#### Making sense of Math in Vis

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Mathematical foