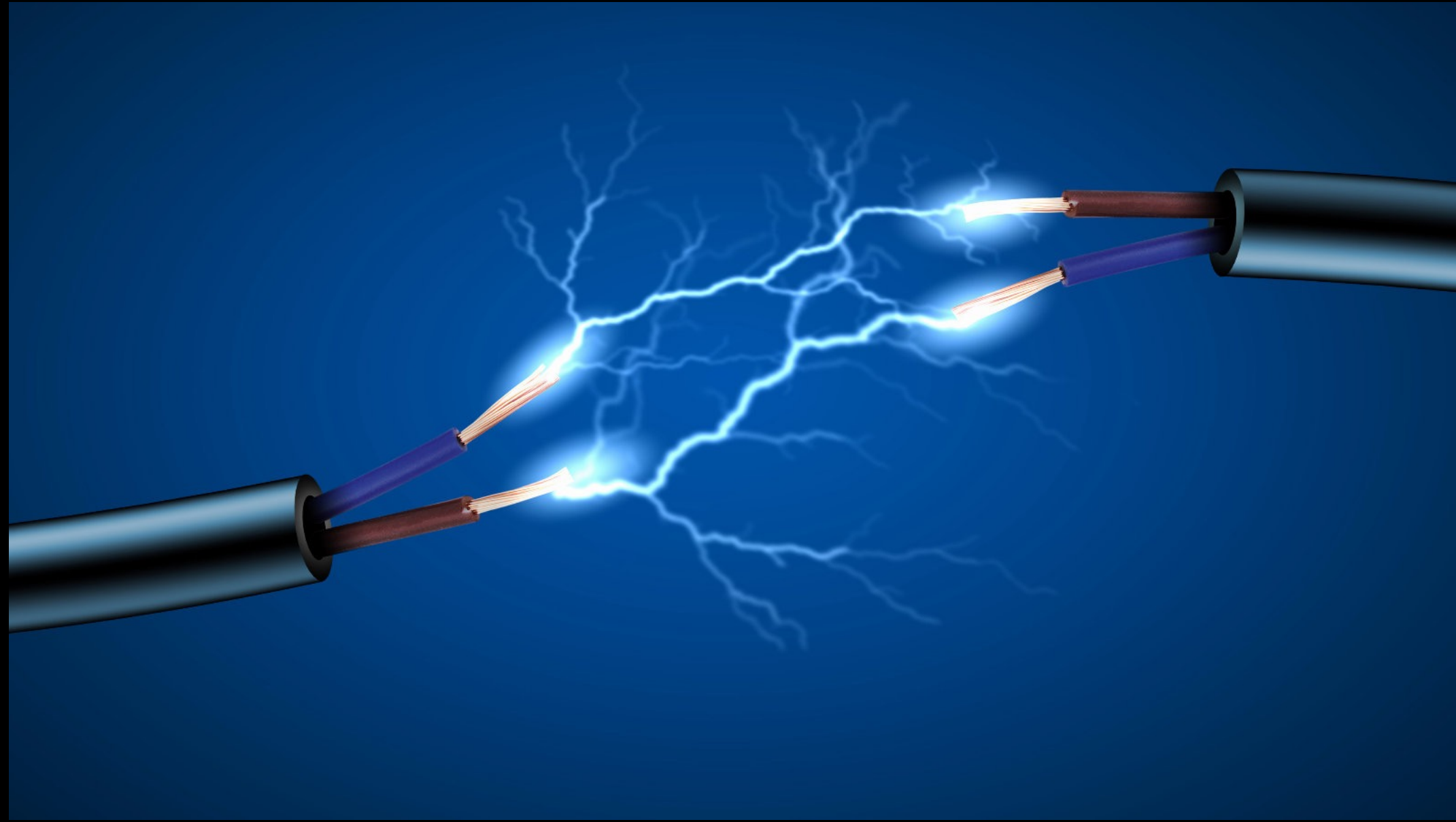
Uppsala University

October 15, 2025

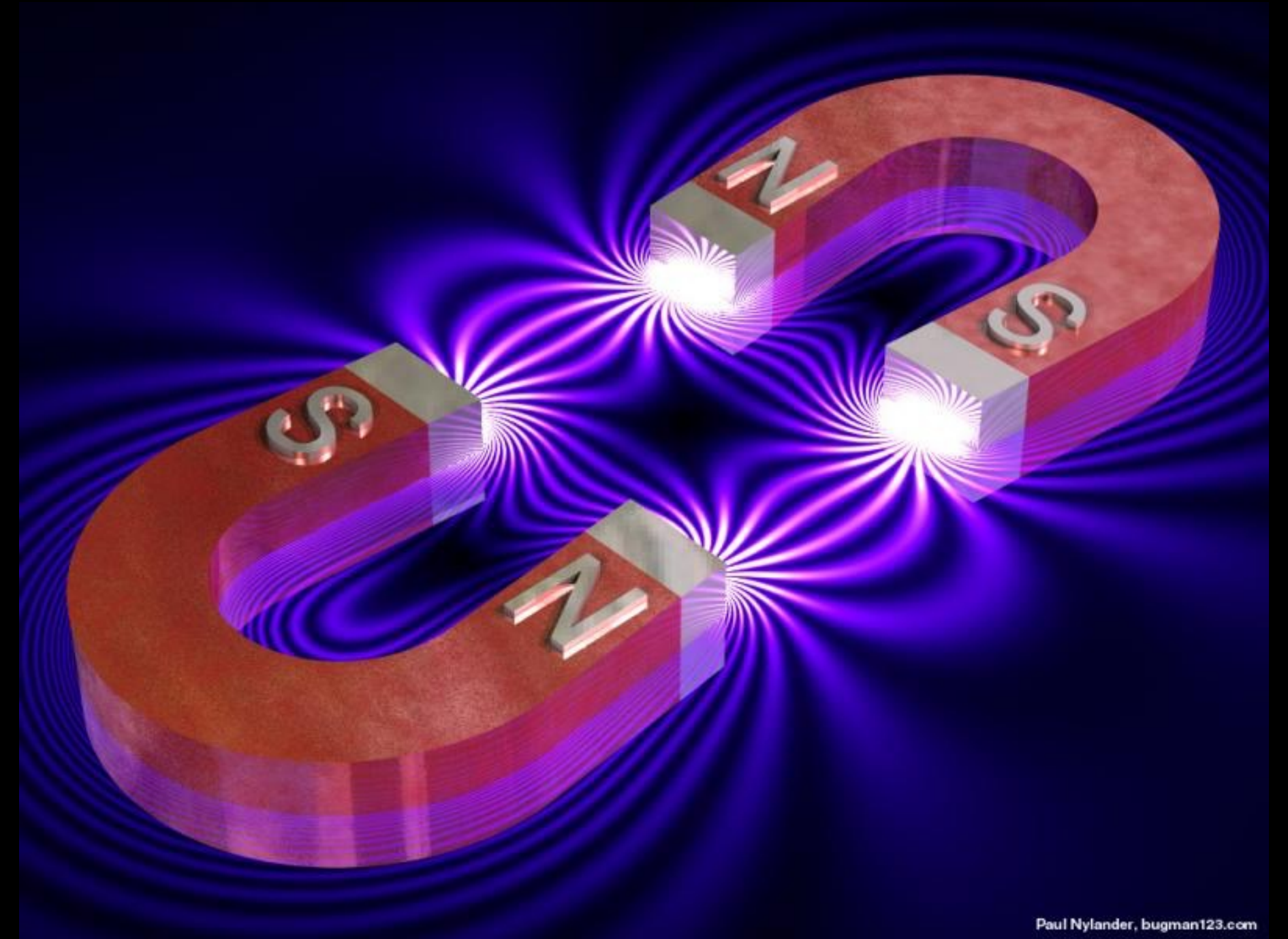


WASP | WALLENBERG AI,
AUTONOMOUS SYSTEMS
AND SOFTWARE PROGRAM

Unification

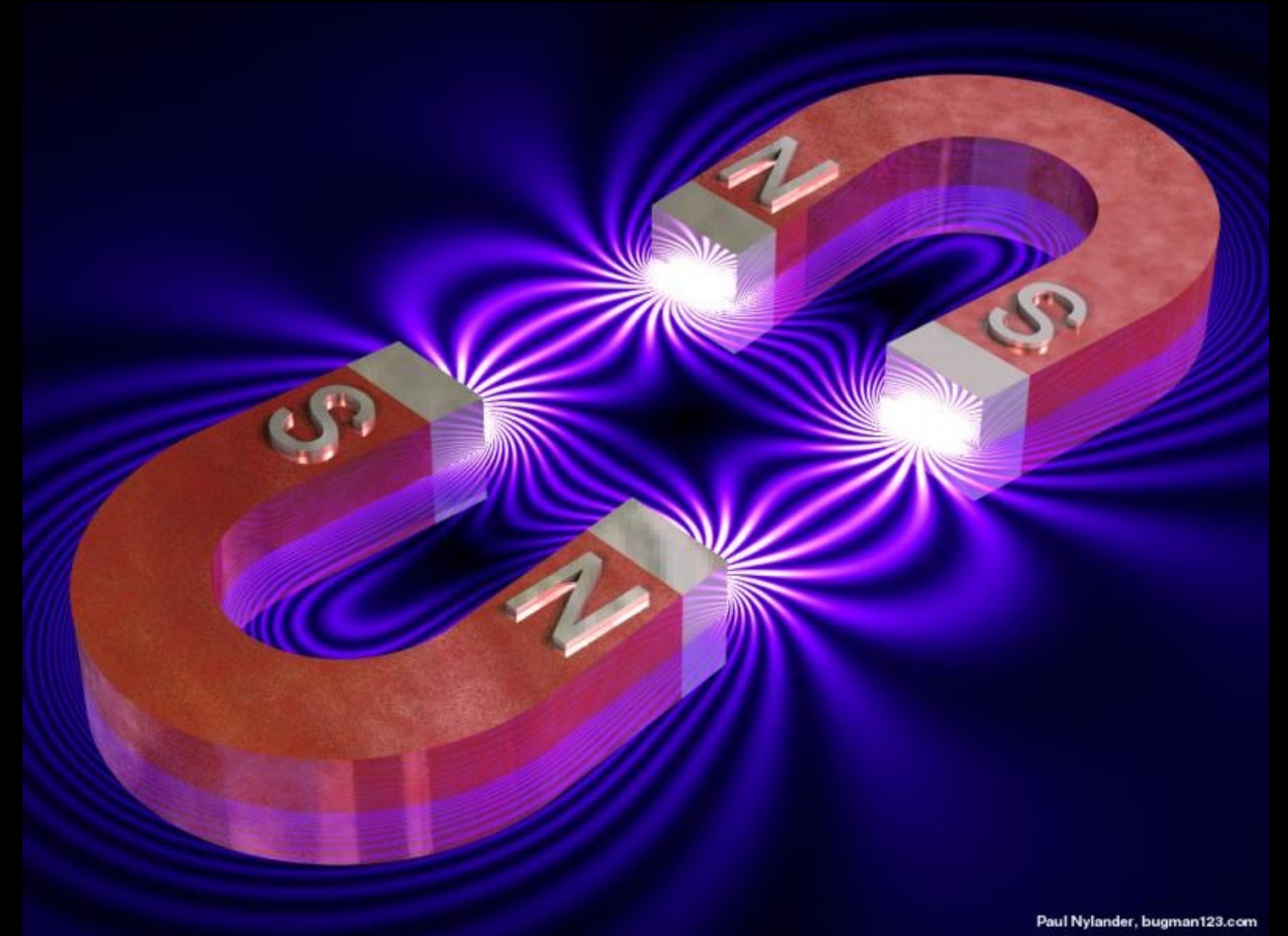
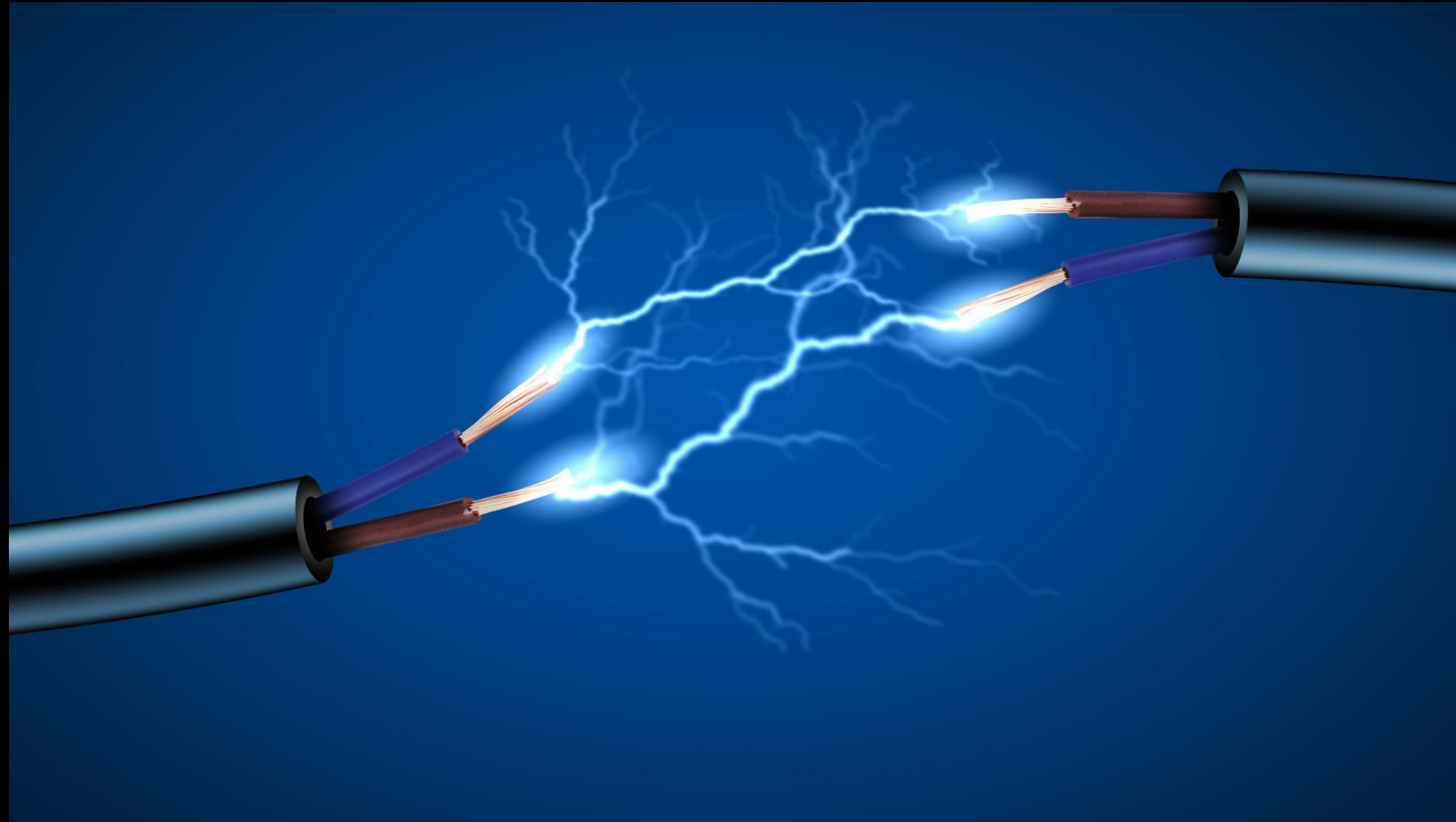


electricity



magnetism

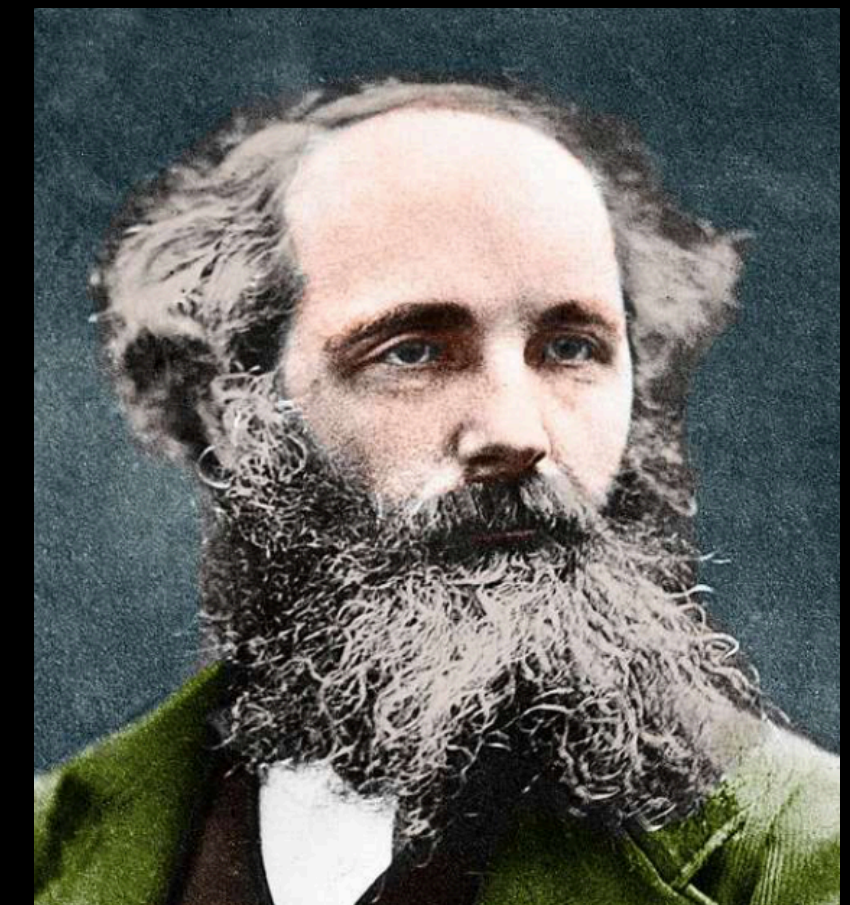
Unification



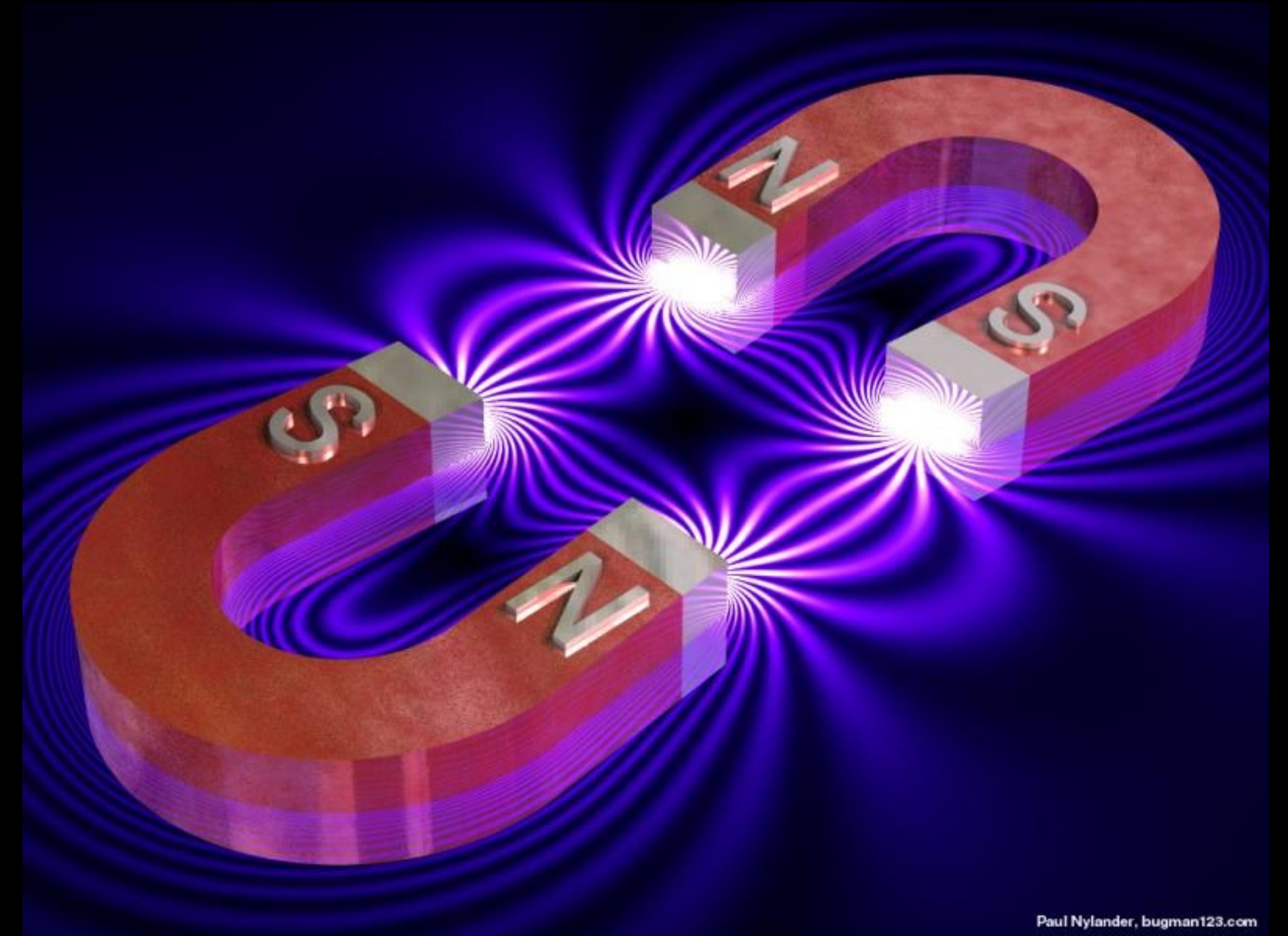
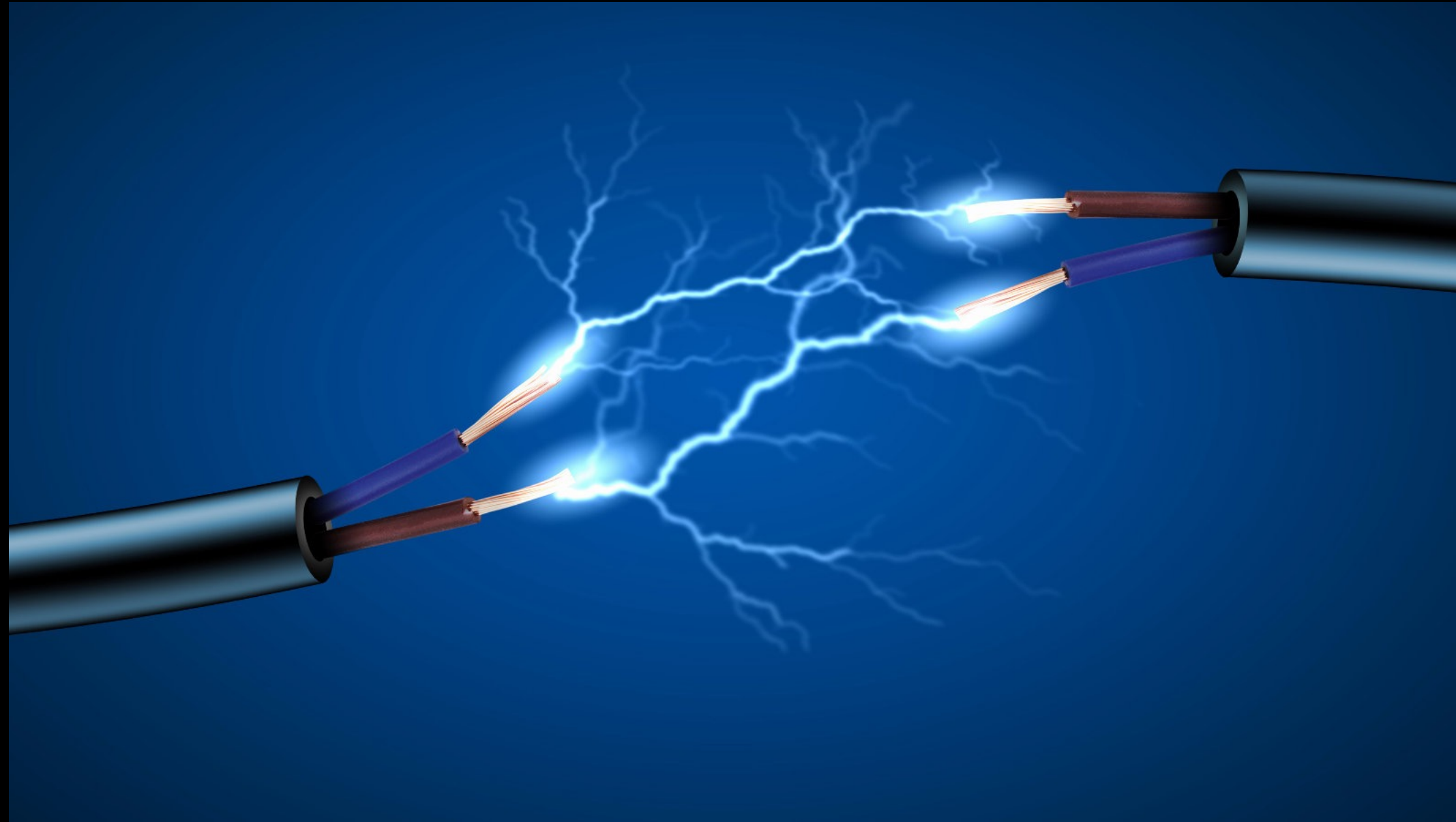
electromagnetism

$$\begin{aligned}\nabla \cdot \mathbf{E} &= 0, & \nabla \times \mathbf{E} + \frac{\partial \mathbf{B}}{\partial t} &= 0 \\ \nabla \cdot \mathbf{B} &= 0, & \nabla \times \mathbf{B} - \mu_0 \epsilon_0 \frac{\partial \mathbf{E}}{\partial t} &= 0\end{aligned}$$

Maxwell's equations



Unification

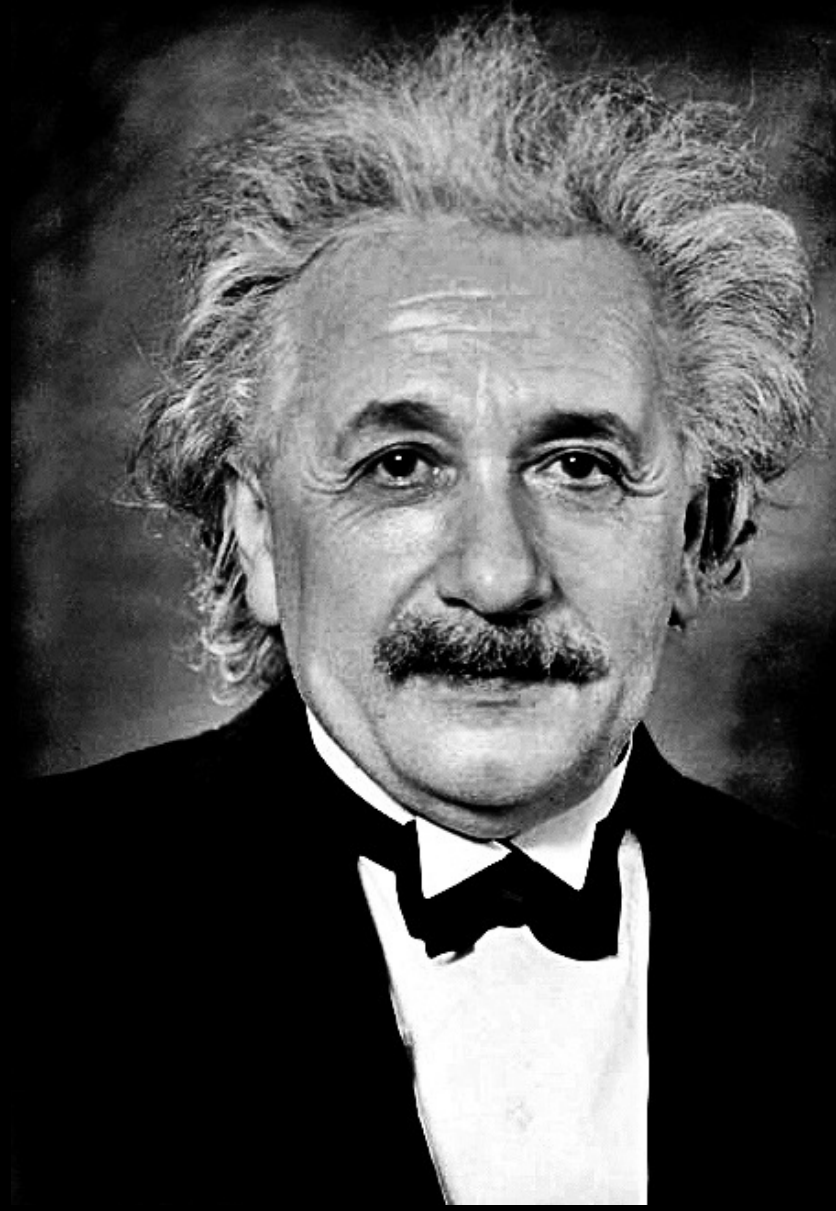


electromagnetism

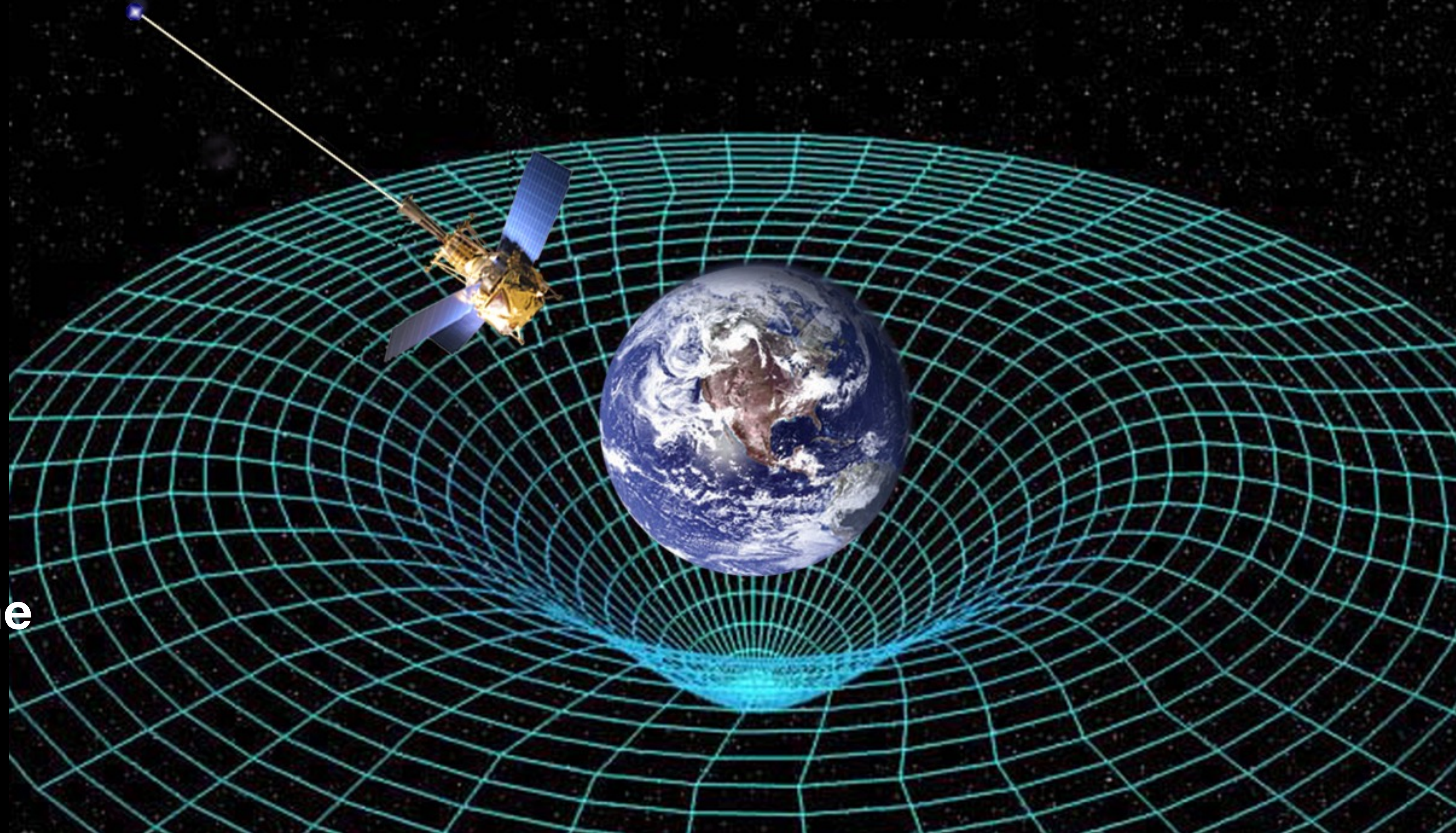
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Electric-magnetic duality



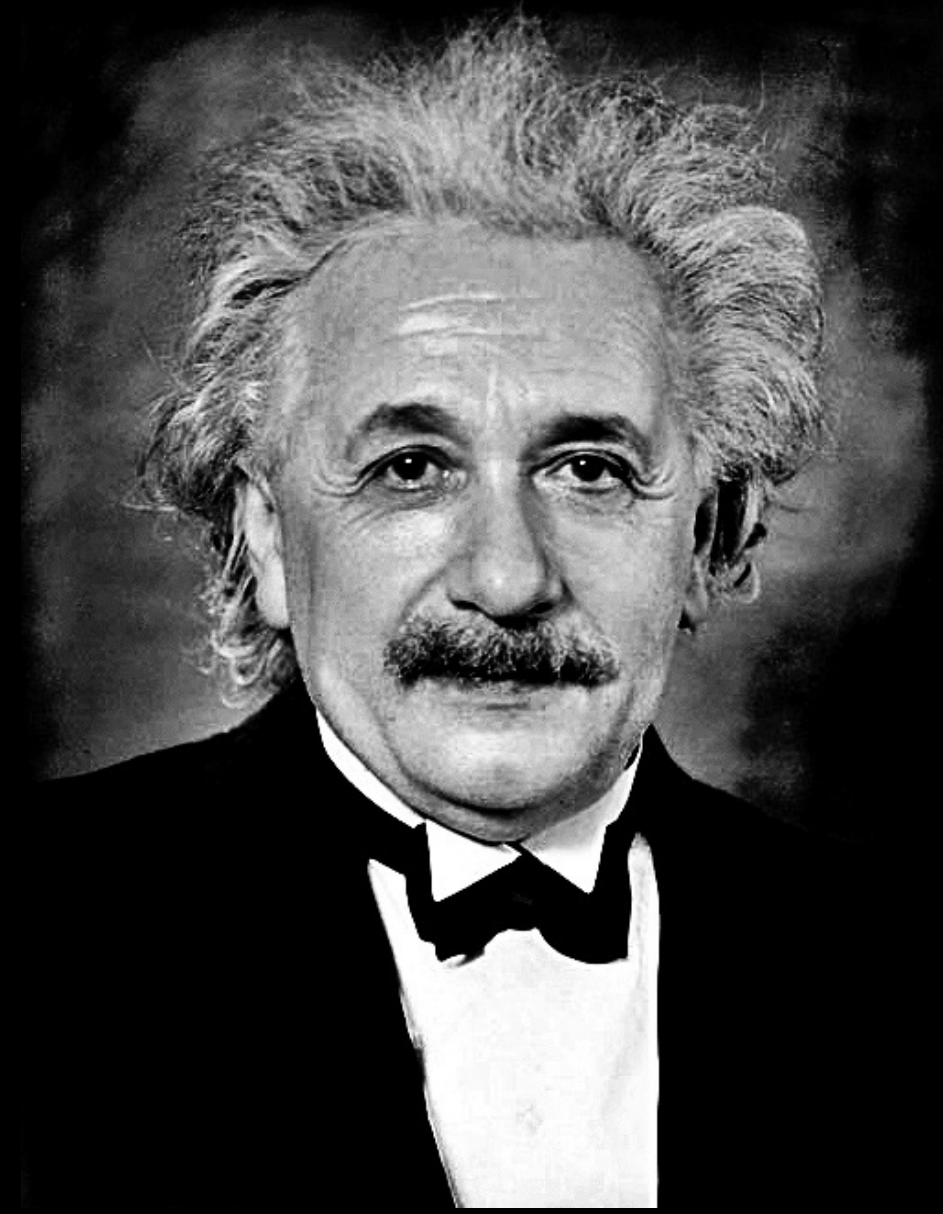


space + time = spacetime



gravity:

mass curves spacetime

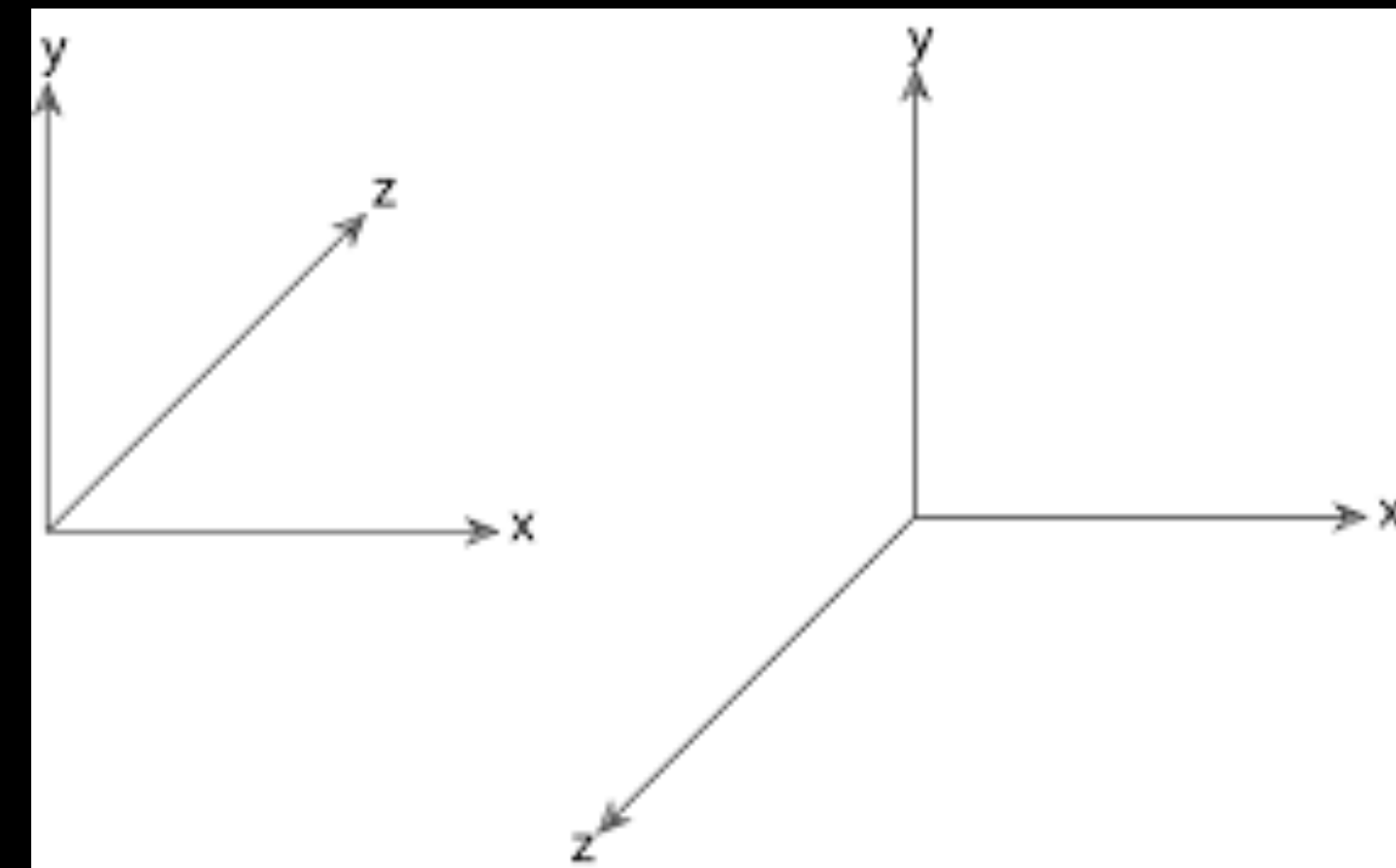


Einstein's general theory of relativity connected differential geometry and physics

Principle of general covariance:

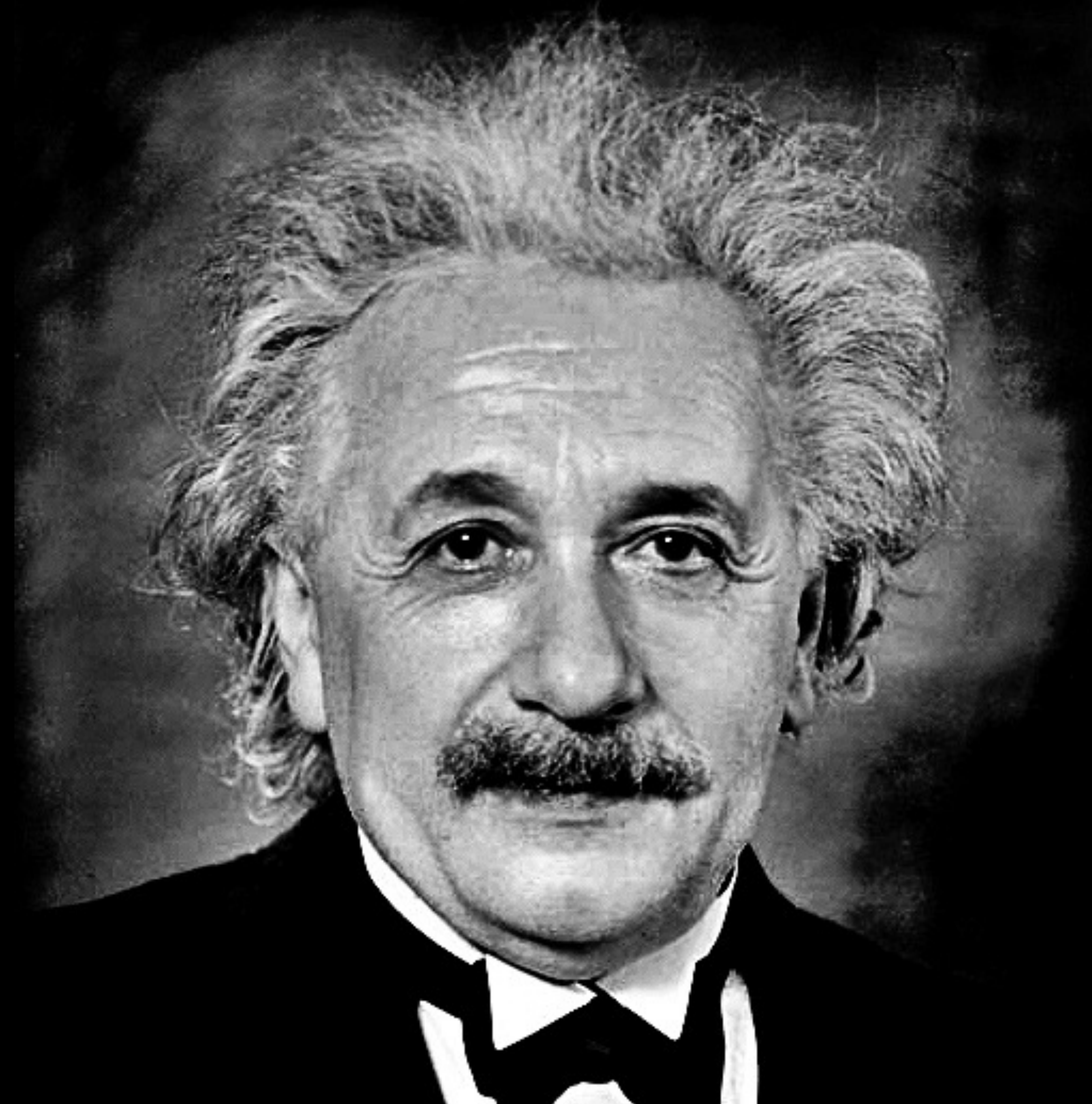
The laws of physics should take the same form independently of which coordinate system we use to represent them

$$R_{\mu\nu}(g) - \frac{1}{2}g_{\mu\nu}R(g) = T_{\mu\nu}(g, F, \dots)$$



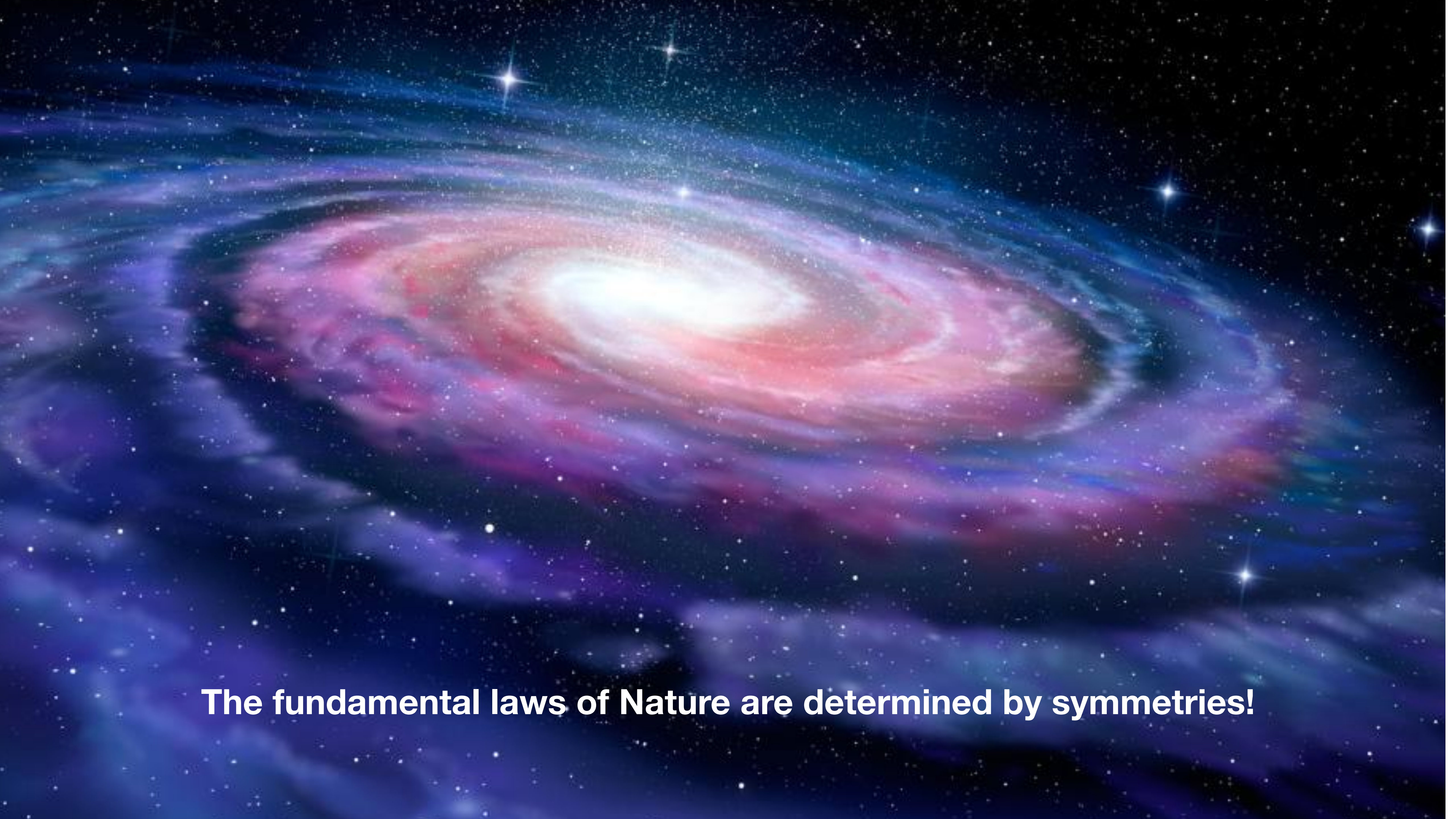
How can it be that mathematics, being after all a product of human thought which is independent of experience, is so admirably appropriate to the objects of reality?

- A. Einstein

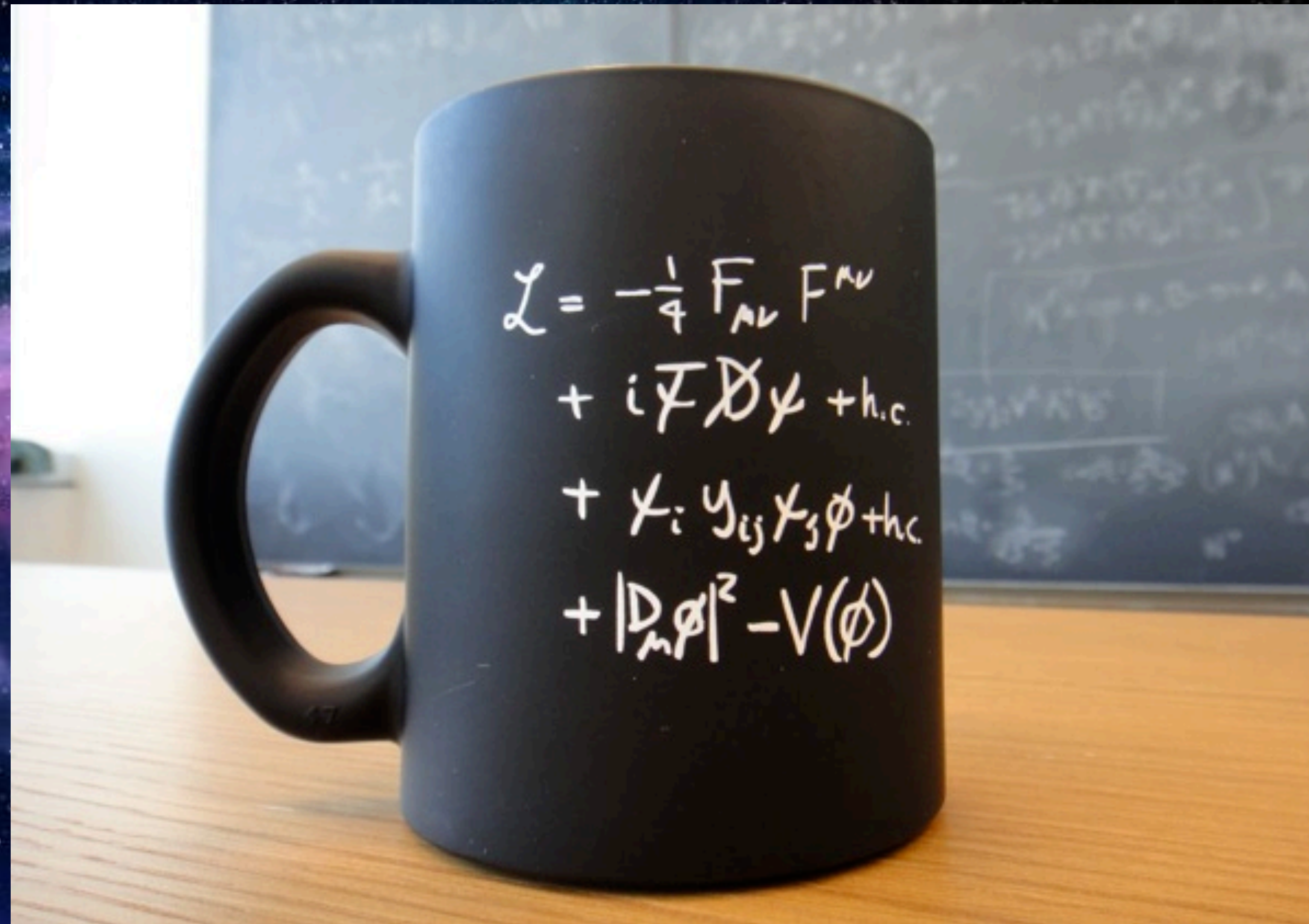


The study of **symmetries** is foundational for the intimate connection between mathematics and physics



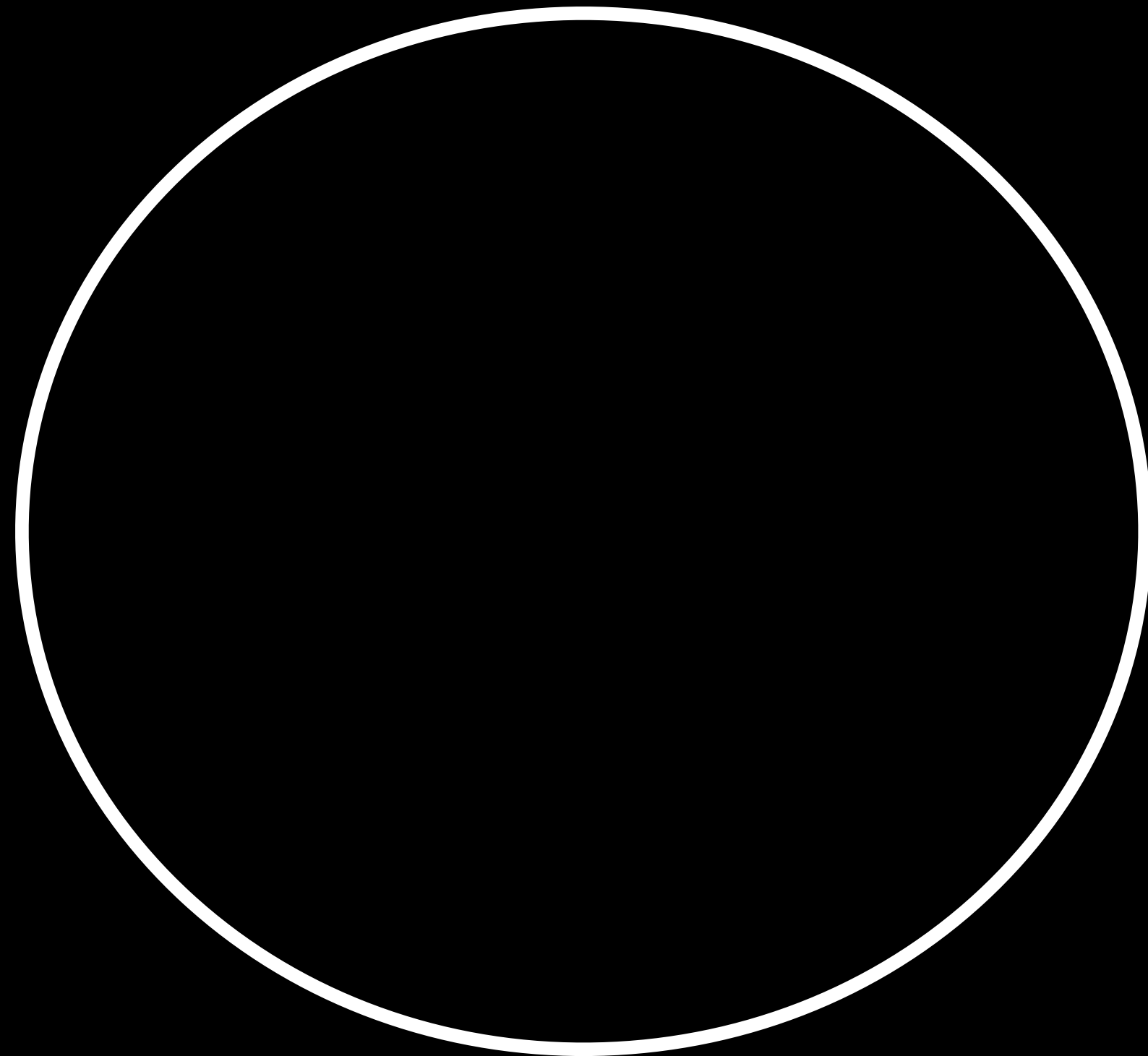


The fundamental laws of Nature are determined by symmetries!

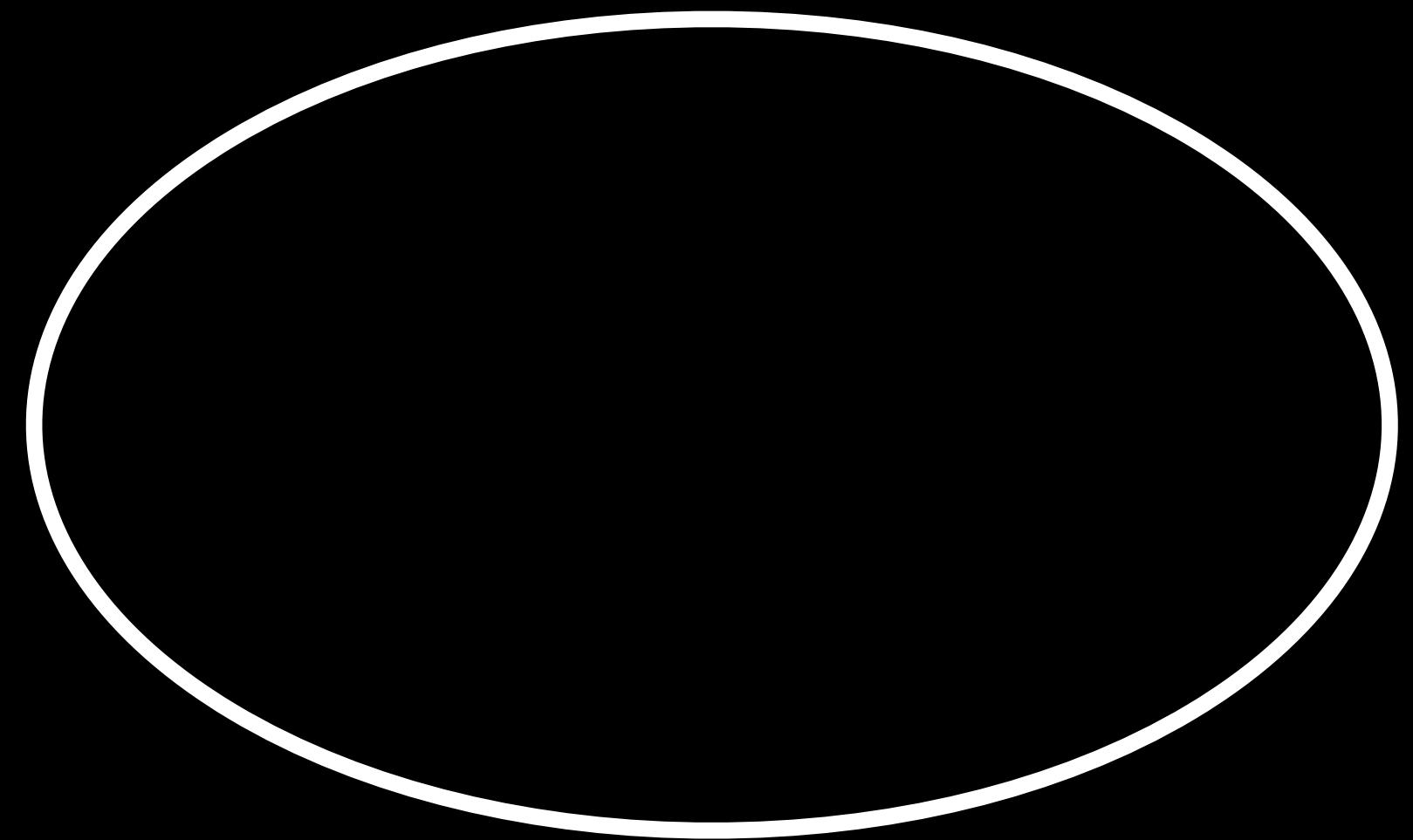


The fundamental laws of Nature are determined by symmetries!

What do we mean by symmetries?

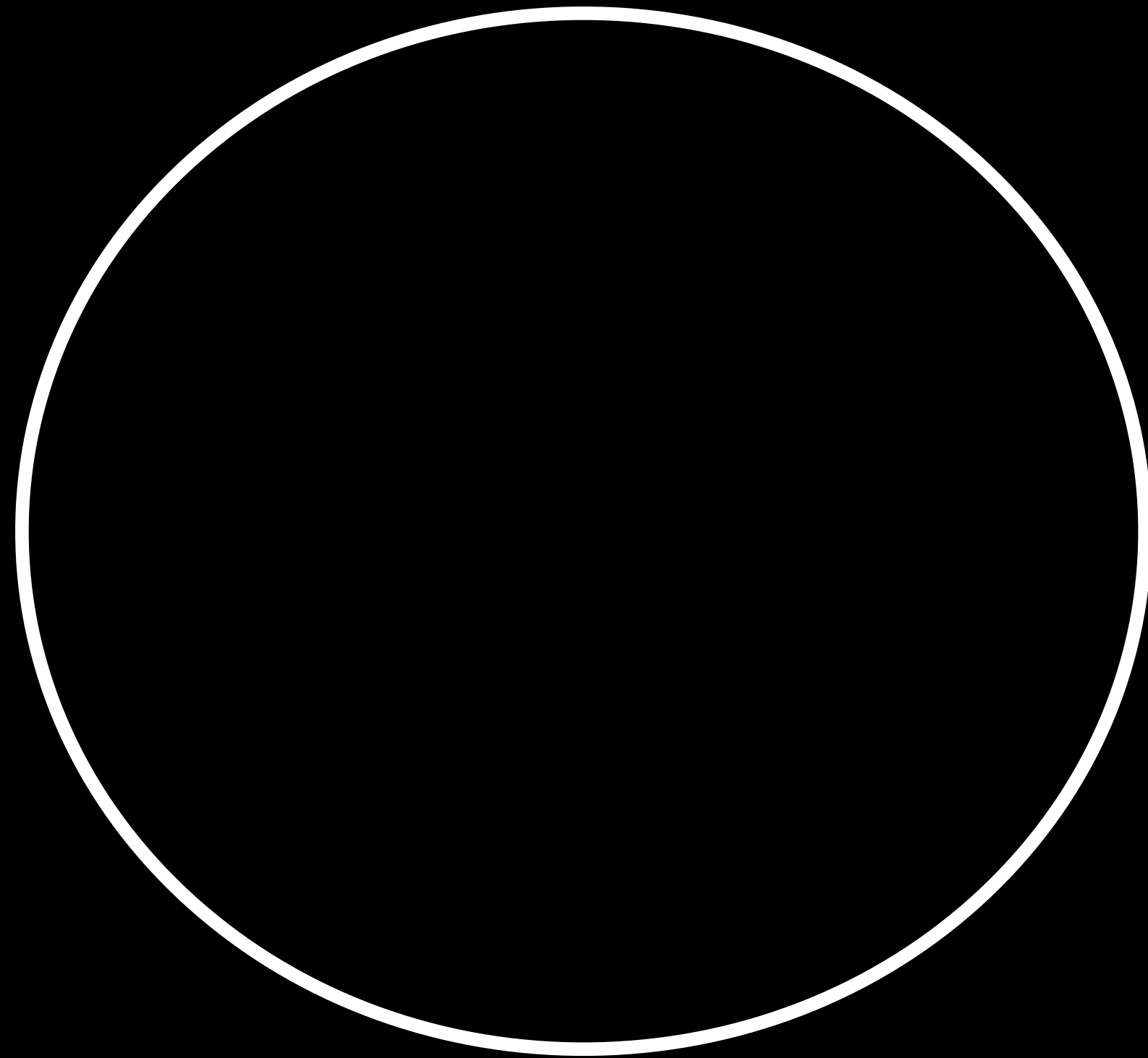


continuous rotational symmetry

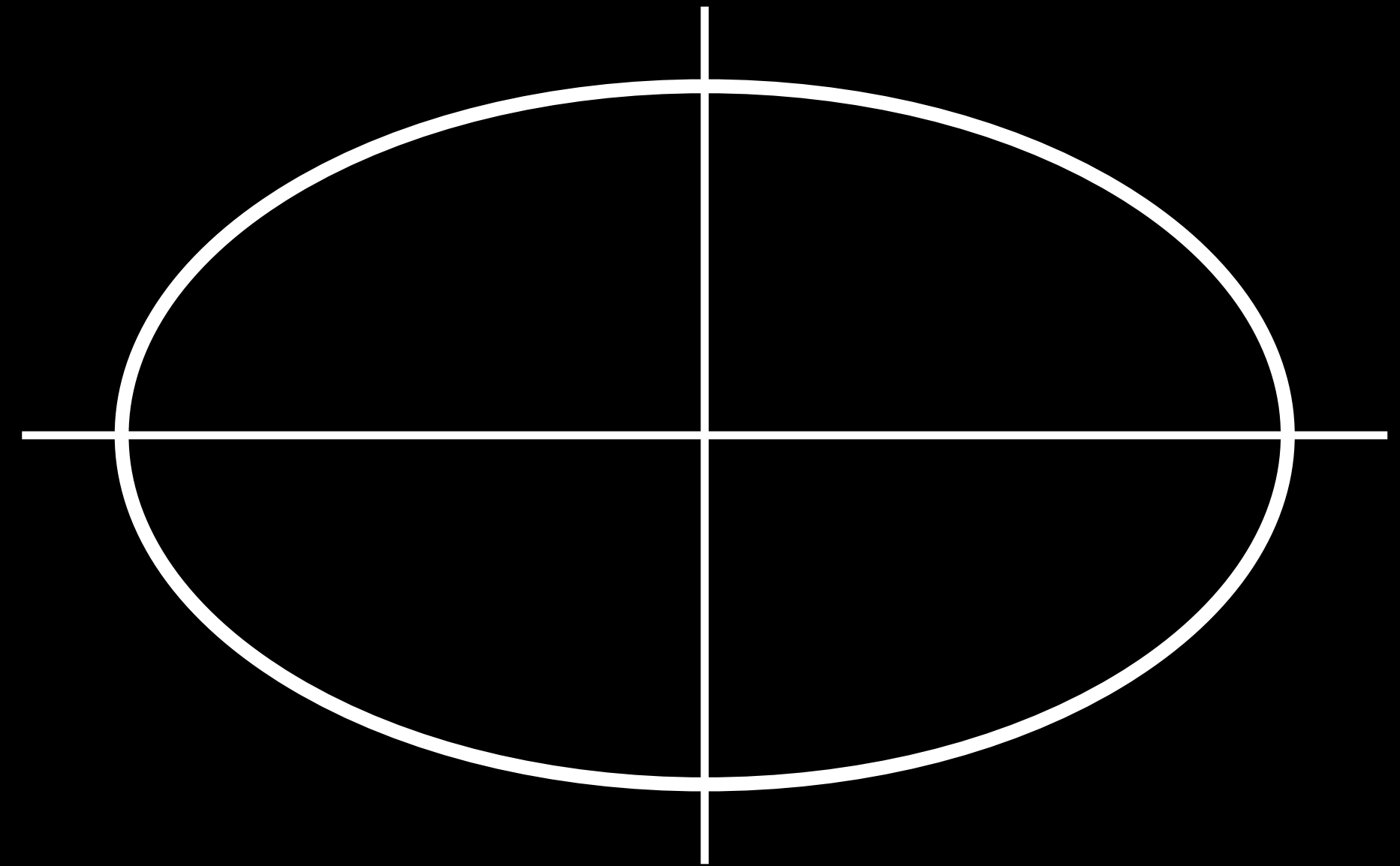


finite reflection symmetry

What do we mean by symmetries?



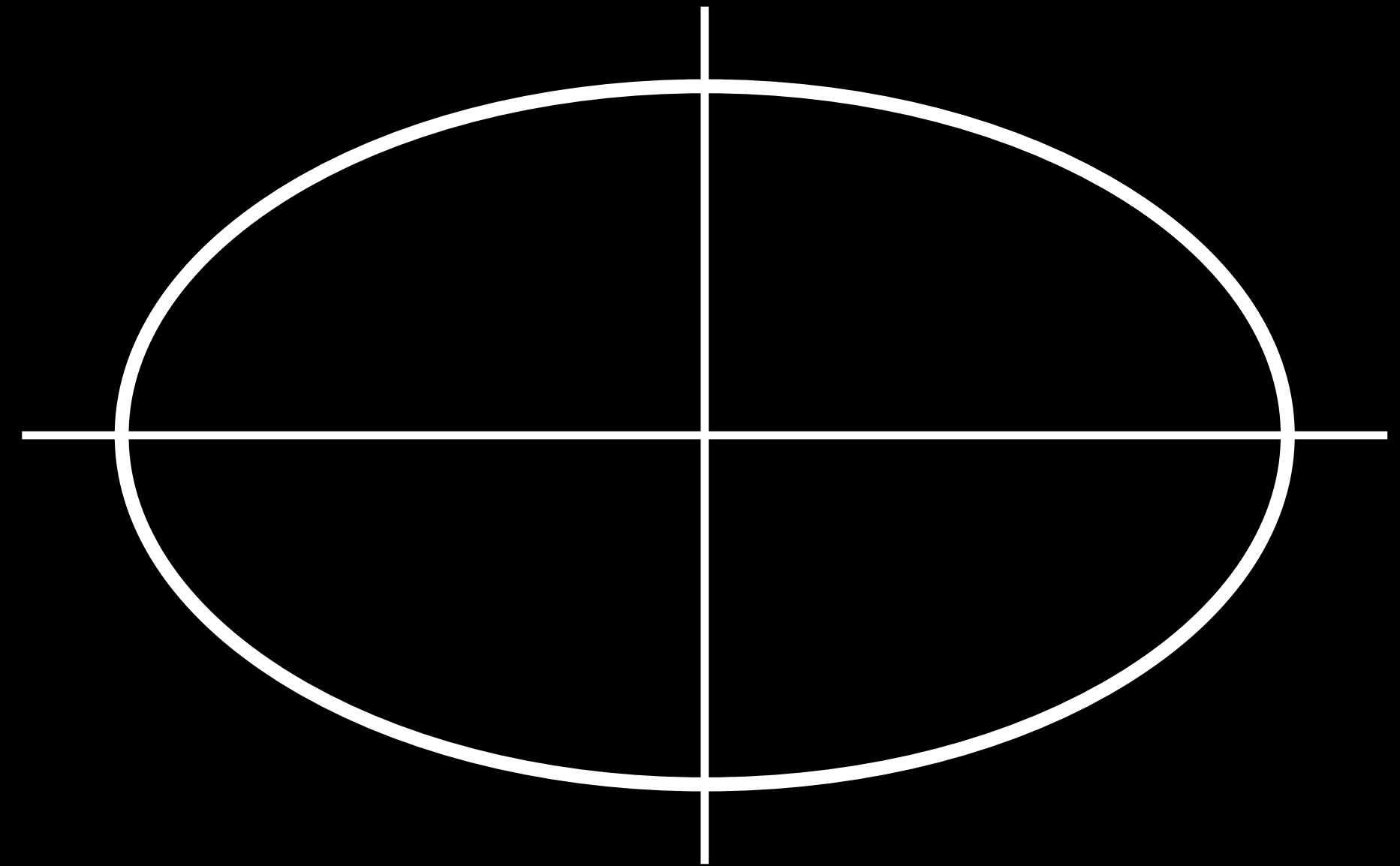
continuous rotational symmetry



finite reflection symmetry

What do we mean by symmetries?

Symmetry transformations
form a ***group***



finite reflection symmetry

Finite simple groups

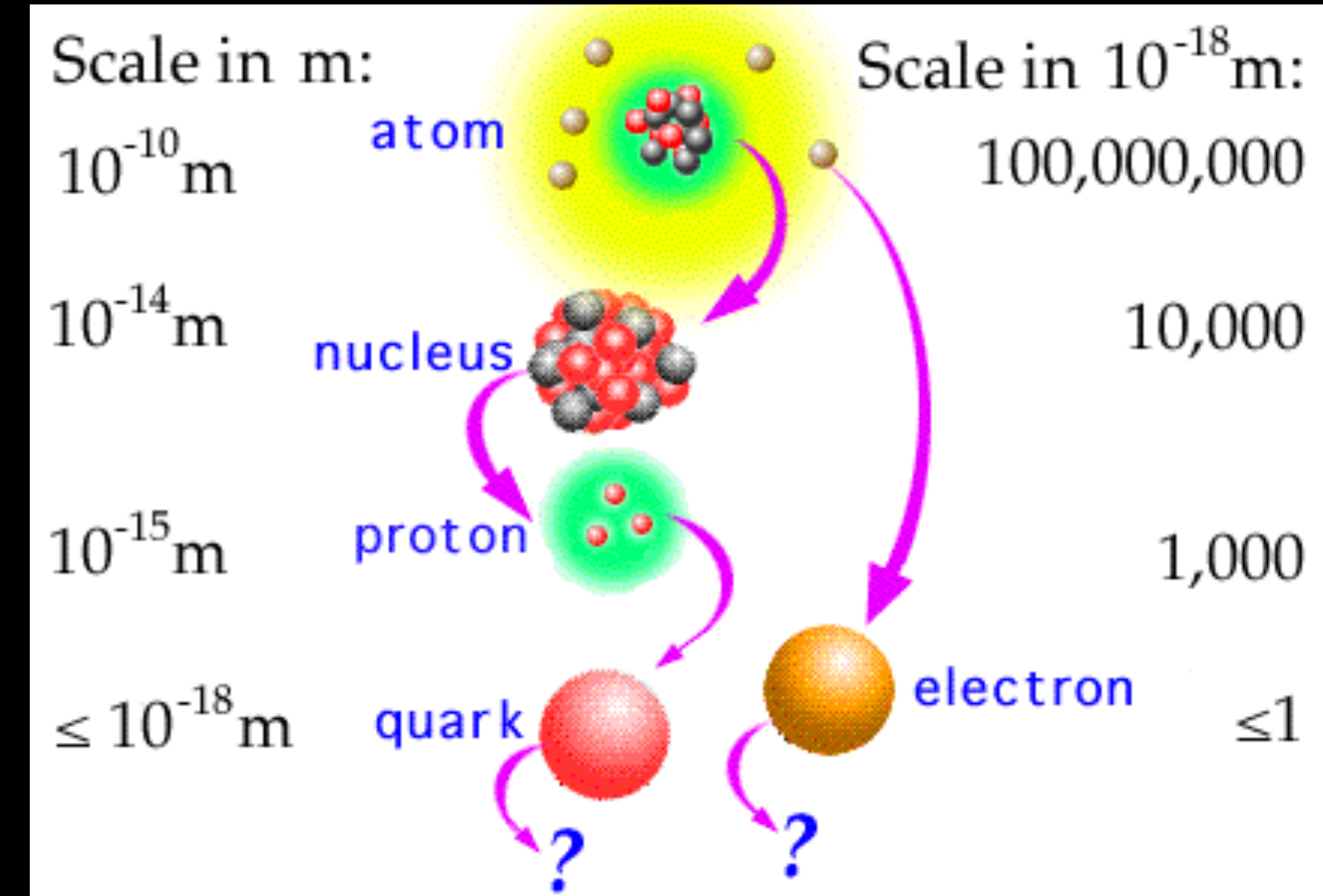
Finite groups that cannot be divided into smaller pieces are called **simple**

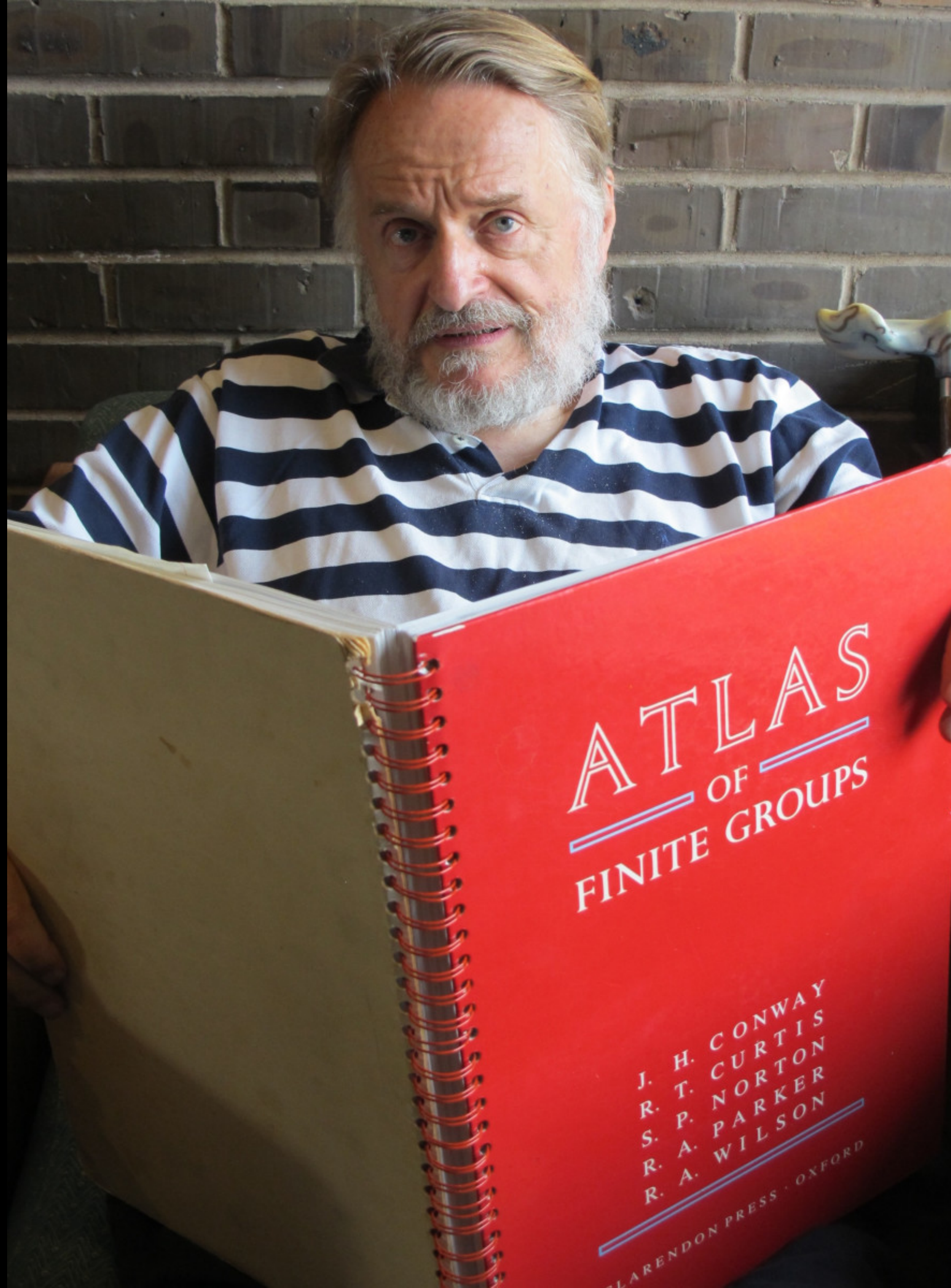


They are like **building blocks of symmetries**

Prime numbers

2, 3, 5, 7, 11, 13,
17, 19, 23, 29, 31,
37, 41, 43, 47, 53,
59, 61, 67, 71, 73,
79, 83, 89, 97





The **classification** of finite simple groups is one of the most extensive projects in mathematics

Complete proof consists of:

10 000+ pages

100+ journals

100+ mathematicians

The Periodic Table Of Finite Simple Groups

$0, C_1, Z_1$
1
1

Dynkin Diagrams of Simple Lie Algebras

C₂
2
C₃
3
C₅
5
C₇
7
C₁₁
11
C₁₃
13
Z_p
C_p
p

$A_1(4), A_1(5)$	$A_2(2)$											${}^2A_3(4)$	$B_2(3)$	$C_3(3)$	$D_4(2)$	${}^2D_4(2^2)$	$G_2(2)'$	
A_5	$A_1(7)$											$B_2(4)$	$C_3(5)$	$D_4(3)$	${}^2D_4(3^2)$	${}^2A_2(9)$		
60	168											25920	4 585 351 680	174 182 400	197 406 720	6 048		
$A_1(9), B_2(2)'$	${}^2G_2(3)'$											$B_2(4)$	$C_3(5)$	$D_4(3)$	${}^2D_4(3^2)$	${}^2A_2(16)$		
A_6	$A_1(8)$											979 200	228 301 000 000 000	4 952 179 814 400	10 151 968 619 520	62 400		
360	504																	
A_7	$A_1(11)$	$E_6(2)$	$E_7(2)$	$E_8(2)$	$F_4(2)$	$G_2(3)$	${}^3D_4(2^3)$	${}^2E_6(2^2)$	${}^2B_2(2^3)$	Tits*	${}^2F_4(2)'$	${}^2G_2(3^3)$	$B_3(2)$	$C_4(3)$	$D_5(2)$	${}^2D_5(2^2)$	${}^2A_2(25)$	
2 520	660	214 841 575 522 005 575 270 400	7 997 476 942 475 794 794 580 487 262 480 802 718 486	107 640 134 100 000 000 384 240 000 000 000 000 000 87 502 776 000 000 000 000	3 311 126 603 366 400	4 245 696	211 341 312	76 532 479 683 774 853 939 200	29 120	17 971 200	10 073 444 472	1 451 520	65 784 756 654 489 600	23 499 295 948 800	25 015 379 558 400	126 000		
$A_3(2)$	$A_1(13)$	$E_6(3)$	$E_7(3)$	$E_8(3)$	$F_4(3)$	$G_2(4)$	${}^3D_4(3^3)$	${}^2E_6(3^2)$	${}^2B_2(2^5)$	${}^2F_4(2^3)$	${}^2G_2(3^5)$	$B_2(5)$	$C_3(7)$	$D_4(5)$	${}^2D_4(4^2)$	${}^2A_3(9)$		
A_8	$A_1(13)$	$E_6(3)$	$E_7(3)$	$E_8(3)$	$F_4(3)$	$G_2(4)$	${}^3D_4(3^3)$	${}^2E_6(3^2)$	${}^2B_2(2^5)$	${}^2F_4(2^3)$	${}^2G_2(3^5)$	$B_2(5)$	$C_3(7)$	$D_4(5)$	${}^2D_4(4^2)$	${}^2A_3(9)$		
20 160	1 092	7 107 703 147 943 463 209 828 238 393 214 443 200	1 271 378 328 428 326 742 200 479 751 139 403 444 534 378 203 778 764 234 617 393 200	107 640 134 100 000 000 384 240 000 000 000 000 87 502 776 000 000 000 000	5 734 420 792 816 671 844 761 600	251 596 800	20 560 831 566 912	14 624 853 916 949 493 633 963 120 680 332 377 600	32 537 600	264 905 352 699 586 176 614 400	49 825 657 439 340 552	4 680 000	273 457 218 604 953 600	8 911 539 000 000 000 000	67 536 471 195 648 000	3 265 920		
A_9	$A_1(17)$	$E_6(4)$	$E_7(4)$	$E_8(4)$	$F_4(4)$	$G_2(5)$	${}^3D_4(4^3)$	${}^2E_6(4^2)$	${}^2B_2(2^7)$	${}^2F_4(2^5)$	${}^2G_2(3^7)$	$B_2(7)$	$C_3(9)$	$D_5(3)$	${}^2D_4(5^2)$	${}^2A_2(64)$		
181 440	2 448	85 528 730 793 343 640 303 832 419 059 342 743 484 734 480 600	111 118 408 114 480 943 778 000 277 000 000 000 000 000 000 107 252 747 503 304 000 000 000	107 640 134 100 000 000 384 240 000 000 000 000 87 502 776 000 000 000 000	19 009 825 523 840 945 451 297 669 120 000	5 859 000 000	67 802 350 642 790 400	85 486 576 147 417 700 489 486 772 287 364 963 120 680 332 377 600	34 093 383 680	1 104 633 130 794 961 447 702 342 409 763 732 364 000	239 189 910 264 352 349 332 632	138 297 600	54 025 731 402 499 584 000	1 289 512 799 941 305 139 200	17 880 203 250 000 000 000	5 515 776		
A_n	$PSL_{n+1}(q), L_{n+1}(q)$	$E_6(q)$	$E_7(q)$	$E_8(q)$	$F_4(q)$	$G_2(q)$	${}^3D_4(q^3)$	${}^2E_6(q^2)$	${}^2B_2(2^{2n+1})$	${}^2F_4(2^{2n+1})$	${}^2G_2(3^{2n+1})$	$B_n(q)$	$C_n(q)$	$D_n(q)$	${}^2D_n(q^2)$	${}^2A_n(q^2)$		
$\frac{n!}{2}$	$\frac{q^{n+1}-1}{q-1} \prod_{i=2}^{n+1} (q^i-1)$	$\frac{q^{2n+1}-1}{q^2-1} \prod_{i=2}^{2n+1} (q^i-1)$	$\frac{q^{2n+1}-1}{q^2-1} \prod_{i=2}^{2n+1} (q^i-1)$	$\frac{q^{2n+1}-1}{q^2-1} \prod_{i=2}^{2n+1} (q^i-1)$	$\frac{q^{2n+1}-1}{q^2-1} \prod_{i=2}^{2n+1} (q^i-1)$	$q^{2n+1}(q^2-1)$	$\frac{q^{2n+1}-1}{(q^2-1)(q^3-1)}$	$\frac{q^{2n+1}-1}{(q^2-1)(q^2-1)}$	$q^{2n+1}(q-1)$	$\frac{q^{2n+1}-1}{(q^2-1)(q-1)}$	$q^{2n+1}(q-1)$	$\frac{q^n-1}{(q-1)} \prod_{i=2}^n (q^i-1)$	$\frac{q^n-1}{(q-1)} \prod_{i=2}^n (q^i-1)$	$\frac{q^{2n}-1}{(q^2-1)} \prod_{i=2}^{2n} (q^i-1)$	$\frac{q^{2n}-1}{(q^2-1)} \prod_{i=2}^{2n} (q^i-1)$	$\frac{q^{2n}-1}{(q^2-1)} \prod_{i=2}^{2n} (q^i-1)$		

- Alternating Groups
- Classical Chevalley Groups
- Chevalley Groups
- Classical Steinberg Groups
- Steinberg Groups
- Suzuki Groups
- Ree Groups and Tits Group*
- Sporadic Groups
- Cyclic Groups

Alternates*
Symbol
Order†

M_{11}	M_{12}	M_{22}	M_{23}	M_{24}	$J(1), J(11)$	HJ	HJM			$F_3, H3M, H3H$		
7 920	95 040	443 520	10 200 960	244 823 040	J_1	J_2	J_3	J_4	HS	McL	He	Ru
					175 560	604 800	50 232 960	86 775 571 046 077 562 880	44 352 000	898 128 000	4 030 387 200	145 926 144 000

*The Tits group ${}^2F_4(2)'$ is not a group of Lie type, but is the (index 2) commutator subgroup of ${}^3F_4(2)$. It is usually given honorary Lie type status.

†For sporadic groups and families, alternate names in the upper left are other names by which they may be known. For specific non-sporadic groups these are used to indicate isomorphisms. All such isomorphisms appear on the table except the family $B_n(2^n) \cong C_n(2^n)$.

The groups starting on the second row are the classical groups. The sporadic Suzuki group is unrelated to the families of Suzuki groups.

‡Finite simple groups are determined by their order with the following exceptions:
 $B_n(q)$ and $C_n(q)$ for q odd, $n > 2$;
 $A_6 \cong A_1(2)$ and $A_1(4)$ of order 20160.

S_2	$O'NS, O-S$	-3	-2	-1	F_3, D	LyS	F_3, E	$M(22)$	$M(23)$	$F_3, M(24)'$	F_2	F_3, M_1
Suz	$O'N$	Co_3	Co_2	Co_1	HN	Ly	Th	Fi_{22}	Fi_{23}	Fi'_{24}	B	M
448 345 497 600	460 815 505 920	495 766 656 000	42 305 421 312 000	4 157 776 806 543 360 000	273 030 912 000 000	51 765 179 004 000 000	90 745 943 887 872 000	64 561 751 654 400	4 089 470 473 293 004 800	1 255 205 709 190 661 721 292 800	4 134 761 842 228 424 191 177 360 344 000 000	896 037 424 764 512 475 866 459 960 750 757 003 754 360 000 000 000

Monster group

M



Borcherds

Fields medal in 1998

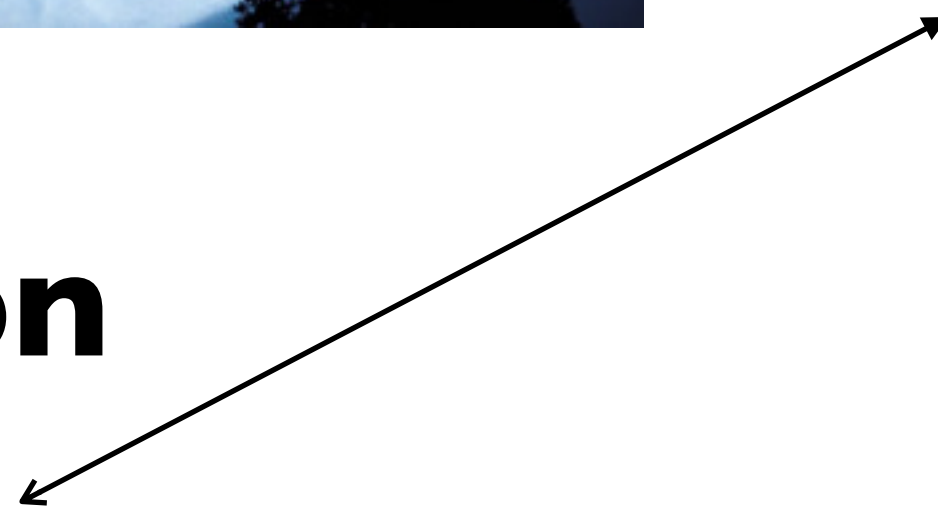


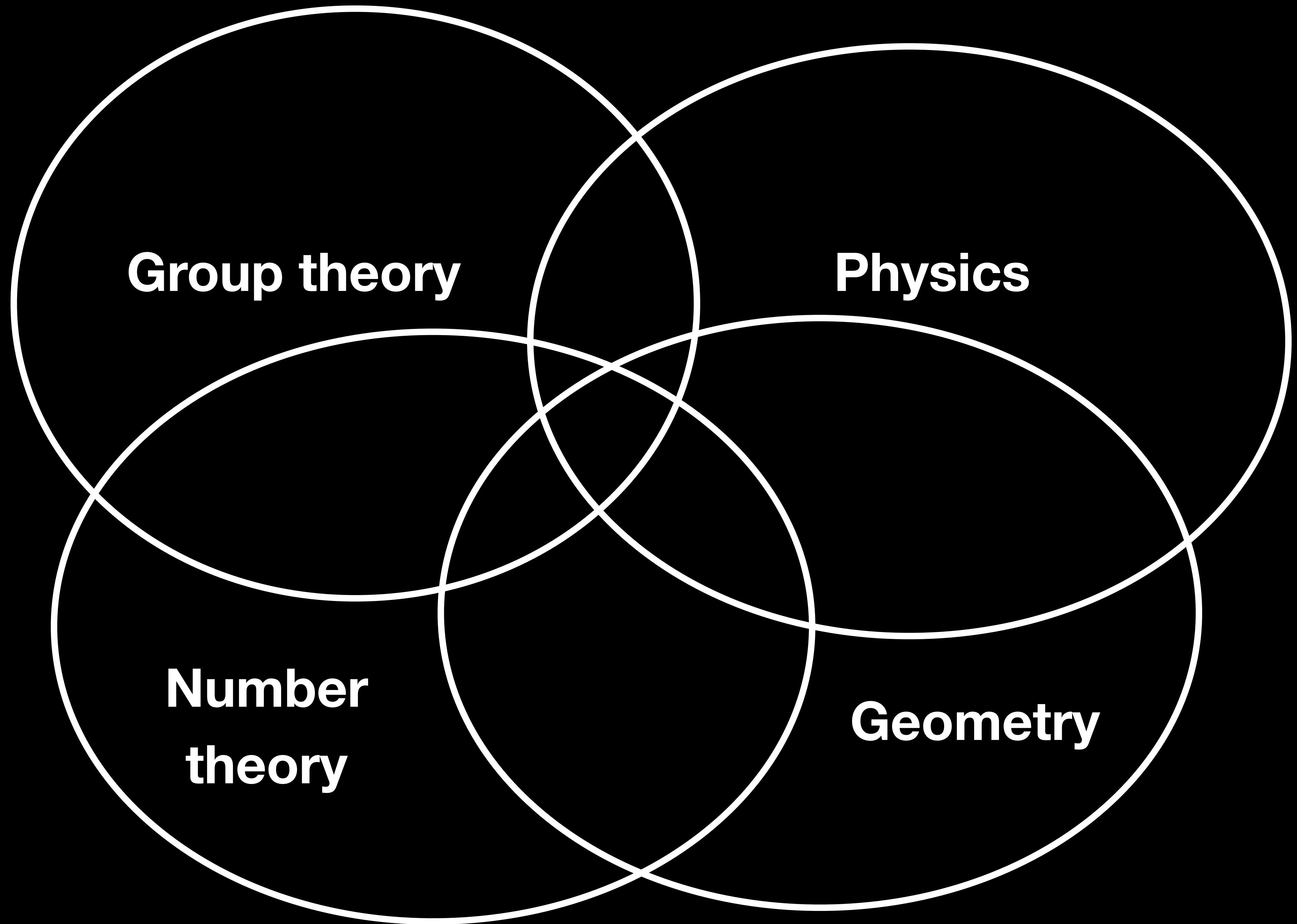
2d conformal field theory
(vertex operator algebra)

[Frenkel, Lepowsky,
Meurman]

Modular function

$J(\tau)$





Group theory

Physics

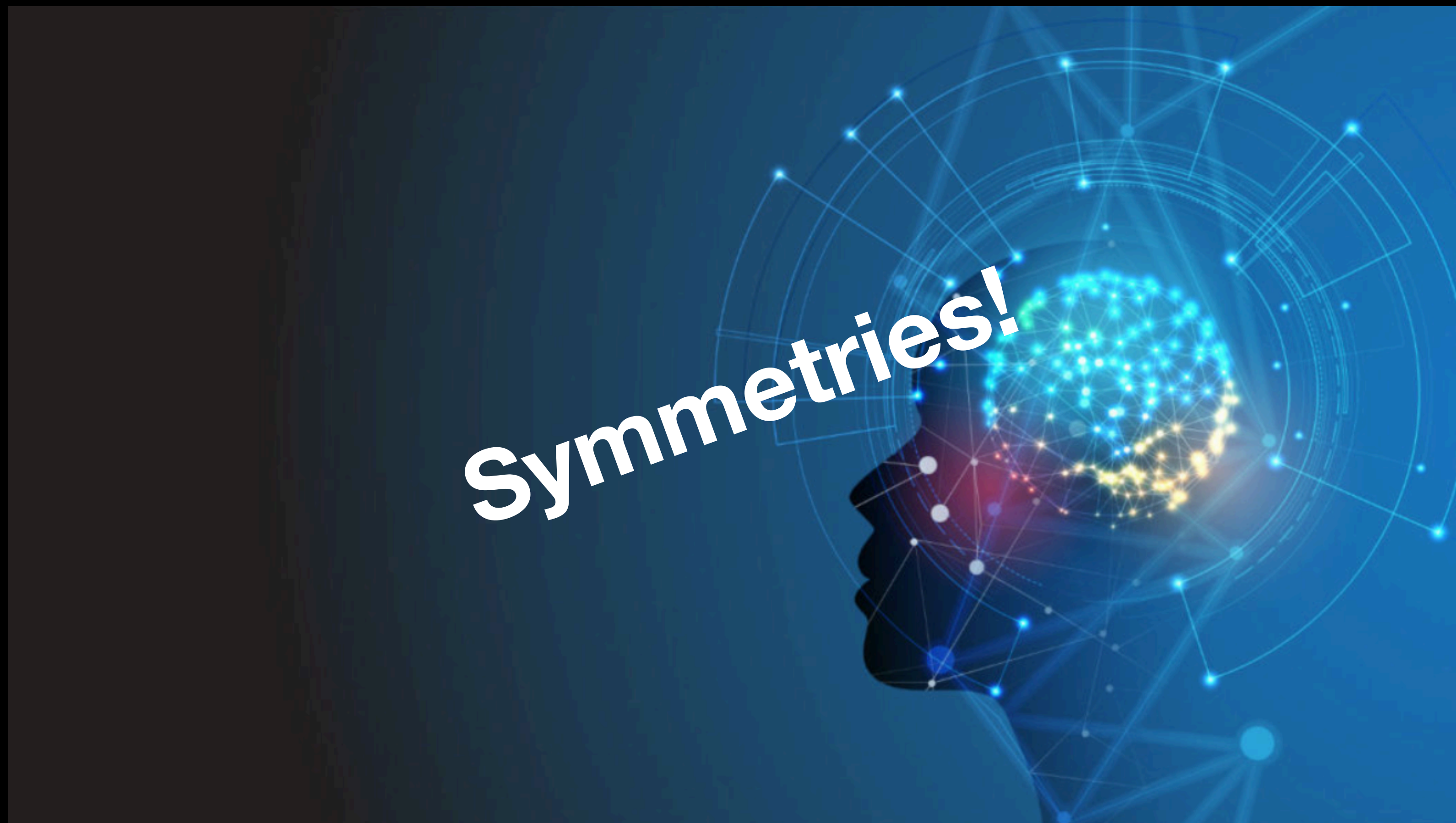
**Number
theory**

Geometry

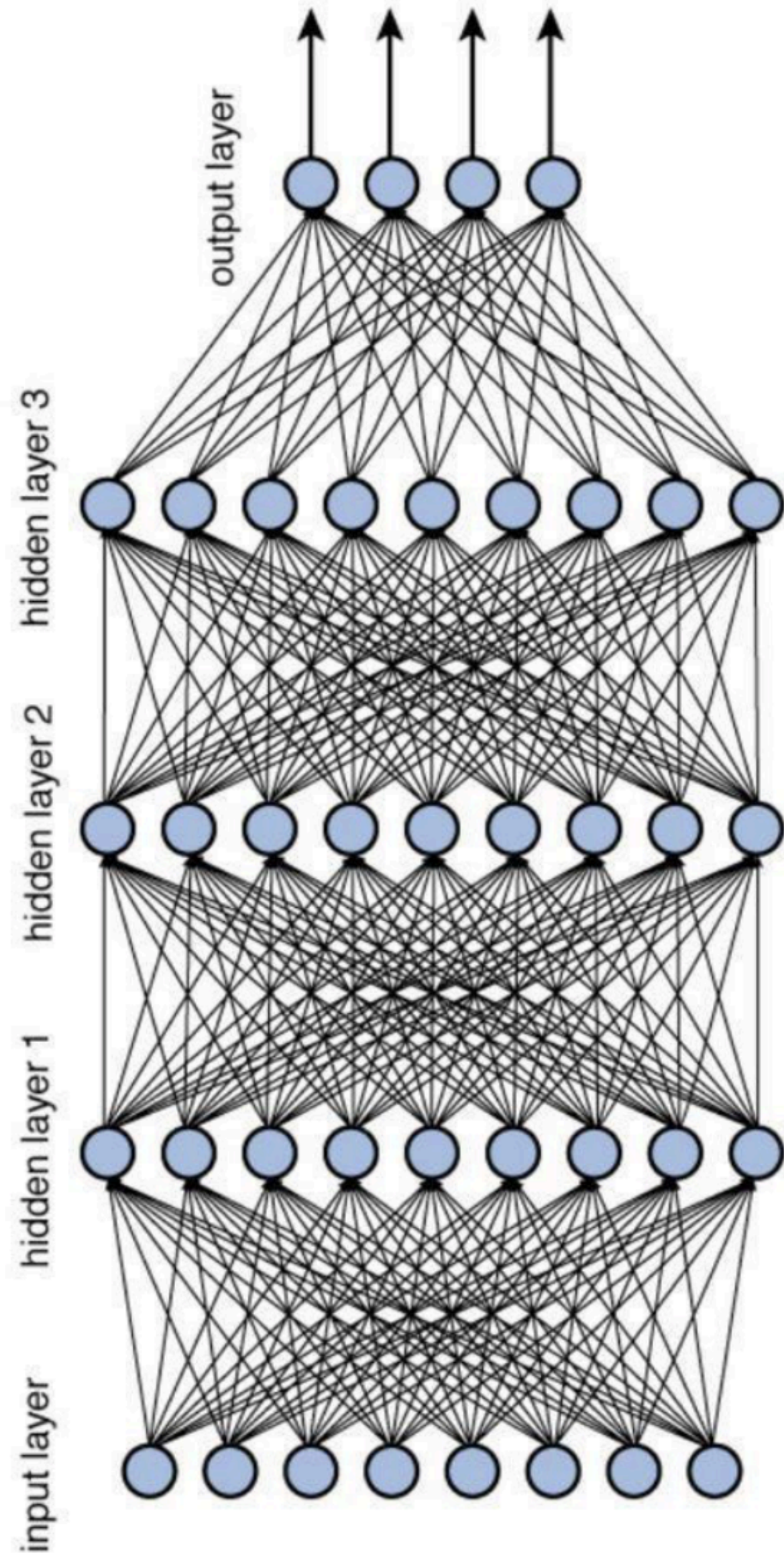
What does all this have to do with AI?



What does all this have to do with AI?



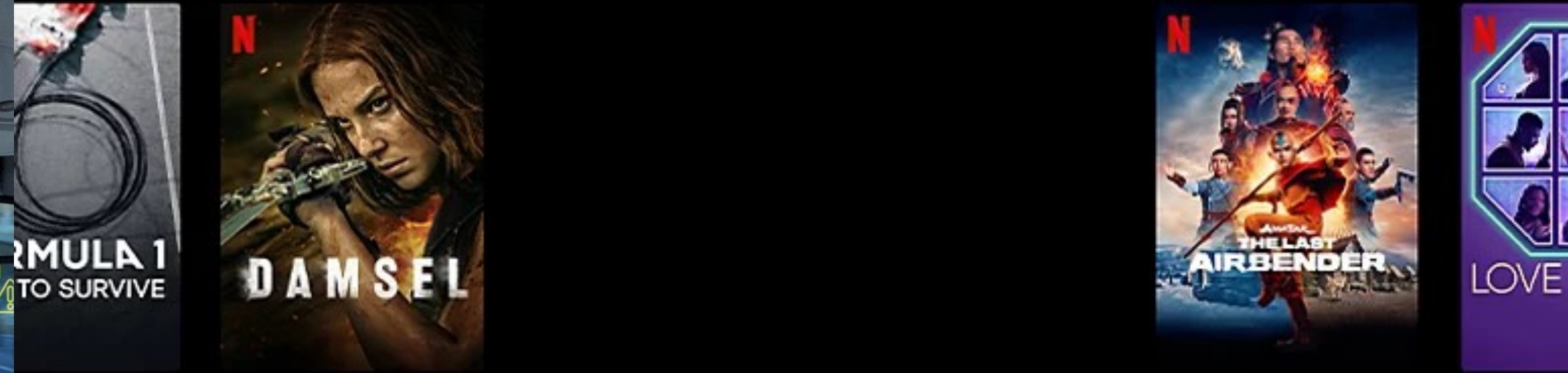
Deep Neural Network



Artificial Intelligence:
Mimicking the intelligence or behavioural pattern of humans or any other living entity.

Machine Learning:
A technique by which a computer can "learn" from data, without using a complex set of different rules. This approach is mainly based on training a model from datasets.

Deep Learning:
A technique to perform machine learning inspired by our brain's own network of neurons.





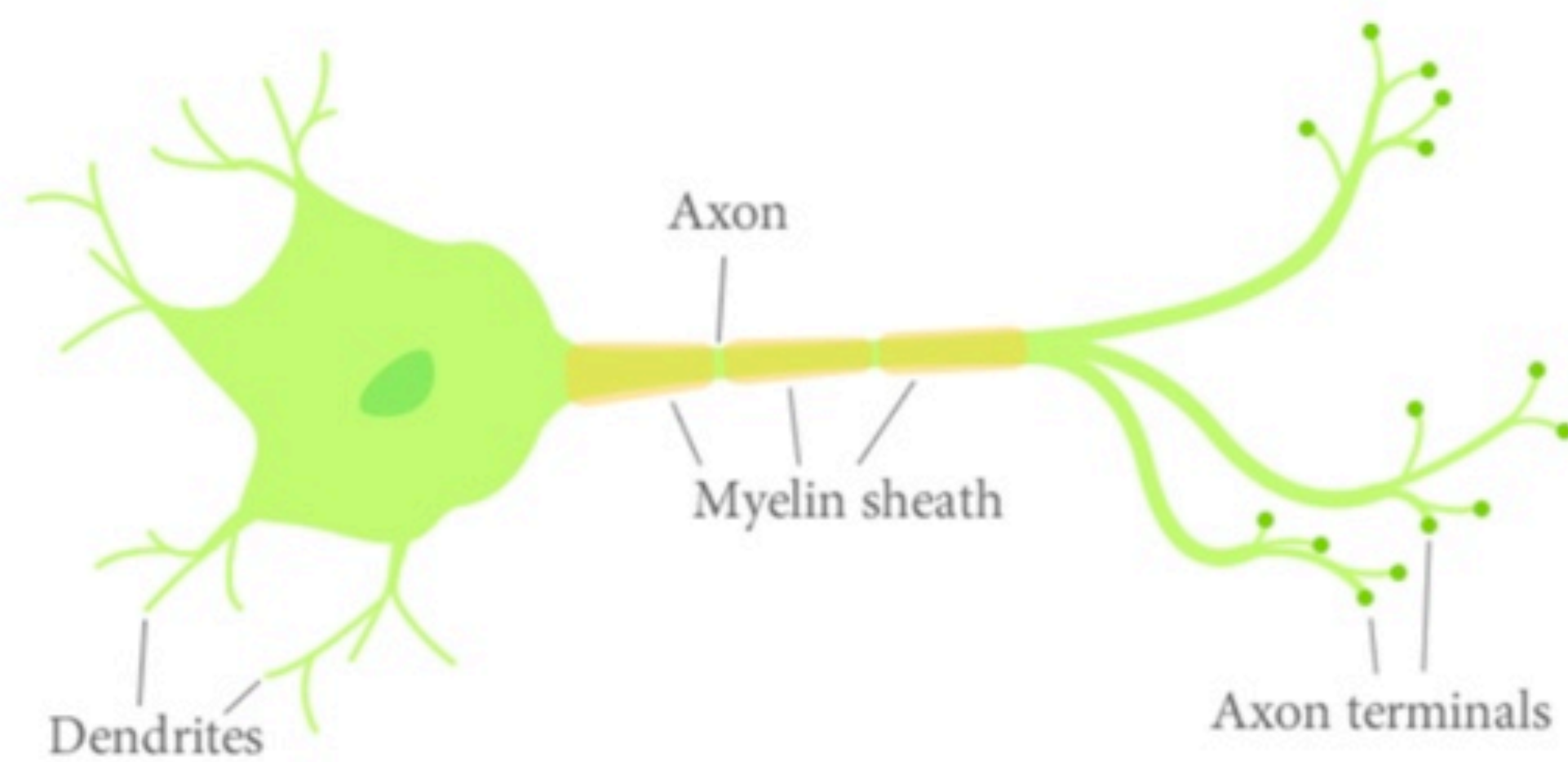




[Pic from thispersondoesnotexist.com]



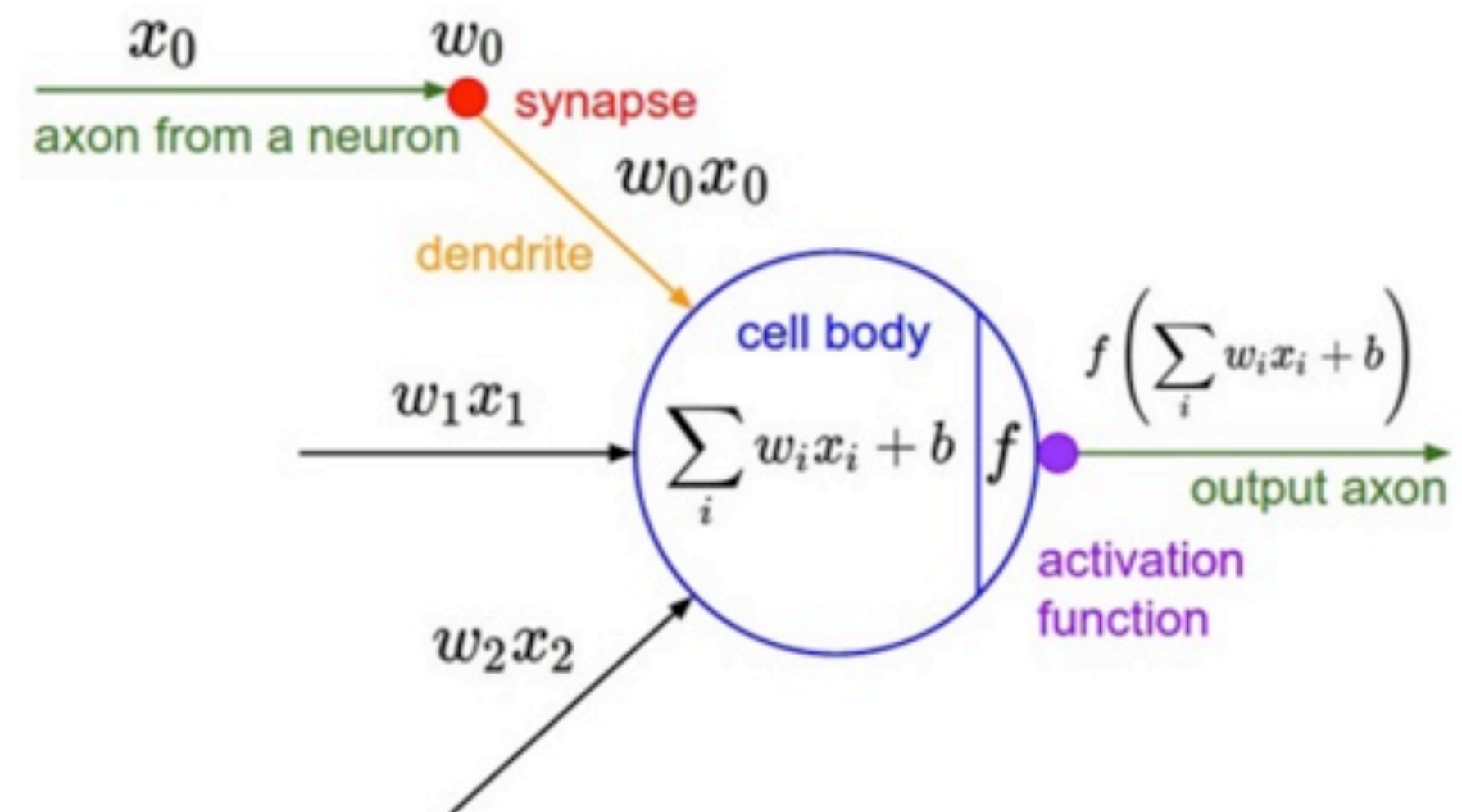
Real Neuron



Artificial Neuron

Artificial neuron:

1. Input layer
2. Hidden layers
3. Output layer





Artificial neuron:

1. Input layer
2. Hidden layers
3. Output layer

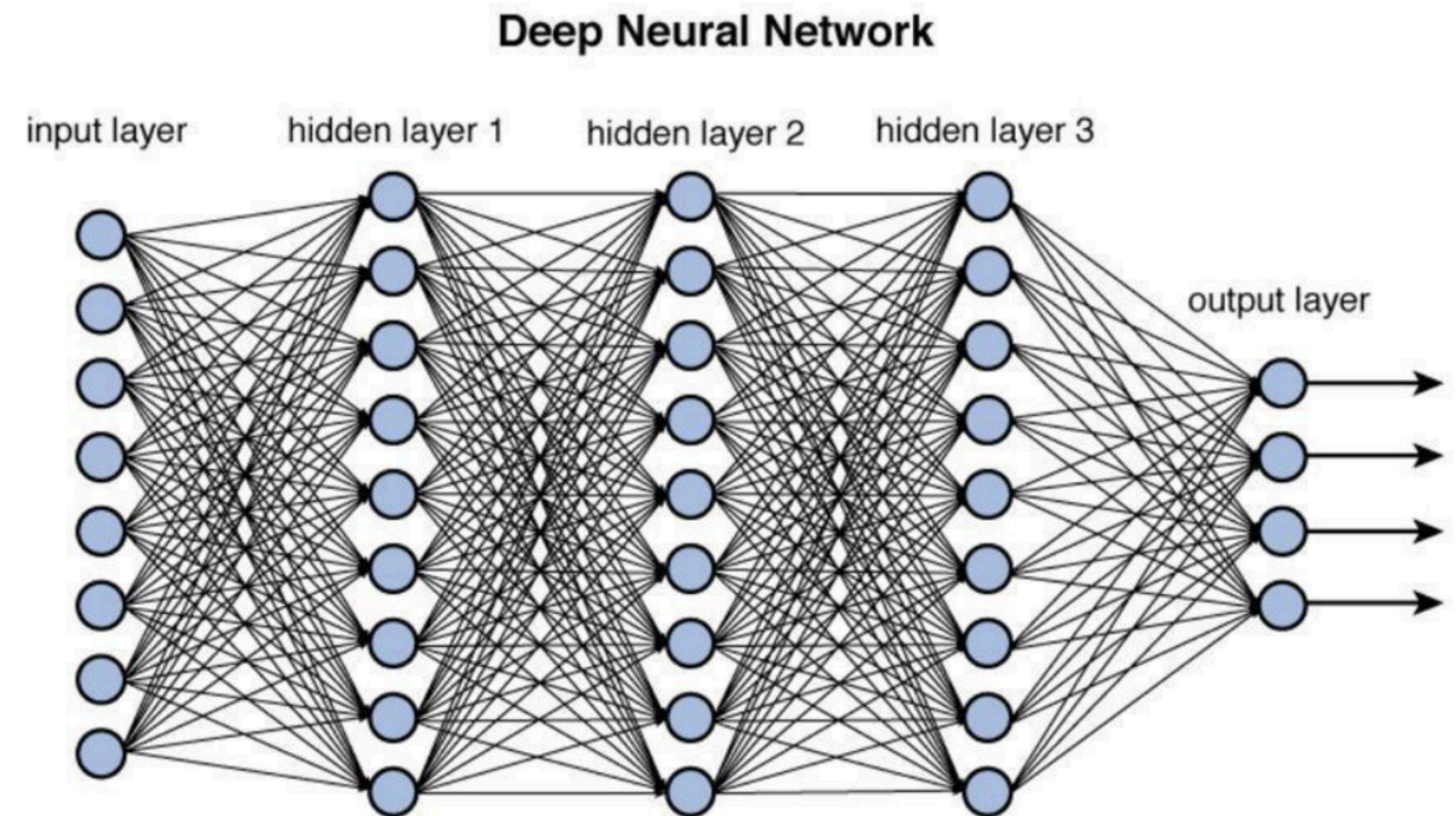


Image classification

Image classification

“skateboard”

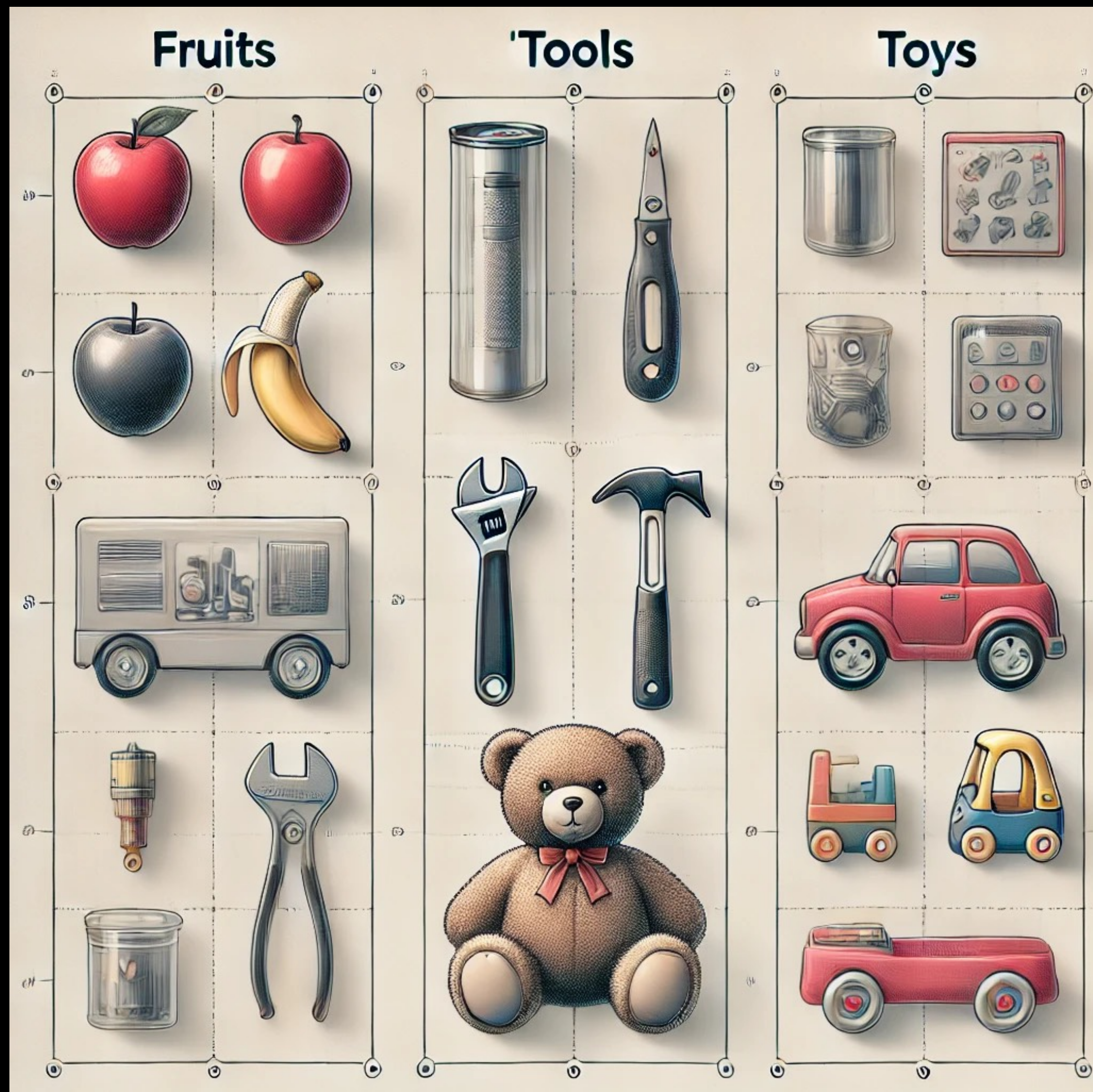


“ribs”

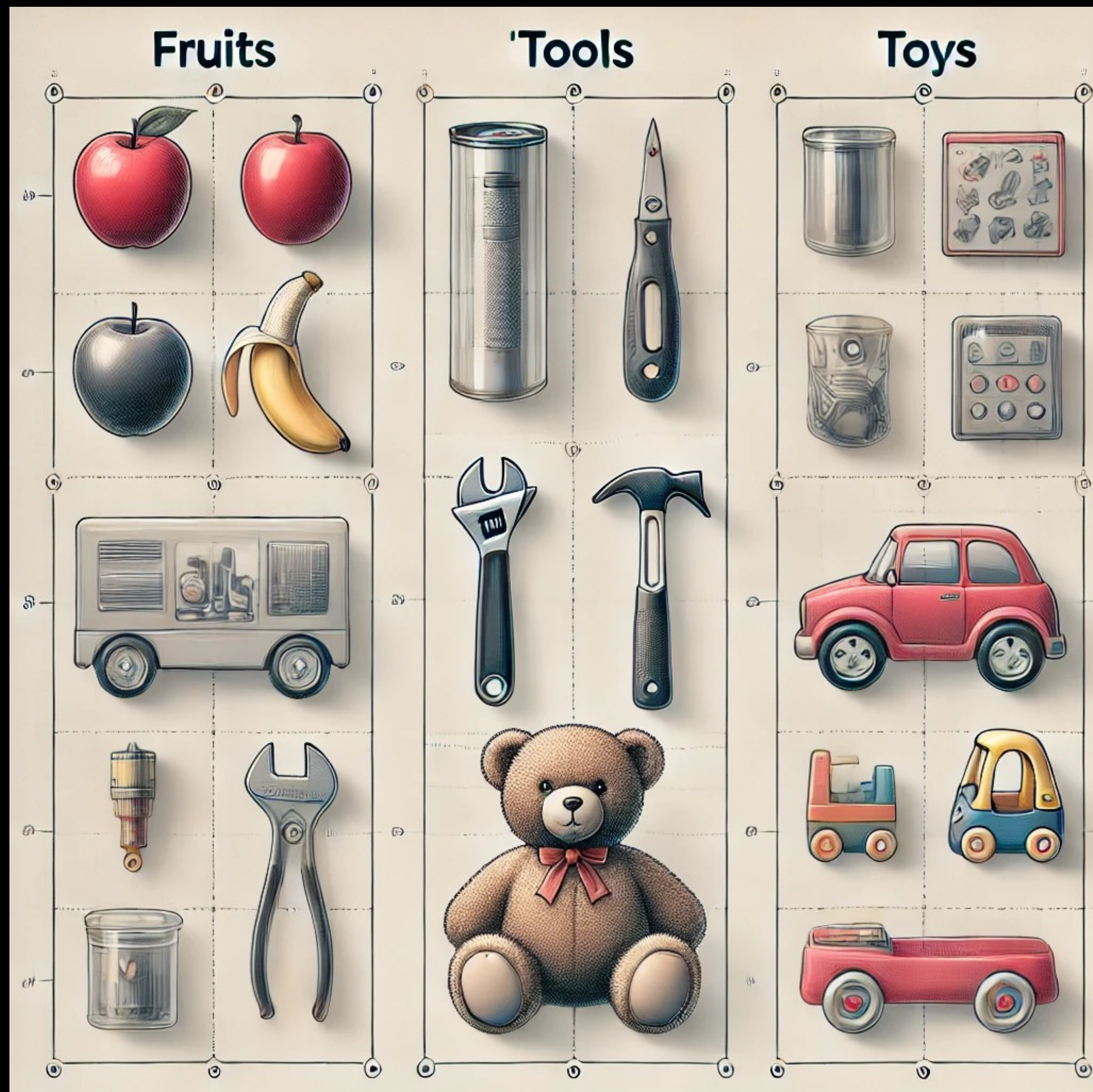


“boxing gloves”

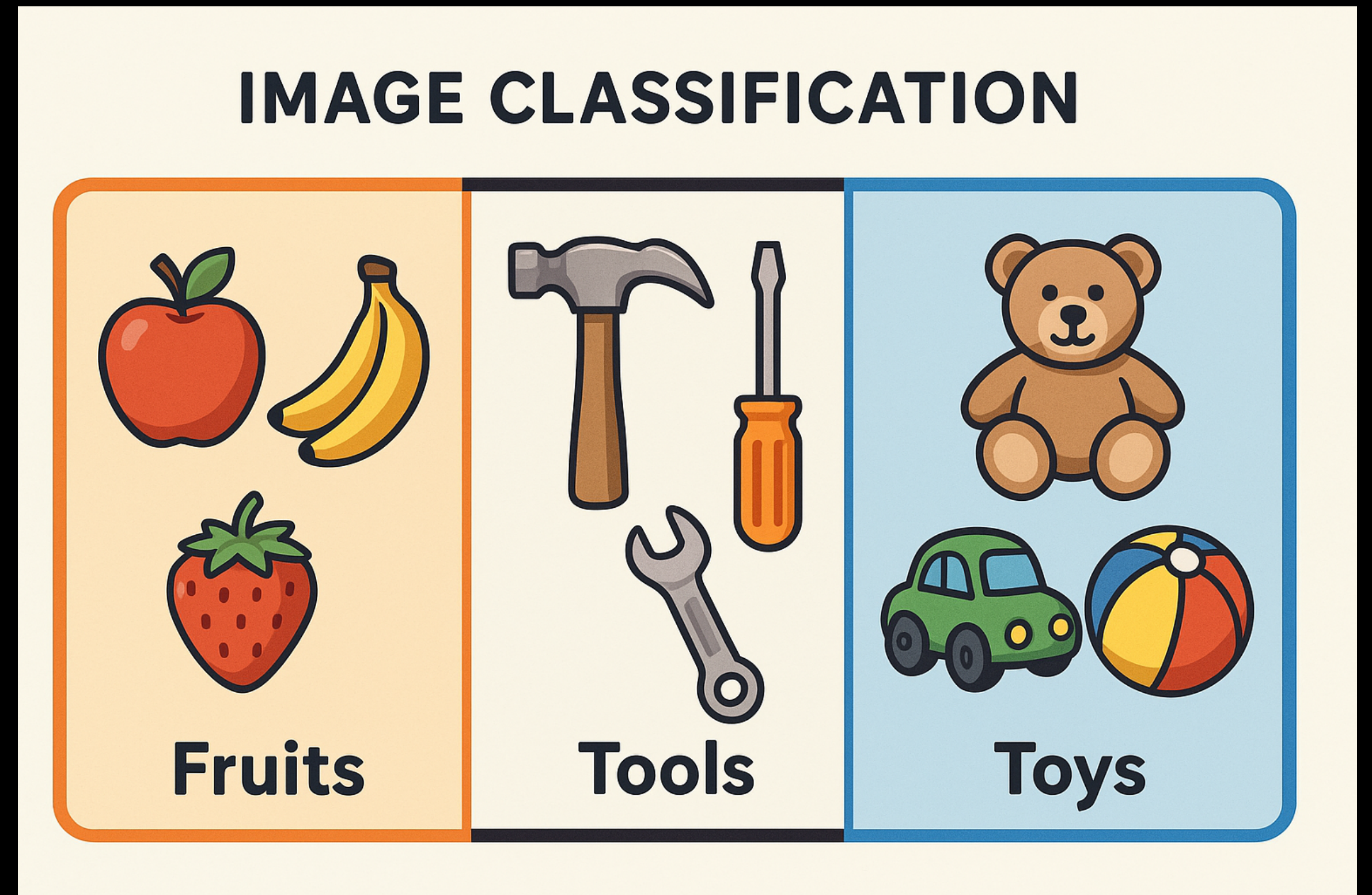




chatGPT's
proposal
1 year ago



chatGPT's
proposal
1 year ago



chatGPT's
proposal
today

Reflection symmetry



reflect



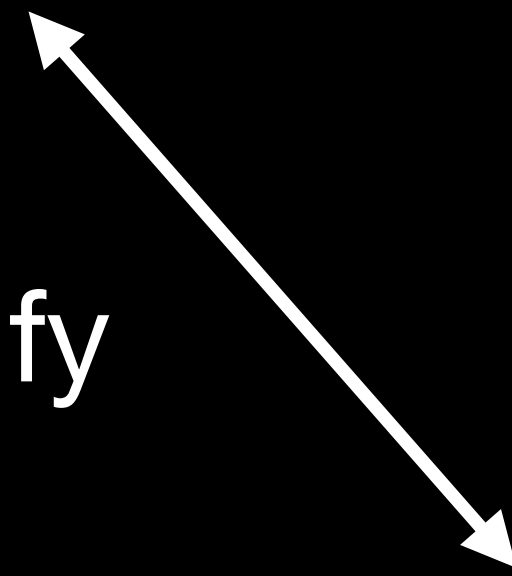
Reflection symmetry



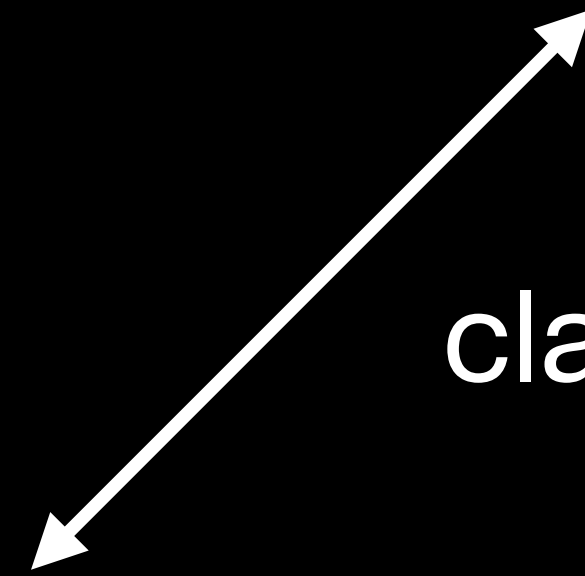
reflect



classify



classify



“boxing glove”

Reflection symmetry



reflect



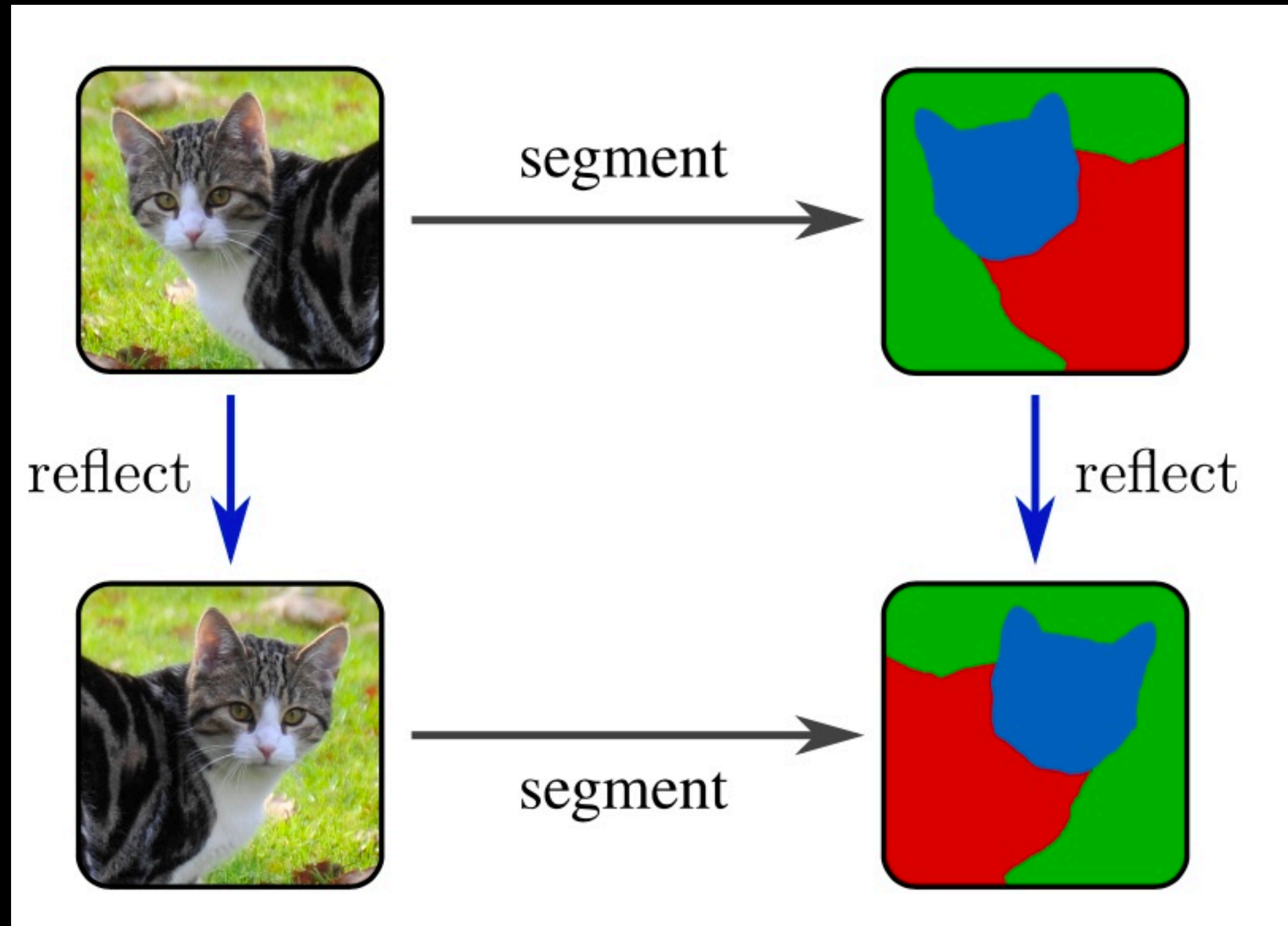
classify

classify

“boxing glove”

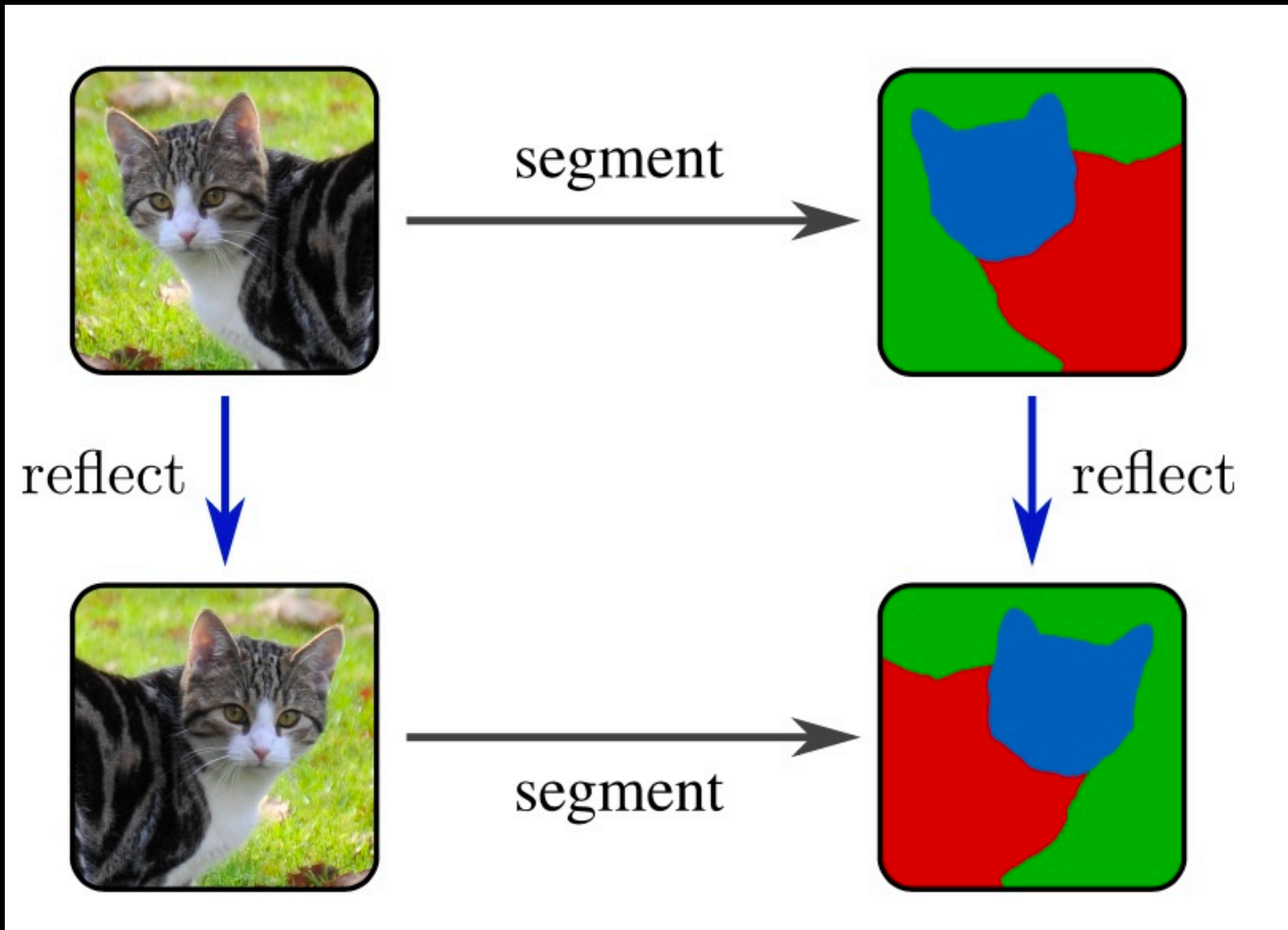
Invariance:
The output is *unchanged*
when we change the input

Segmentation



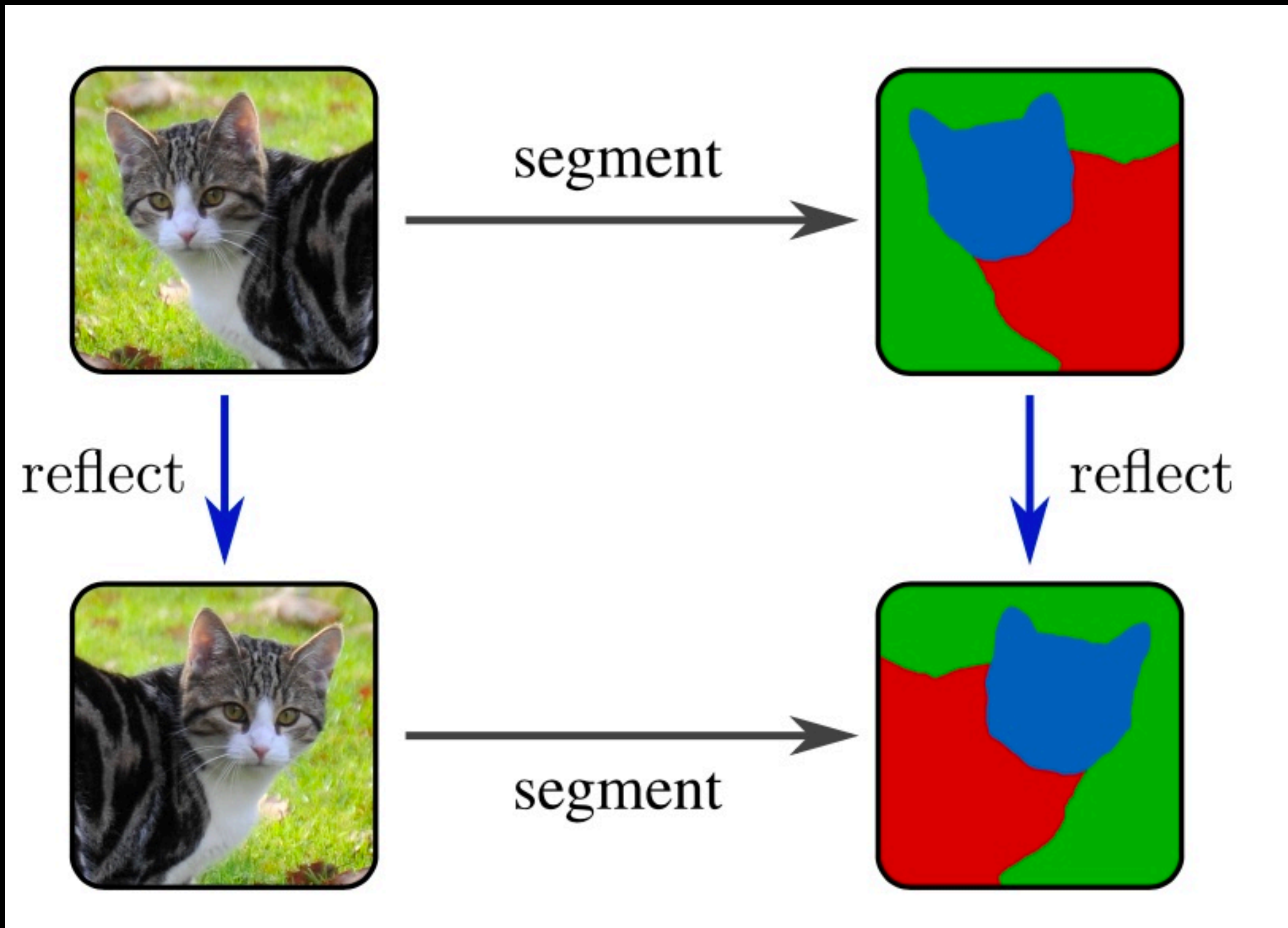
[Image from: Weiler, Forré, Verlinde, Welling (2023)]

Segmentation

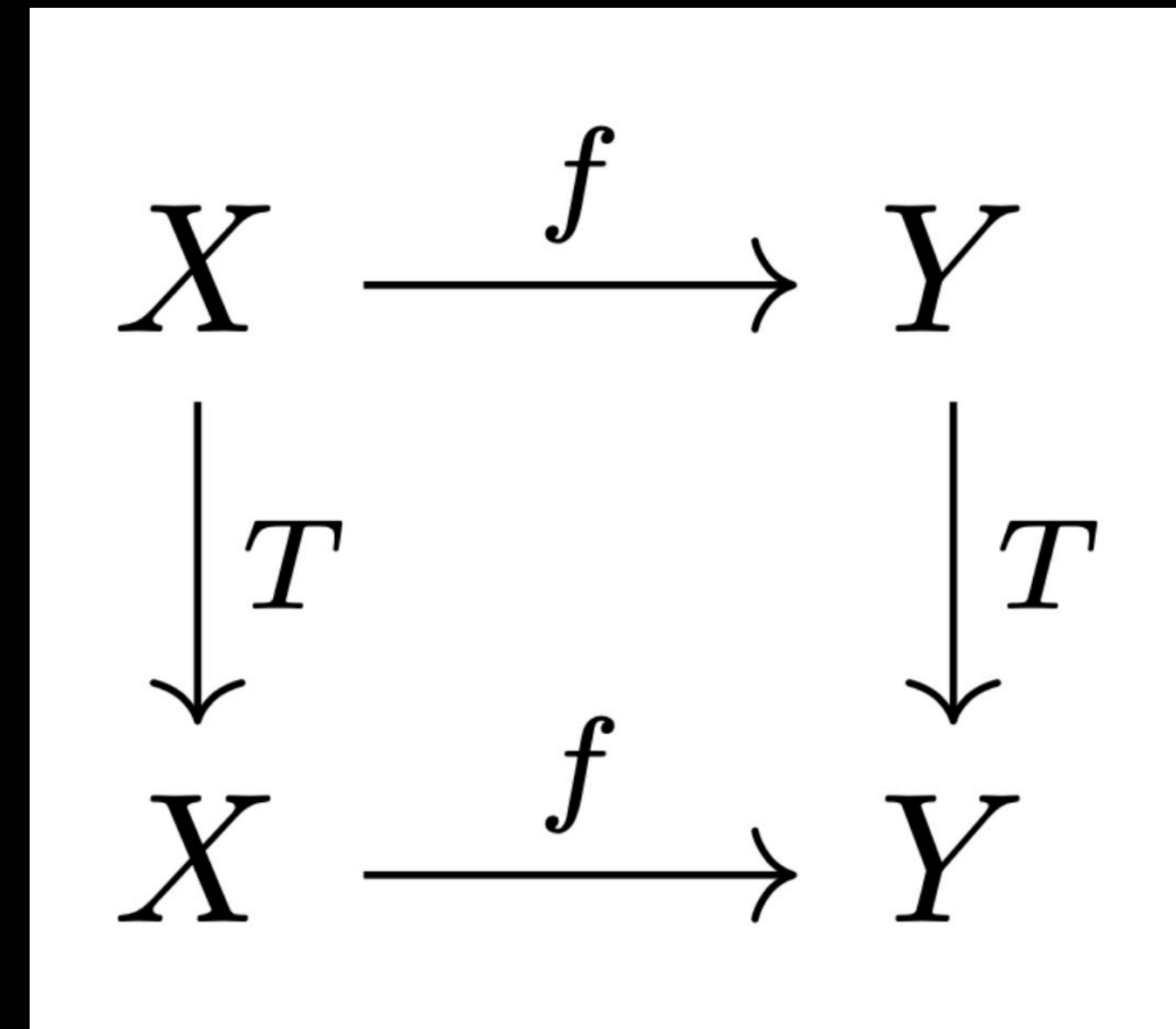


Equivariance:
The output *transforms*
according to the
transformation of the input

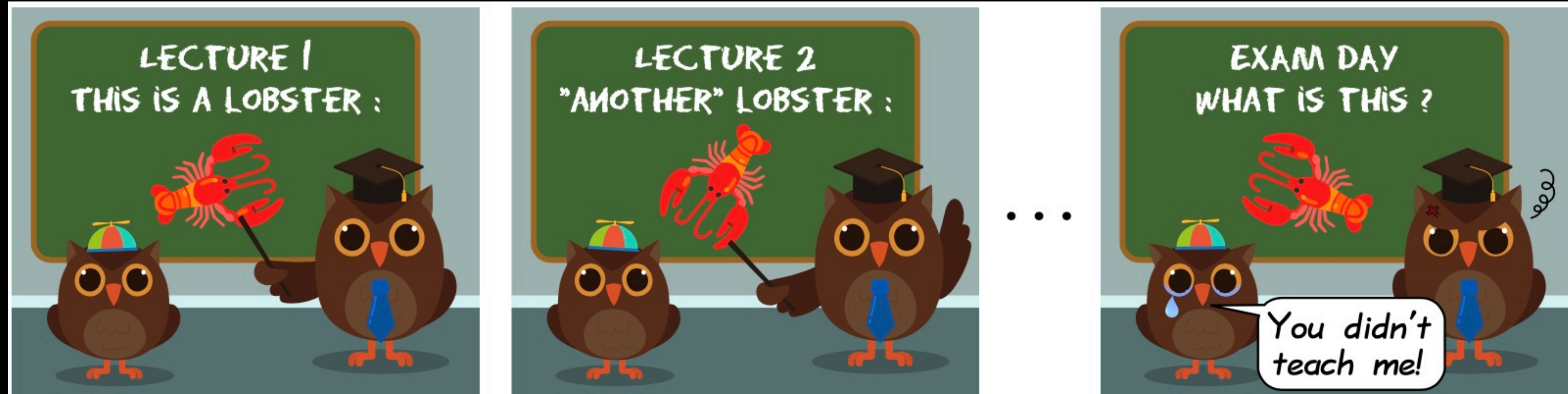
Segmentation

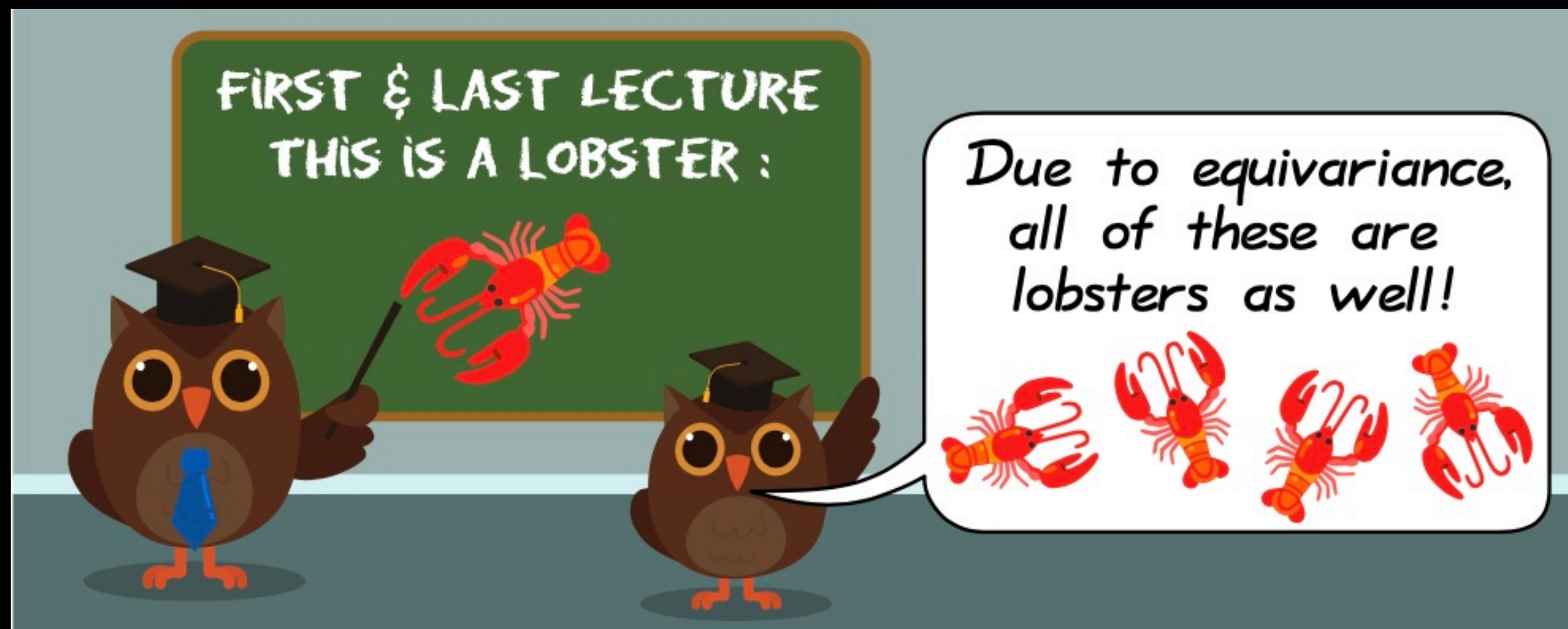
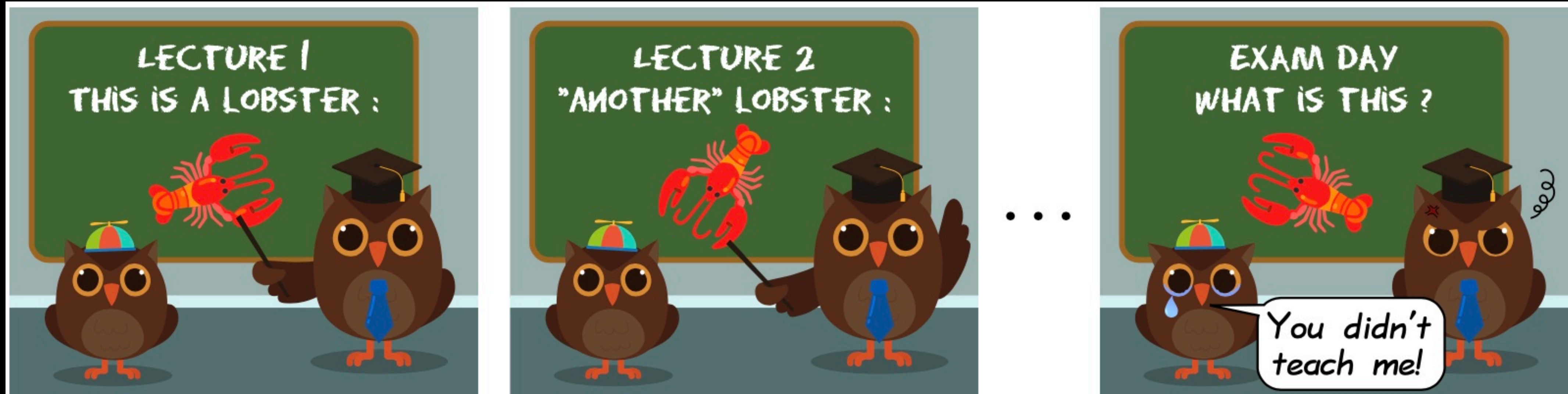


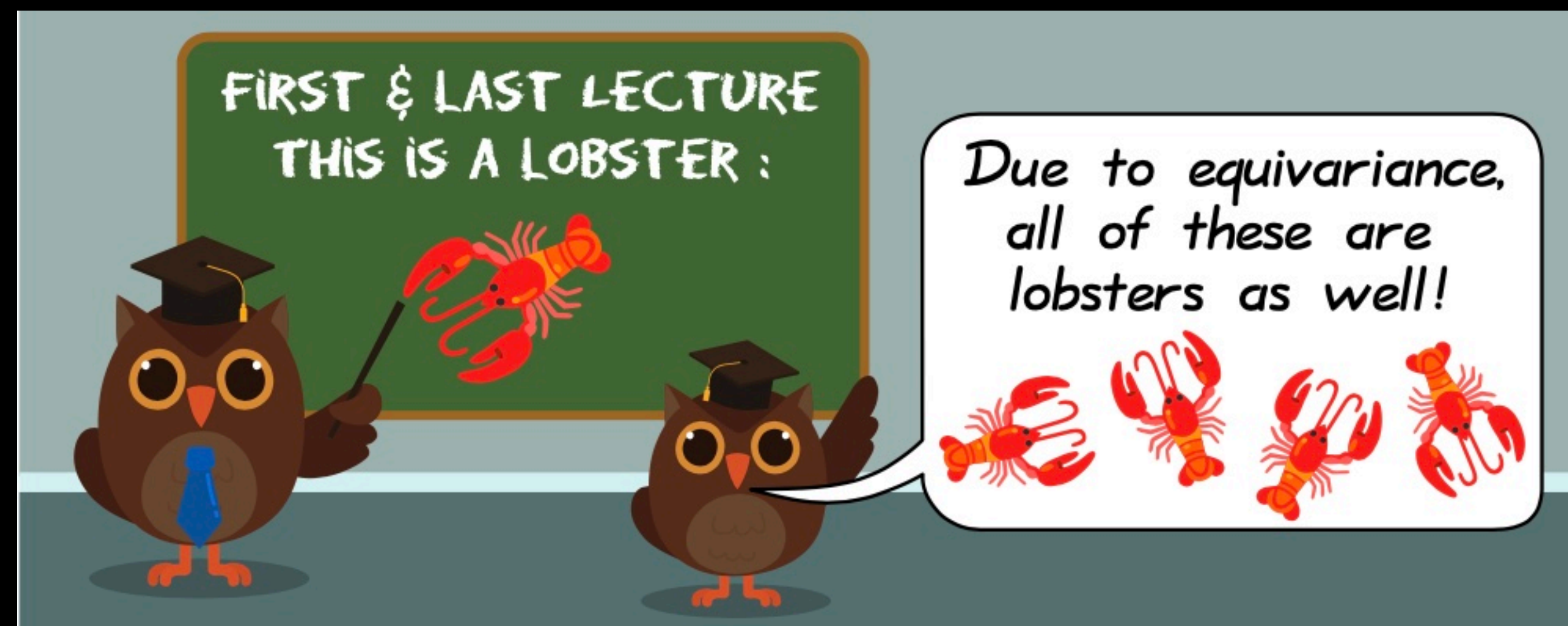
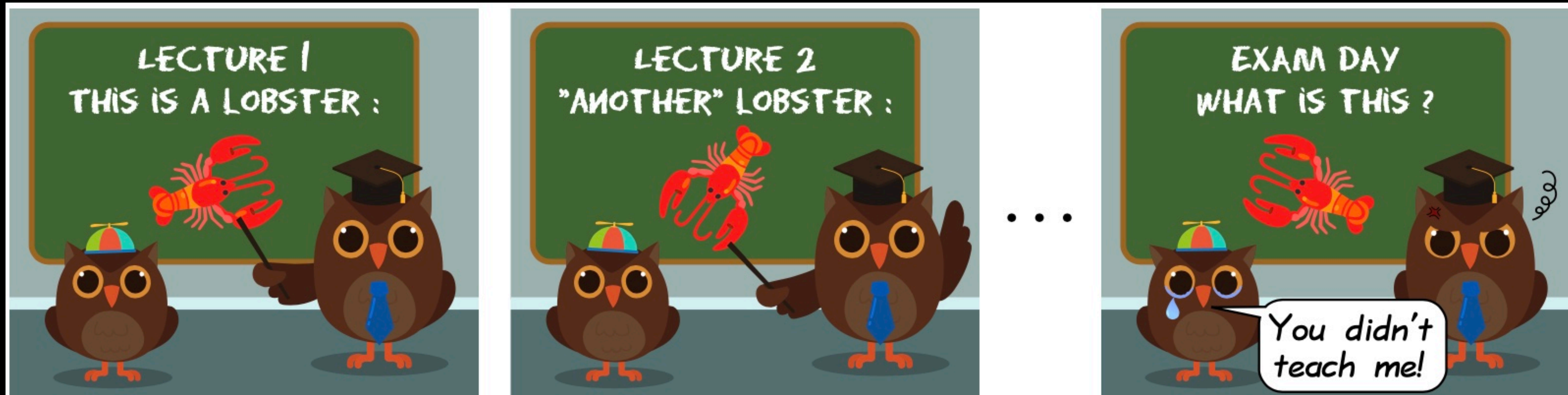
commutative
diagram



$$f(Tx) = Tf(x)$$





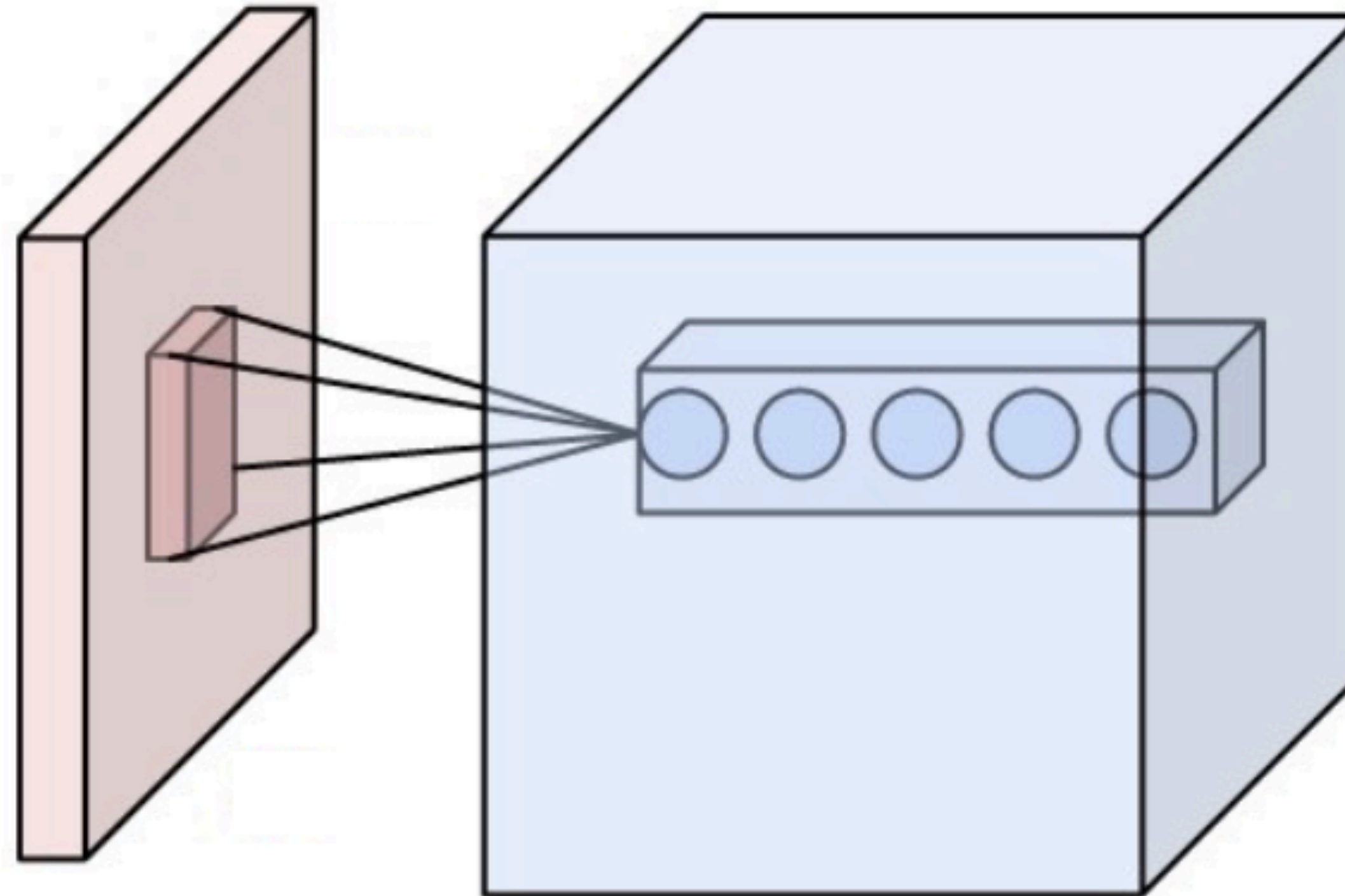


Design neural networks
that have **intrinsic symmetries**
(equivariance)

Convolutional Neural Networks

“Convolutional networks are simply neural networks that use convolution in place of general matrix multiplication in at least one of their layers.”

[Goodfellow, Bengio, Courville]



Mathematical structure

For each layer we have a **feature map**:

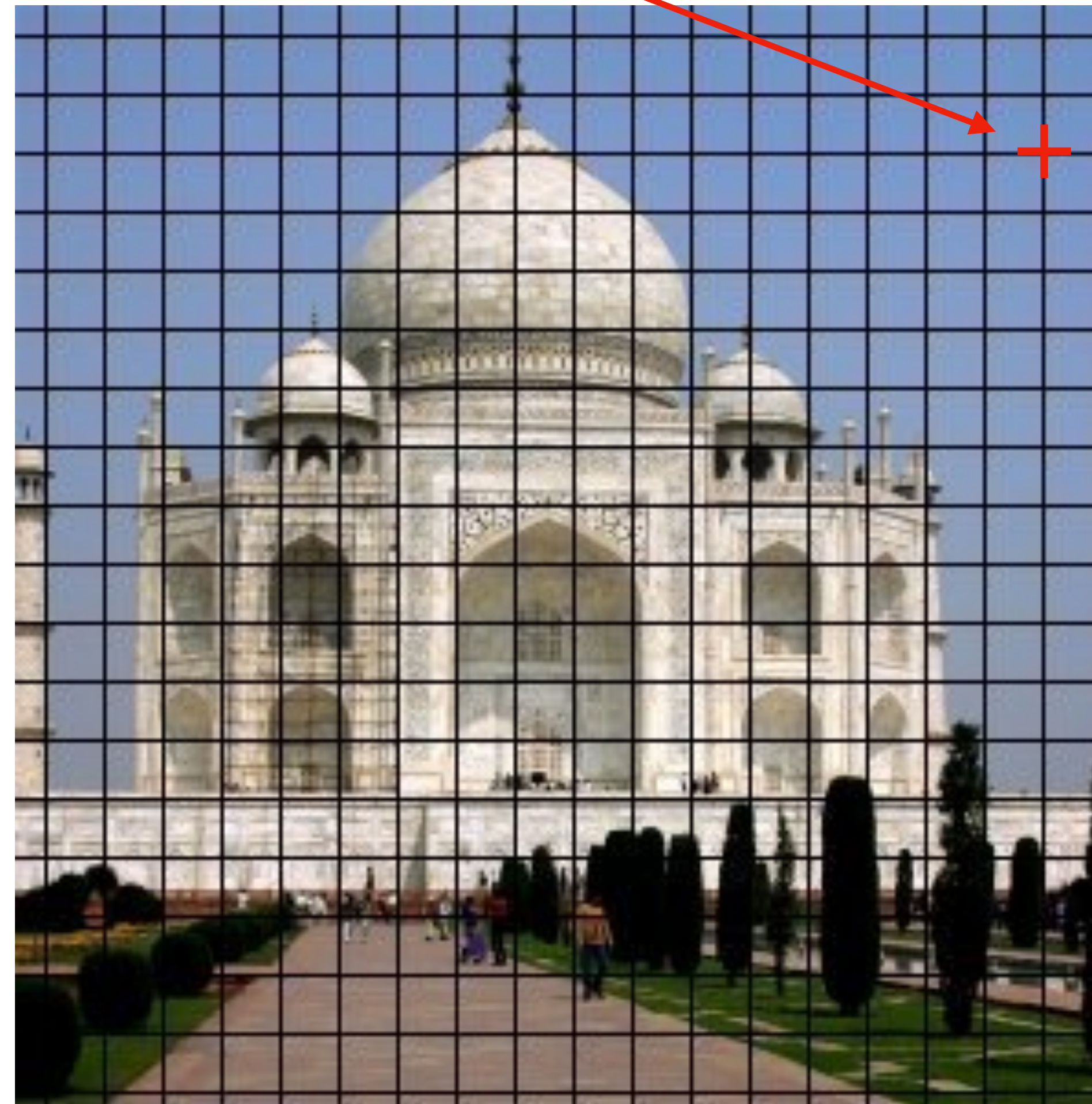
$$f : \mathbb{Z}^2 \rightarrow \mathbb{R}^K$$

Mathematical structure

For each layer we have a **feature map**:

no. of channels

$$f : \mathbb{Z}^2 \rightarrow \mathbb{R}^{\textcircled{K}}$$



(p, q)

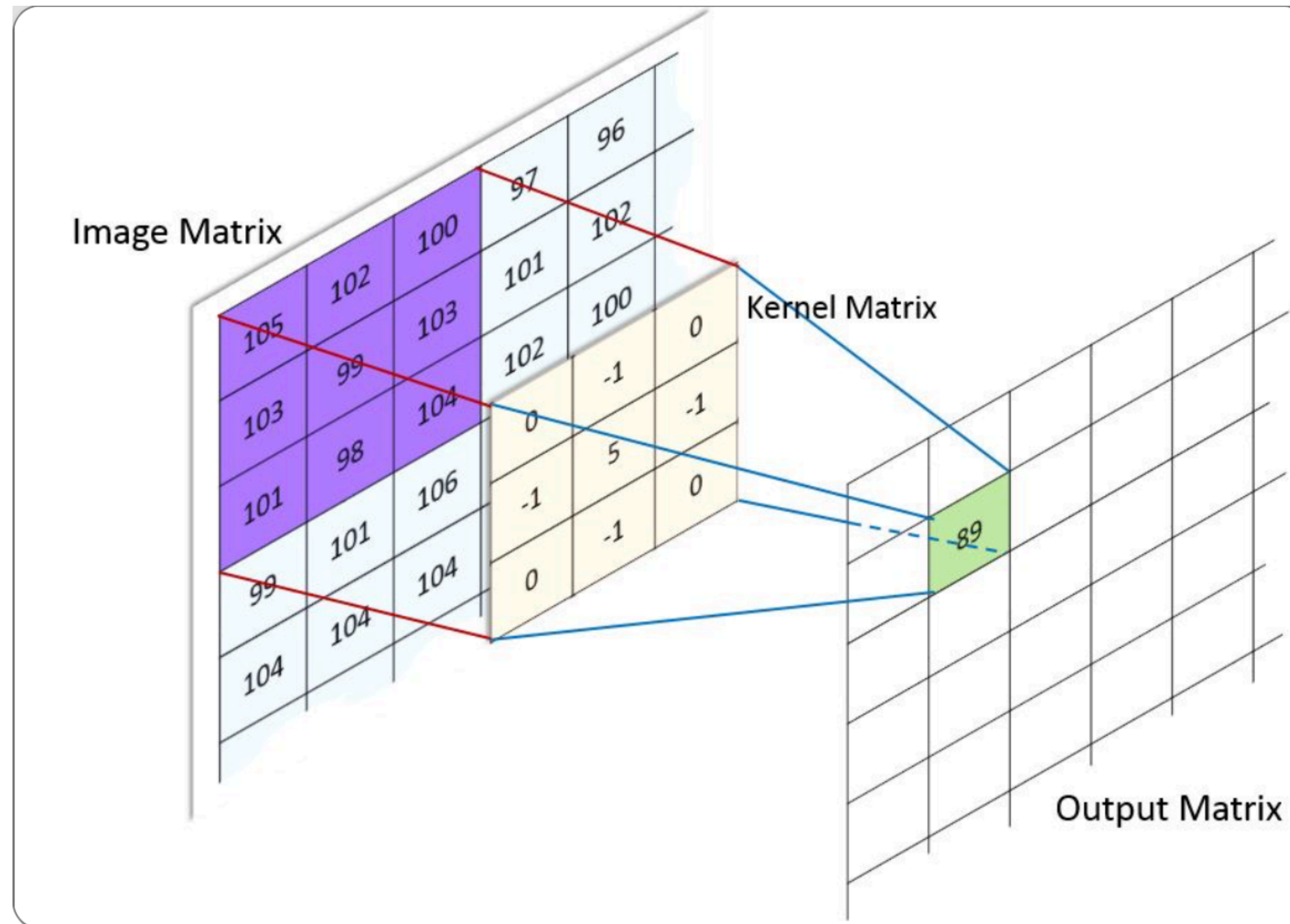
pixel coordinate

Kernel (filter): $\psi : \mathbb{Z}^2 \rightarrow \mathbb{R}^K$

Convolution: $[f * \psi](x) = \sum_{y \in \mathbb{Z}^2} \sum_{k=1}^K f_k(y) \psi_k(x - y)$

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[Figure from machinelearninguru.com]

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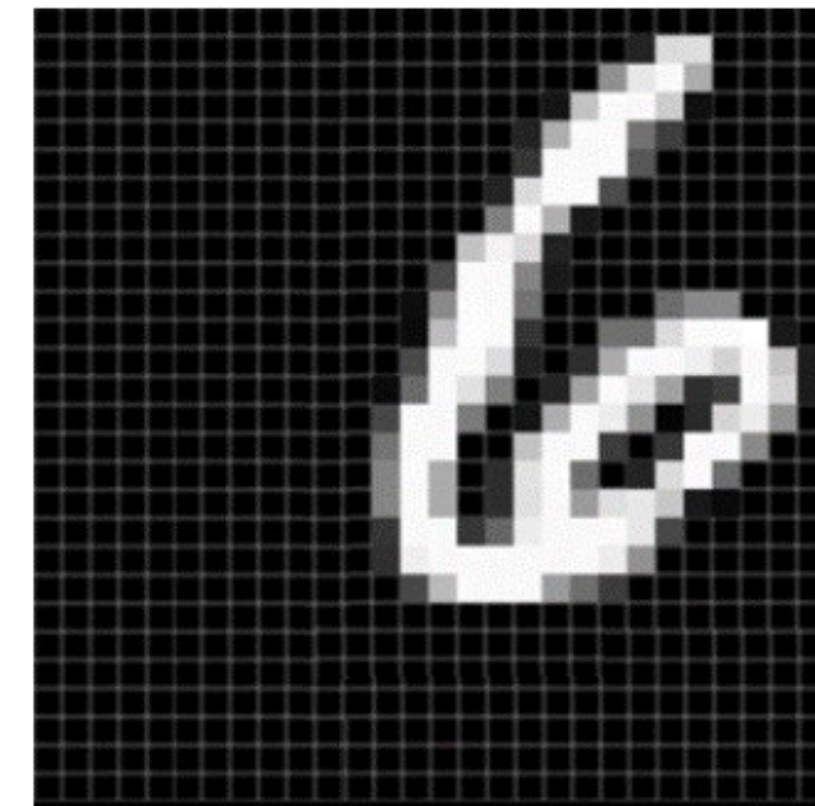
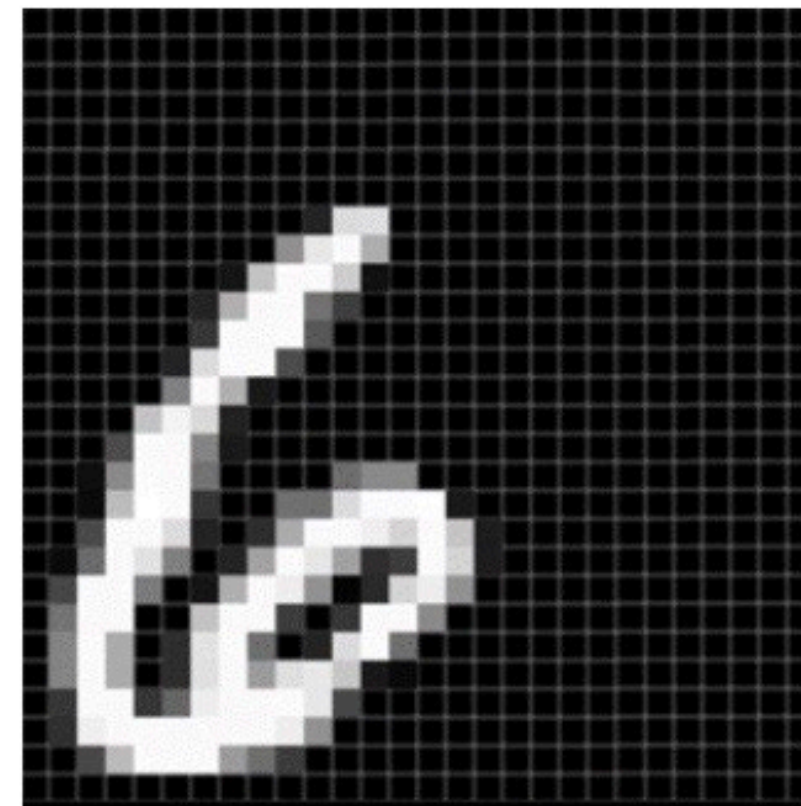
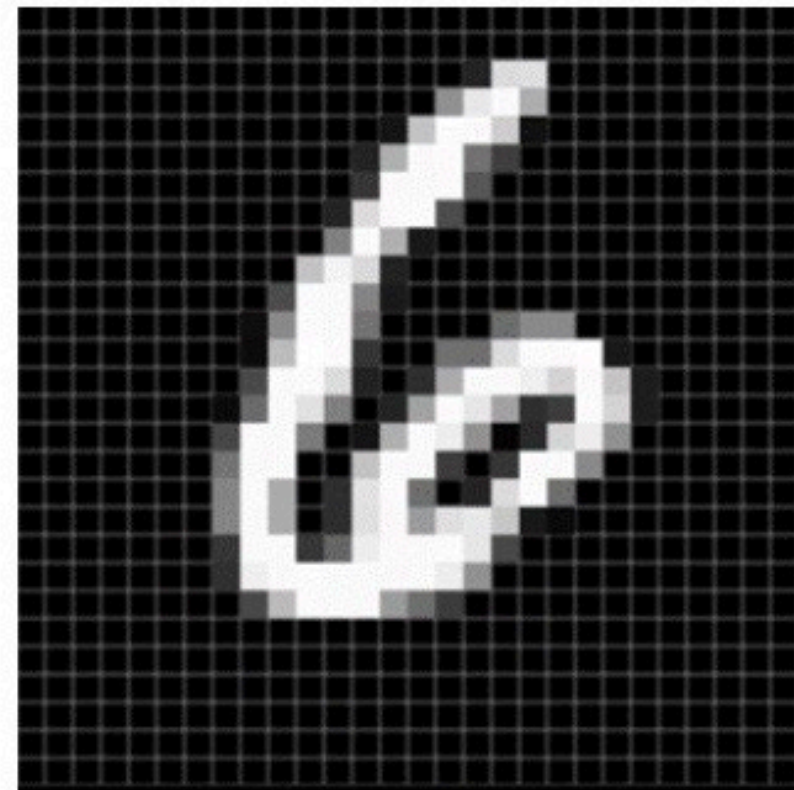
Translation map: $[T(t)f](x) = f(x + t)$

Convolution is equivariant w.r.t. translations

$$[T(t)f] * \psi = T(t)[f * \psi]$$

Convolution is **equivariant w.r.t. translations**

$$[T(t)f] * \psi = T(t)[f * \psi]$$



But what about more general symmetries?

Locally, we can think of feature maps as functions $f : G/H \rightarrow V$

Example: $G = \mathbb{Z}^2$ $H = \{1\}$ $V = \mathbb{R}^K$

Feature maps are sections! $f : \mathbb{Z}^2 \rightarrow \mathbb{R}^K$

Locally, we can think of feature maps as functions $f : G/H \rightarrow V$

Example: $G = \mathbb{Z}^2$ $H = \{1\}$ $V = \mathbb{R}^K$

Feature maps are sections! $f : \mathbb{Z}^2 \rightarrow \mathbb{R}^K$

This is a **vector bundle**:

$$\begin{array}{ccc} V & \longrightarrow & P \\ & & \downarrow p \\ & & G/H \end{array}$$

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Example: $G = \mathbb{Z}^2$ $H = \{1\}$ $V = \mathbb{R}^K$

Feature maps are sections! $f : \mathbb{Z}^2 \rightarrow \mathbb{R}^K$

General structure of group equivariant CNNs:

$$\left\{ \begin{array}{l} \text{Feature space of a} \\ G - \text{equivariant CNN} \end{array} \right\} \cong \left\{ \begin{array}{l} \text{Sections of vector} \\ \text{bundles } P \rightarrow G/H \end{array} \right\}$$

Layers defined with group-equivariant convolutions:

$$[f * \psi](g) = \int_G \sum_{k=1}^K f_k(h) \psi_k(gh) dh$$

$$\left\{ \begin{array}{l} \text{Feature space of a} \\ G\text{-equivariant CNN} \end{array} \right\} \cong \left\{ \begin{array}{l} \text{Sections of vector} \\ \text{bundles } P \rightarrow G/H \end{array} \right\}$$

Sections of $P \rightarrow G/H$ belong to the **induced representation**:

$$\mathcal{F} = \text{Ind}_H^G \rho = \{f : G \rightarrow V \mid f(gh) = \rho(h^{-1})f(g)\}$$

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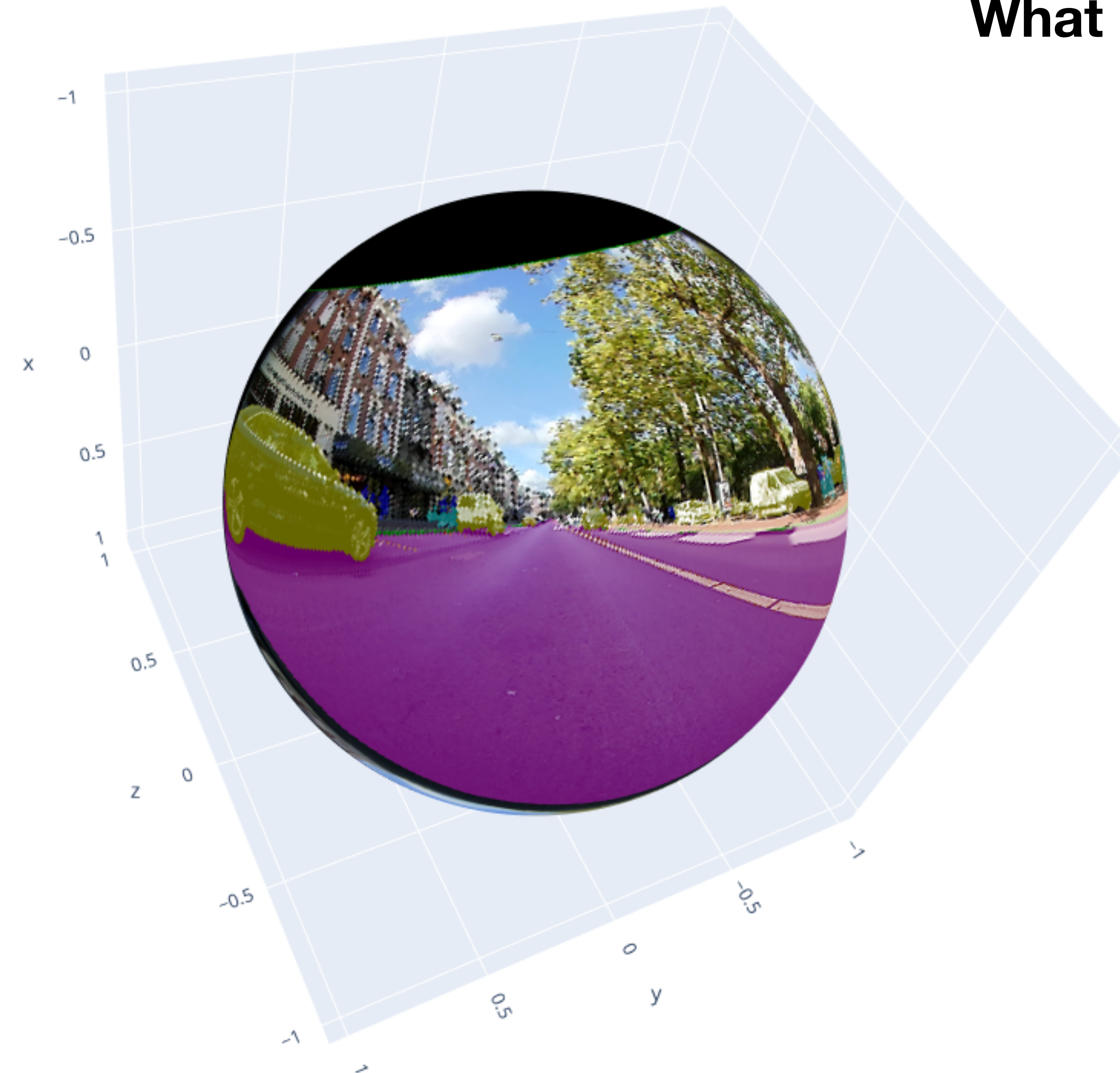
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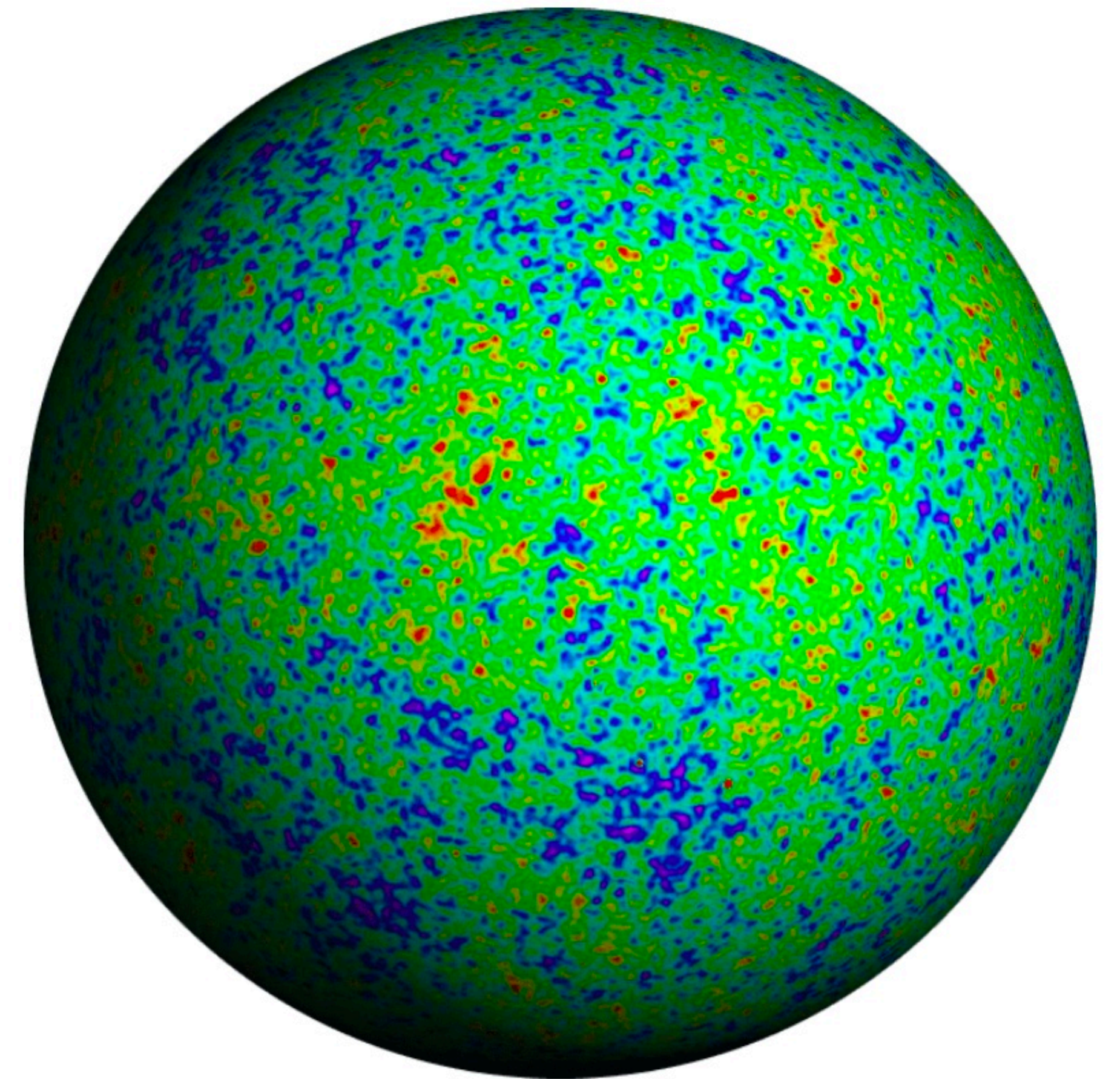
$$\text{Hom}_G(\mathcal{F}, \mathcal{F}')$$

(intertwining operators)

What if the input data is curved?



[Image from the Woodscape dataset, projected onto a sphere]



Cosmic microwave background radiation

Example: Spherical signals

By Gerken, Carlsson, Linander, Ohlsson, Petersson, **D.P.**

[ICML 2022, arXiv: 2202.03990]

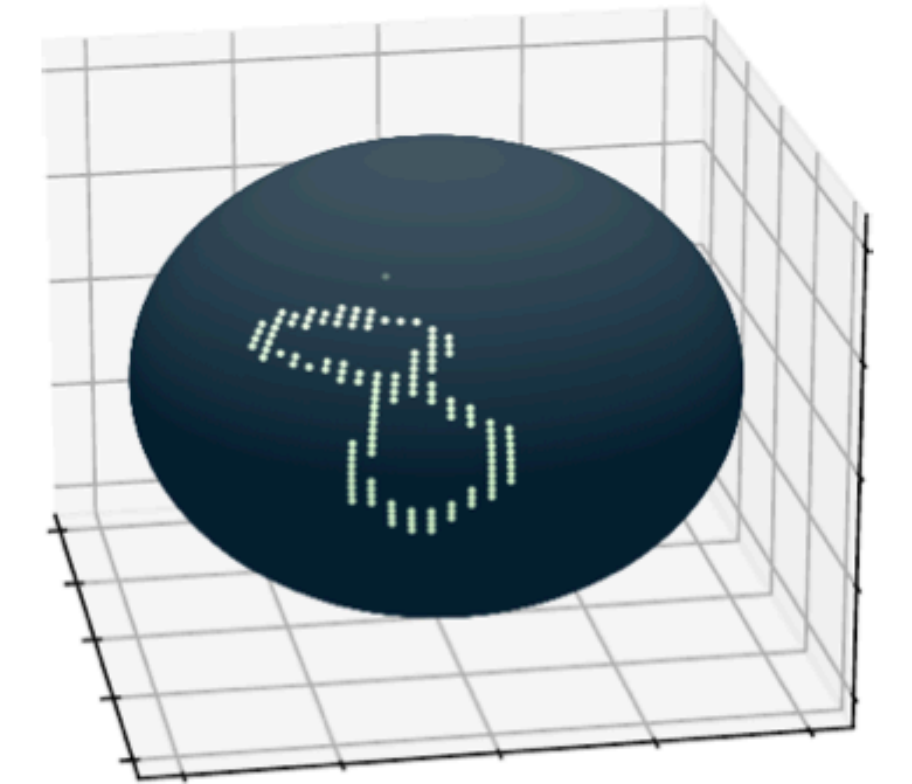
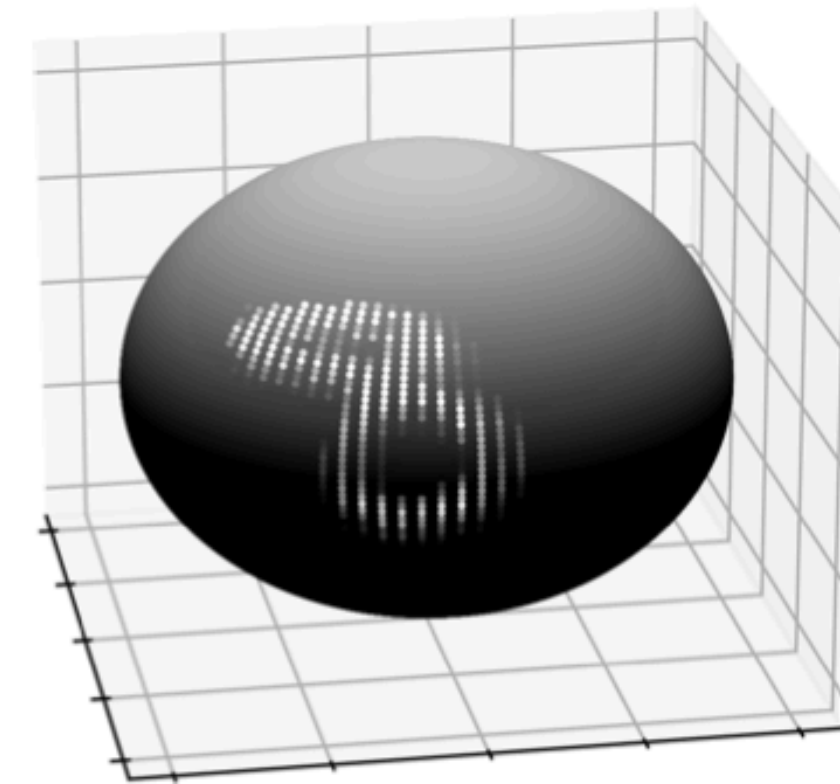
$$G = SO(3)$$

$$H = SO(2)$$

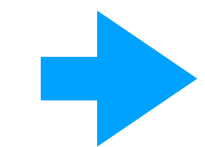
$$G/H \cong S^2$$

Feature maps

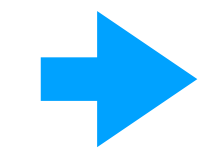
$$f : S^2 \rightarrow \mathbb{R}^K$$



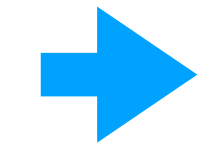
Relevant for :



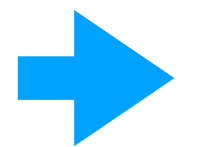
Omnidirectional vision



Weather and climate data



Cosmology & astrophysics



Medical imaging

$$(\kappa \star f)(R) = \int_{S^2} \kappa(R^{-1}x) f(x) dx$$

$$(\kappa \star f)(R) = \int_{SO(3)} \kappa(S^{-1}R) f(S) dS$$

HEAL-SWIN: A Vision Transformer On The Sphere

Oscar Carlsson^{*ab} Jan E. Gerken^{*a} Hampus Linander^a Heiner Spieß^c Fredrik Ohlsson^d

Christoffer Petersson^{ea}

Daniel Persson^a

Abstract

High-resolution wide-angle fisheye images are becoming more and more important for robotics applications such as autonomous driving. However, using ordinary convolutional neural networks or vision transformers on this data is problematic due to projection and distortion losses introduced when projecting to a rectangular grid on the plane. We introduce the HEAL-SWIN transformer, which combines the highly uniform Hierarchical Equal Area iso-Latitude Pixelation (HEALPix) grid used in astrophysics and cosmology with the Hierarchical Shifted-Window (SWIN) transformer to yield an efficient and flexible model capable of training on high-resolution, distortion-free spherical data. In HEAL-SWIN, the nested structure of the HEALPix grid is used to perform the patching and windowing operations of the SWIN transformer, enabling the network to process spherical representations with minimal computational overhead. We demonstrate the superior performance of our model on both synthetic and real automotive datasets, as well as a selection of other image datasets, for semantic segmentation, depth regression and classification tasks. Our code is publicly available¹.

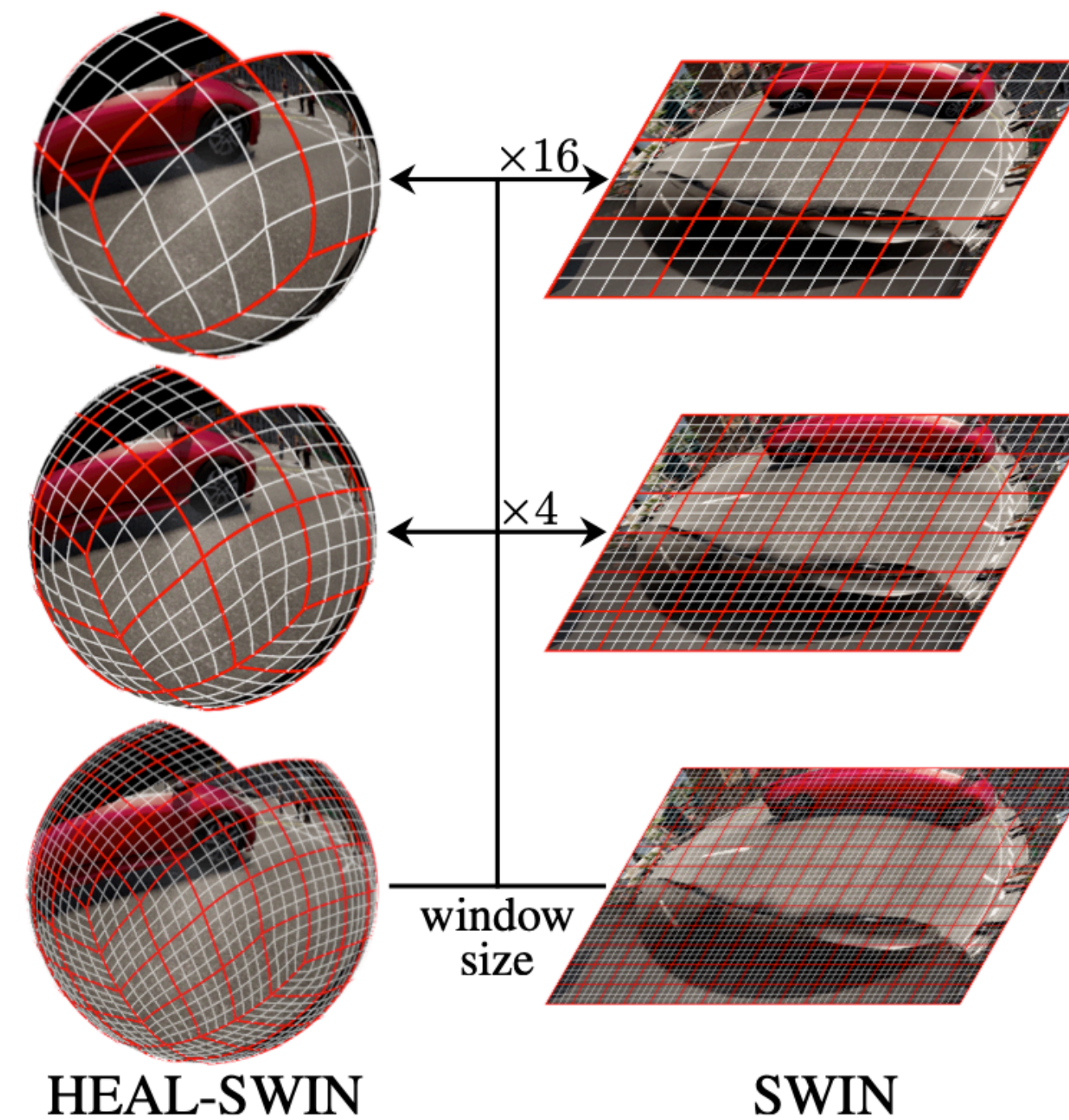


Figure 1. Our HEAL-SWIN model uses the nested structure of the HEALPix grid to lift the windowed self-attention of the SWIN model onto the sphere.

PEAR: Equal Area Weather Forecasting on the Sphere

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Abstract

Machine learning methods for global medium-range weather forecasting have recently received immense attention. Following the publication of the Pangu Weather model, the first deep learning model to outperform traditional numerical simulations of the atmosphere, numerous models have been published in this domain, building on Pangu’s success. However, all of these models operate on input data and produce predictions on the Driscoll–Healy discretization of the sphere which suffers from a much finer grid at the poles than around the equator. In contrast, in the Hierarchical Equal Area iso-Latitude Pixelization (HEALPix) of the sphere, each pixel covers the same surface area, removing unphysical biases. Motivated by a growing support for this grid in meteorology and climate sciences, we propose to perform weather forecasting with deep learning models which natively operate on the HEALPix grid. To this end, we introduce Pangu Equal Area (PEAR), a transformer-based weather forecasting model which operates directly on HEALPix-features and outperforms the corresponding model on Driscoll–Healy without any computational overhead. *Code will be made available.*

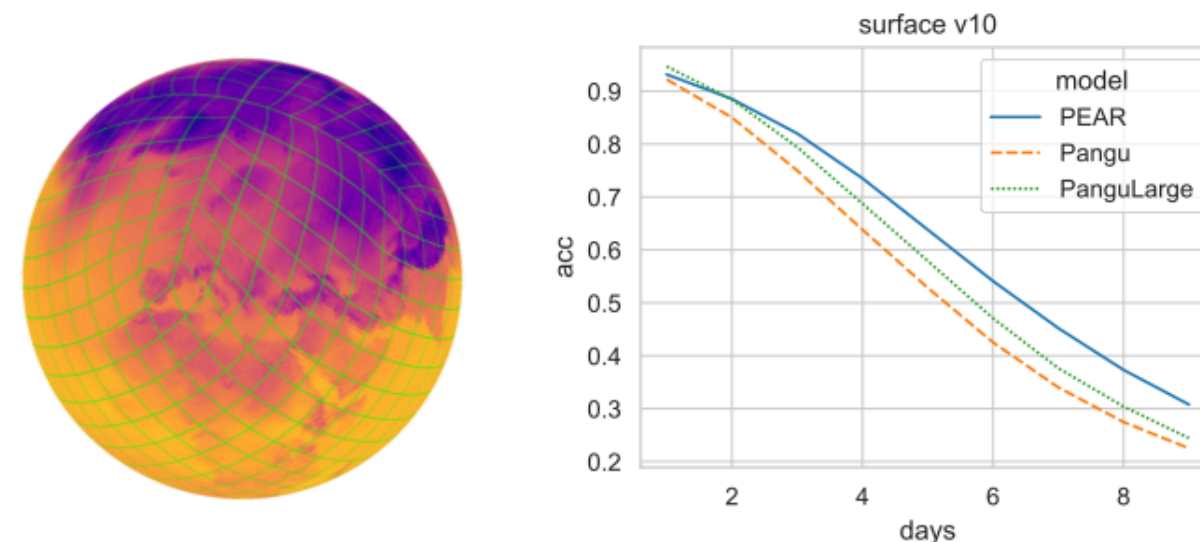
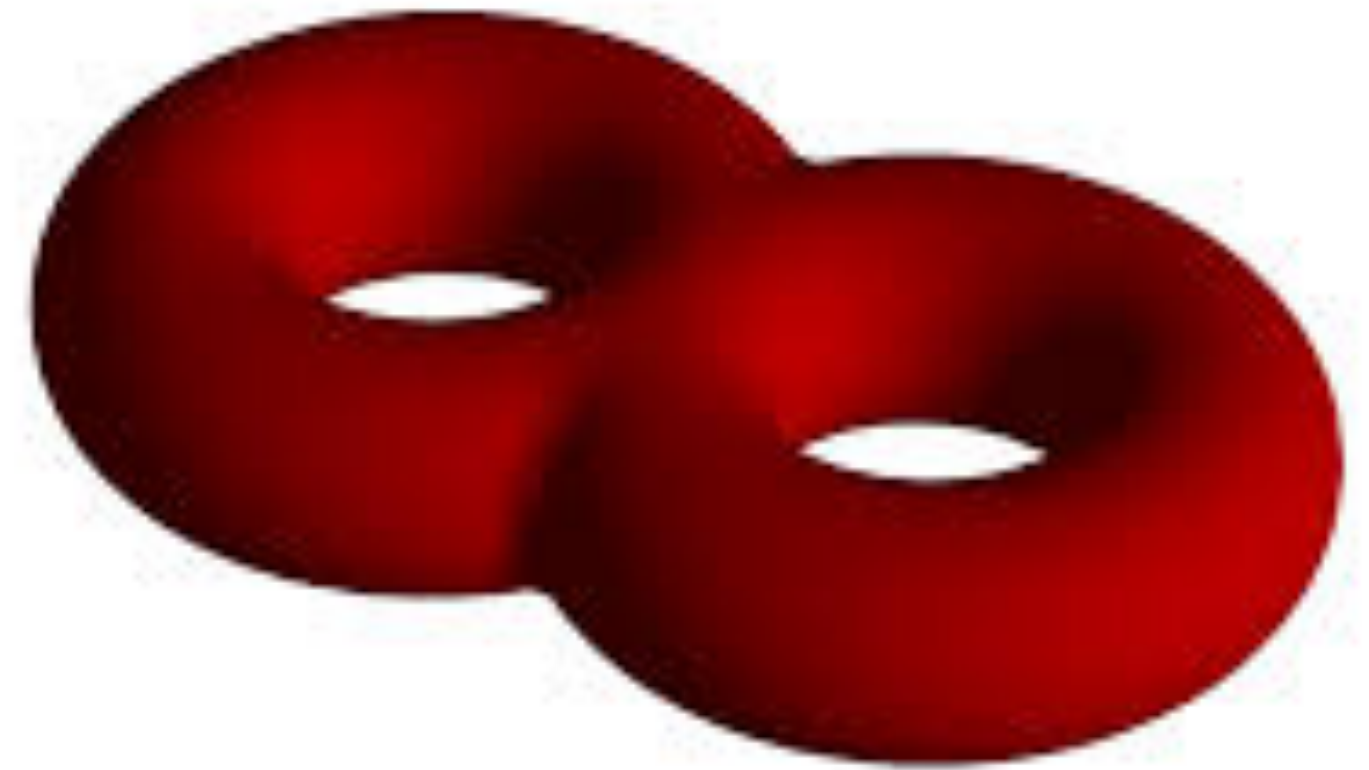
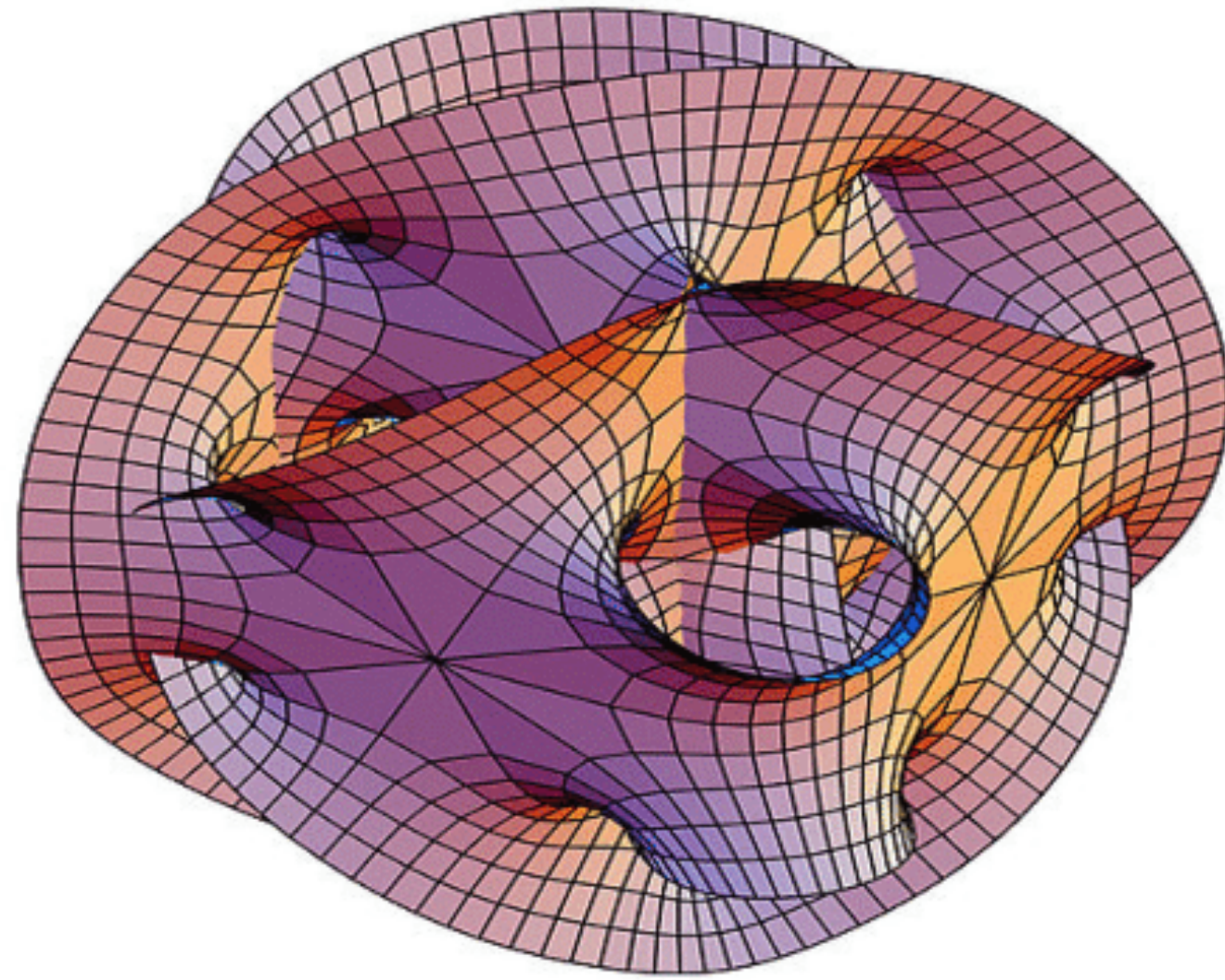
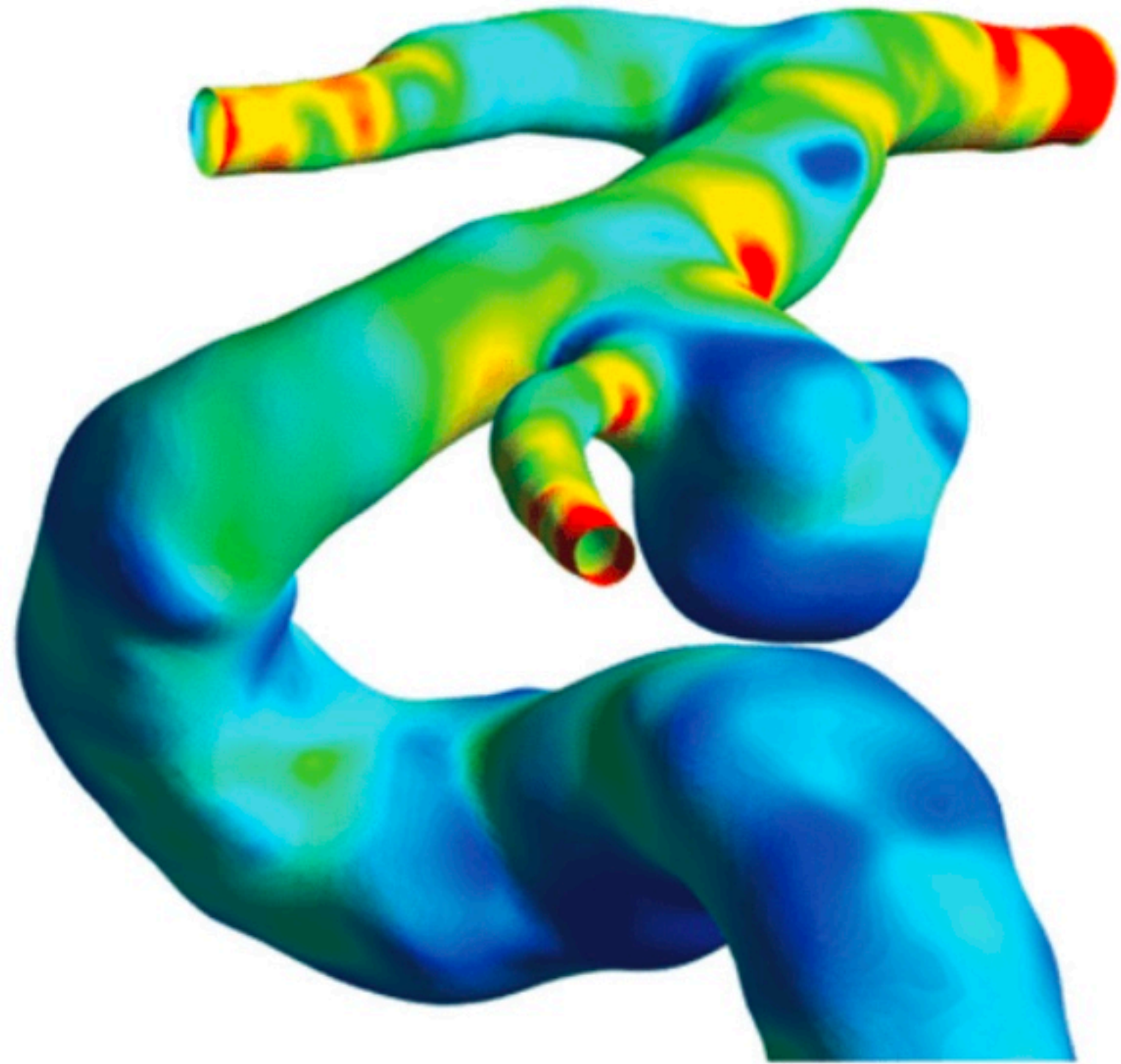
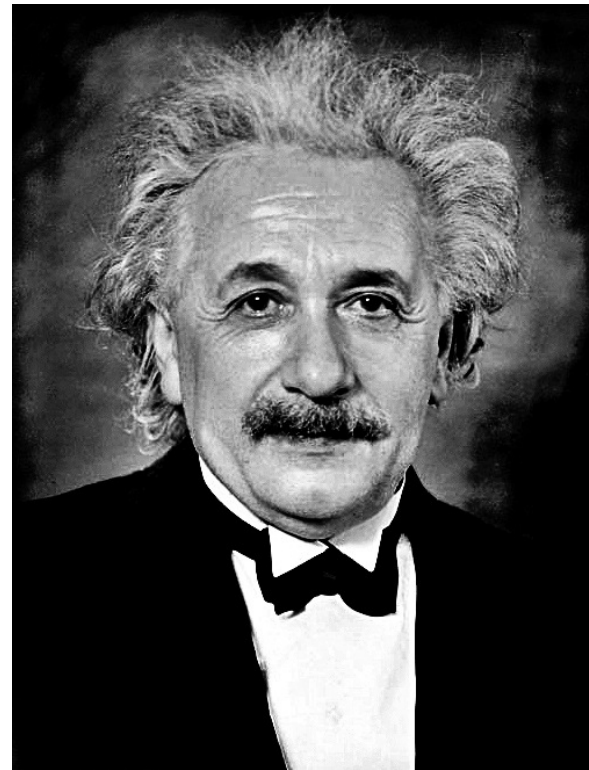
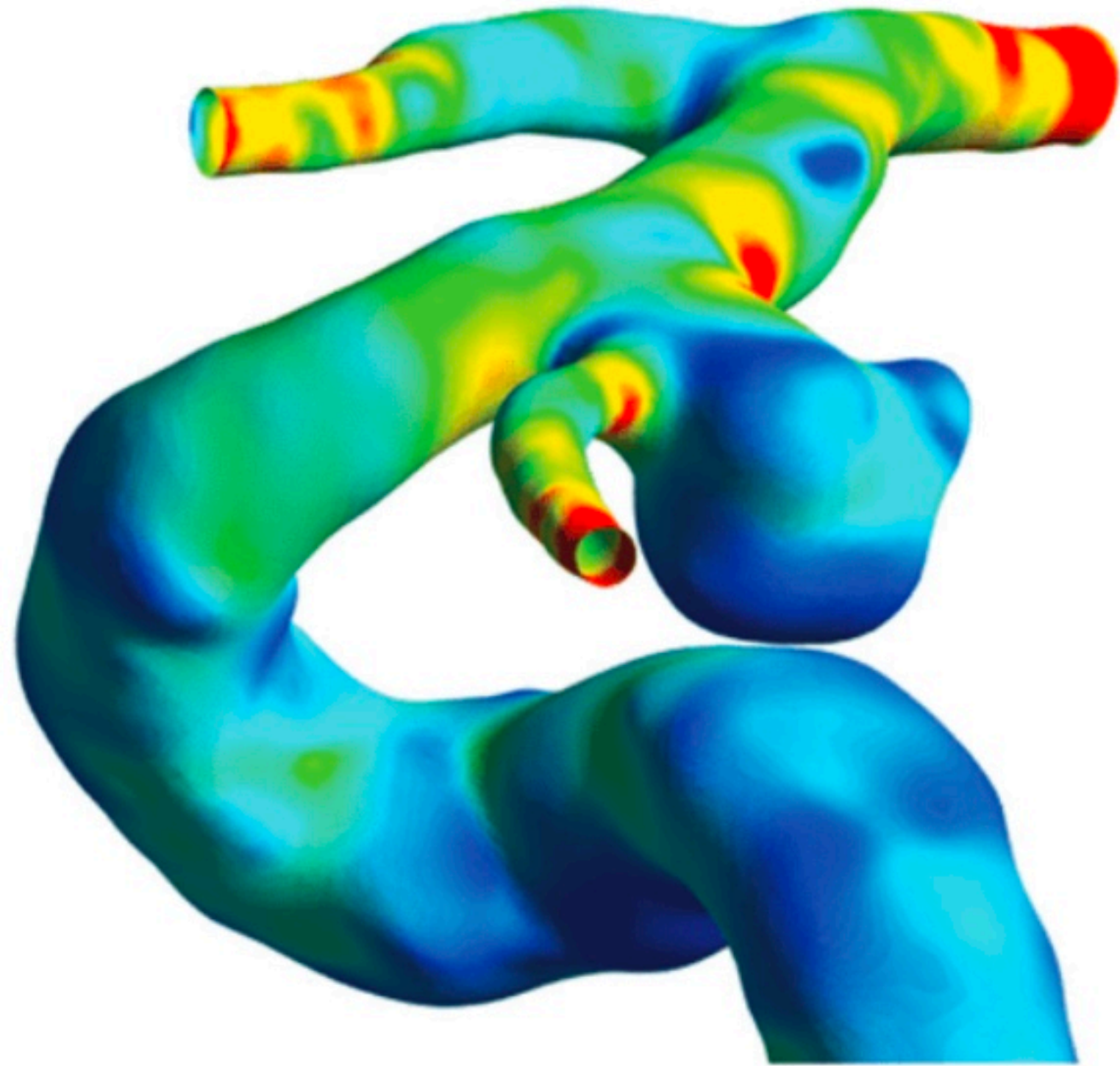
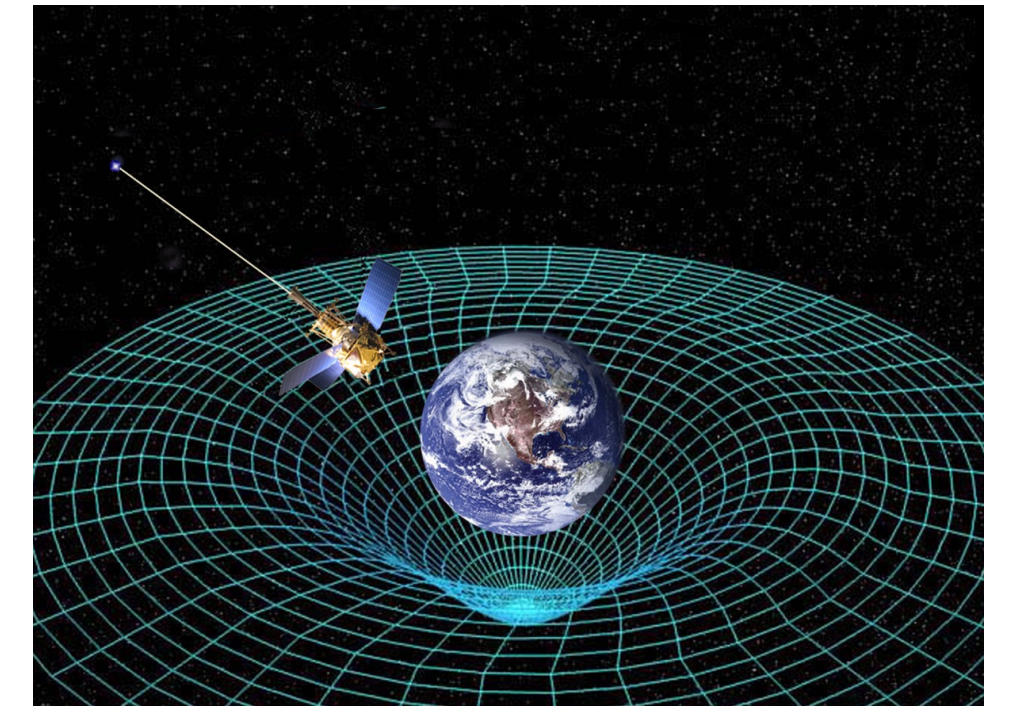


Figure 1: Left: Predicted surface level temperature from PEAR. Green lines show the HEALPix cell boundaries at 3 levels of course-graining above the model resolution. Right: Anomaly correlation coefficient (ACC) (higher is better) for surface level northward wind component with forecast horizon up to 10 days. PEAR outperforms the almost 8 times larger PanguLarge at longer forecast horizons.

Geometric deep learning: Deep learning on manifolds



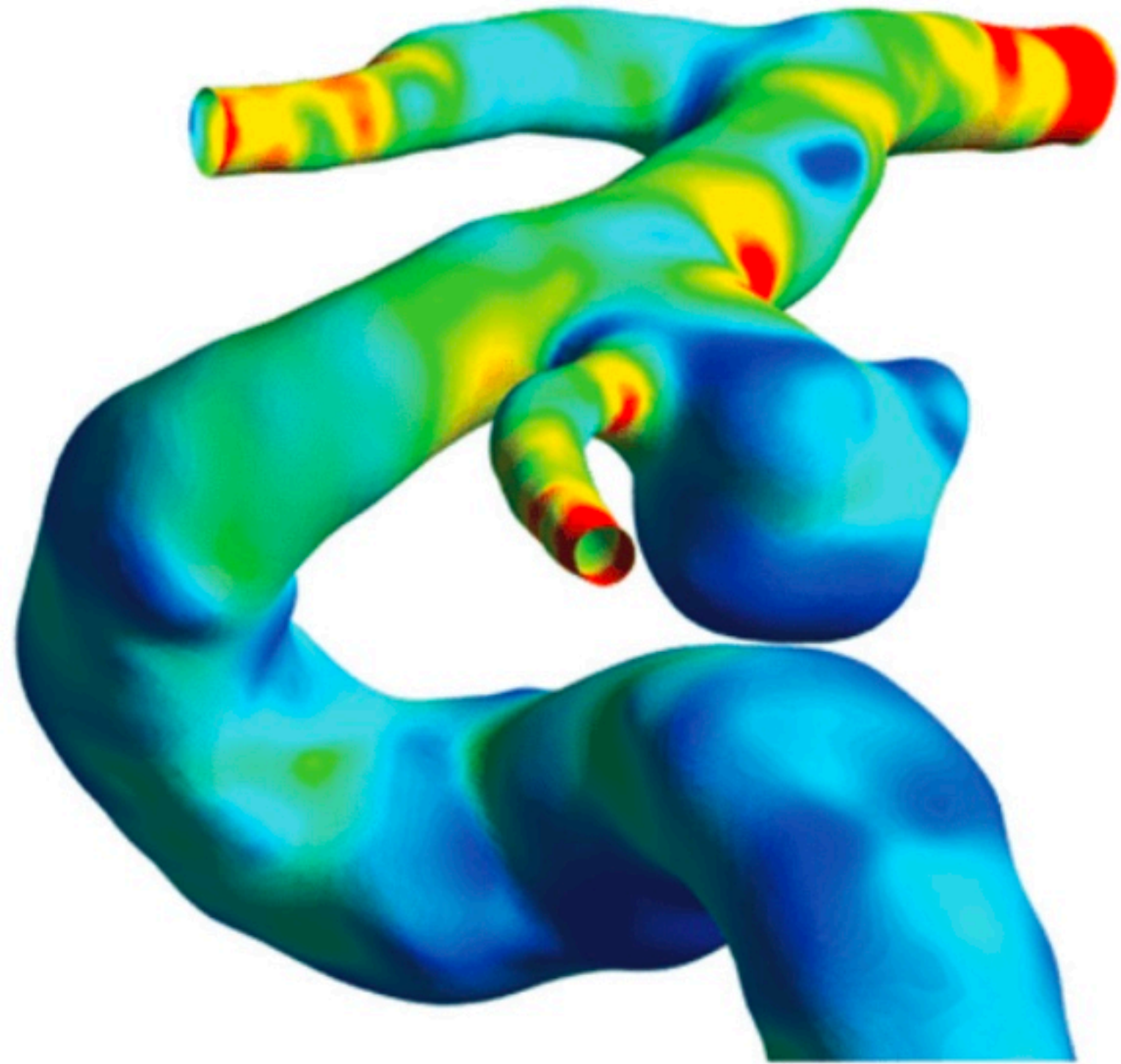
Geometric deep learning



Recall Einstein's

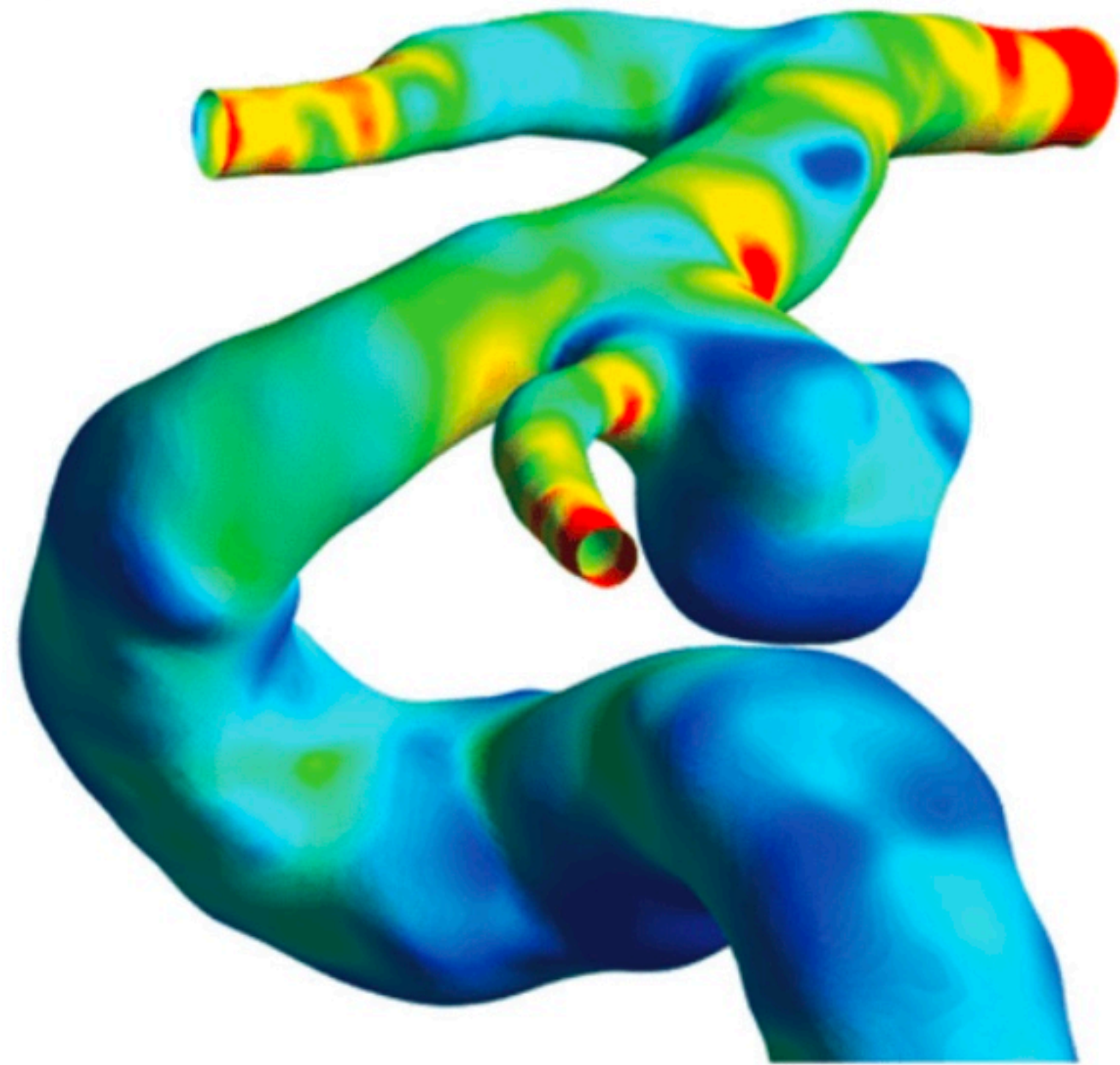
Principle of general covariance:
The laws of physics should take the same form independently of which coordinate system we use to represent them

Geometric deep learning - A unified framework for deep learning

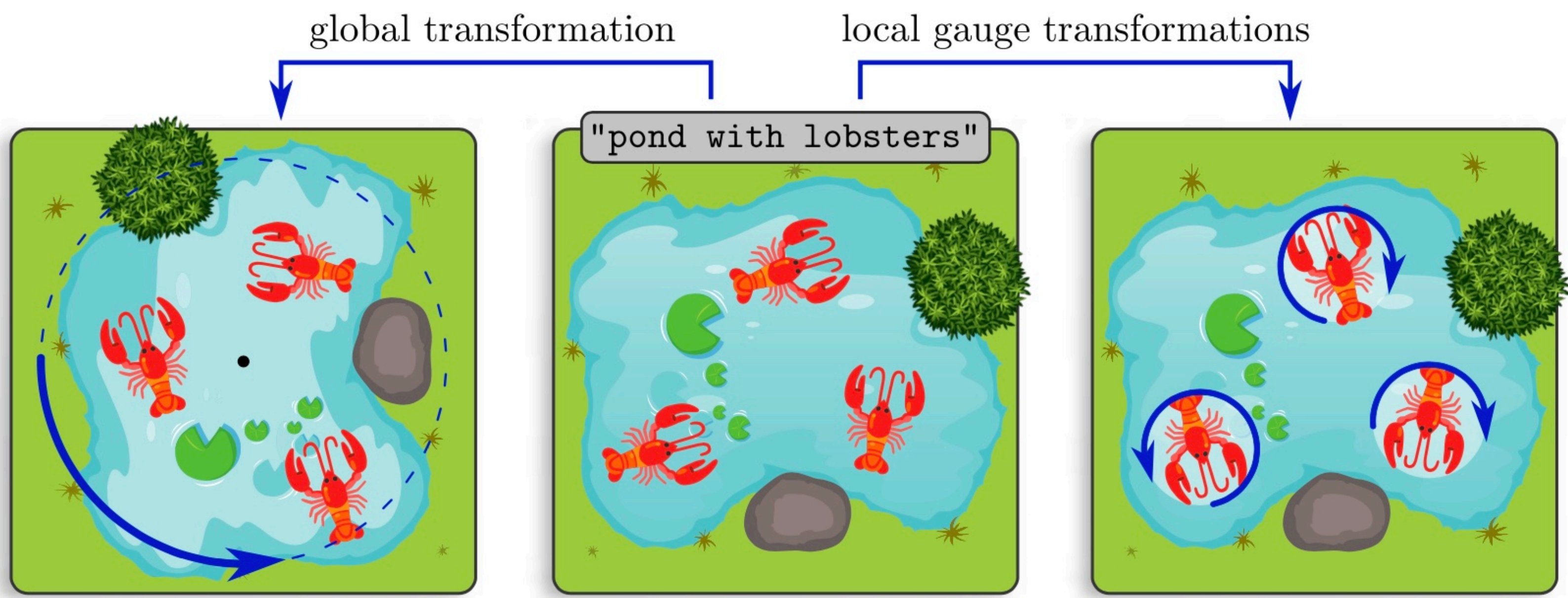


Principle of geometric deep learning:
The equations governing neural networks should be equivariant with respect to all **local** and **global** symmetries of the input data

Geometric deep learning - A unified framework for deep learning

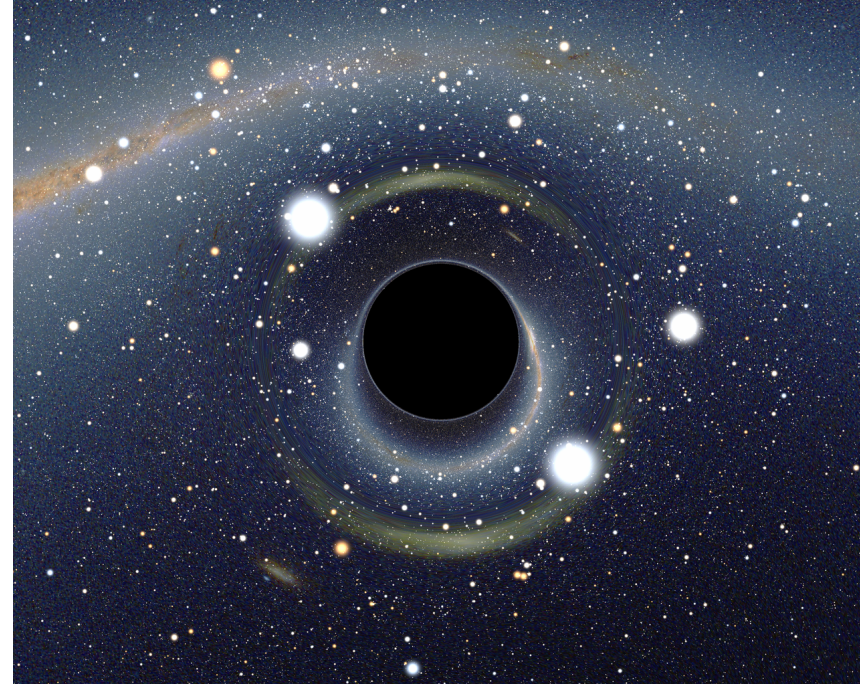


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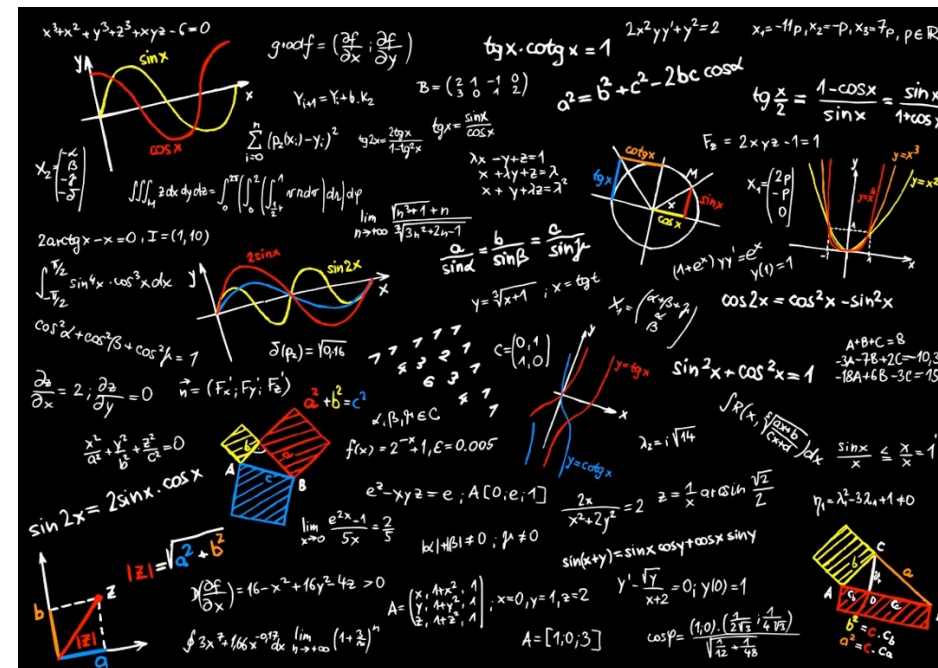
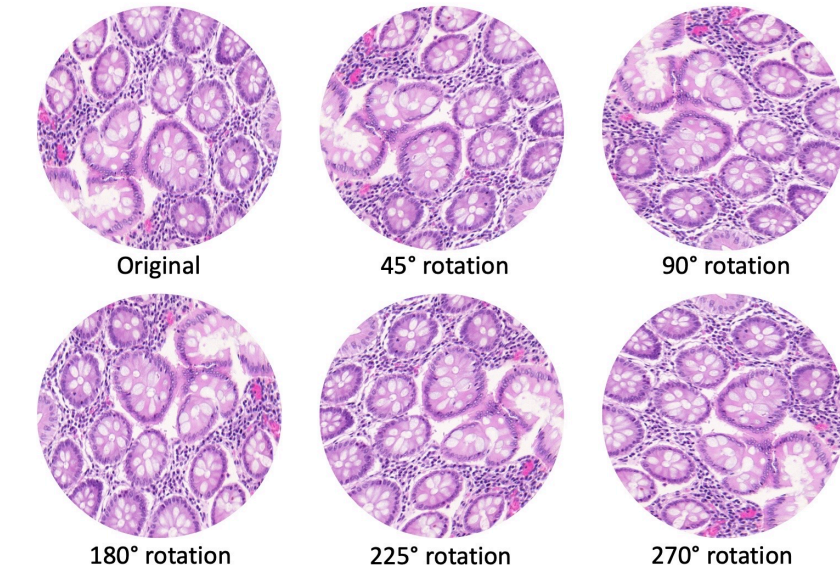


[Images from: Weiler, Forré, Verlinde, Welling (2023)]

Physics

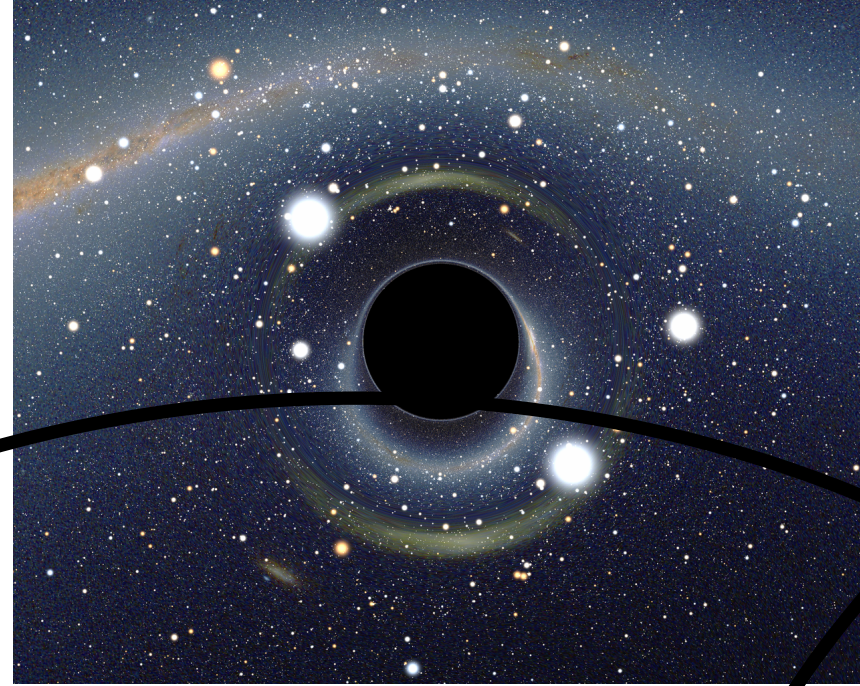


AI

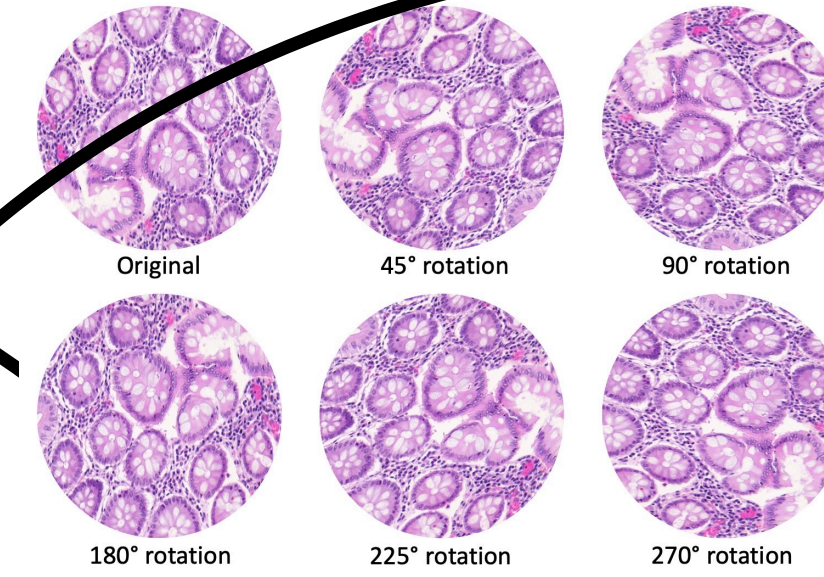


Mathematics

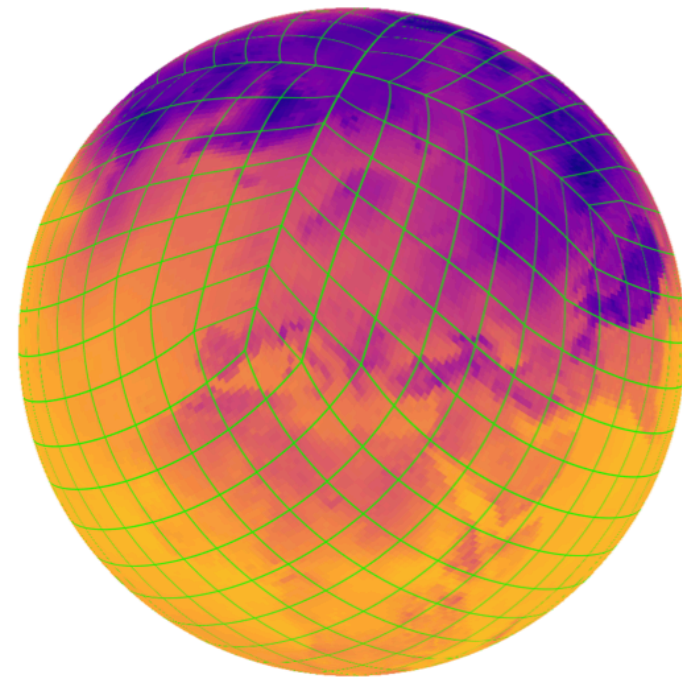
Physics



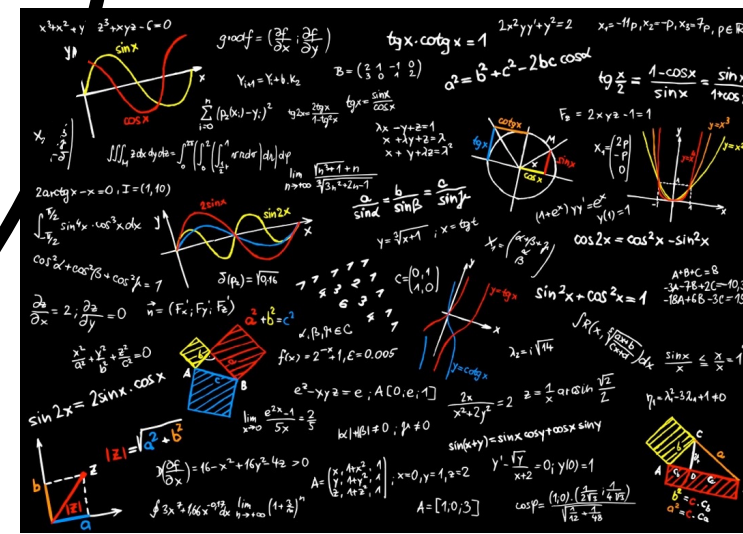
AI



Earth science



Mathematics



Biology/Chemistry



A vibrant, multi-colored spiral galaxy with a central black hole, surrounded by a complex network of stars and filaments. The galaxy's colors transition from blue and purple in the center to orange and red towards the edges. The surrounding space is filled with a dense network of stars and filaments, creating a web-like structure. The overall scene is set against a dark, starry background.

TACK!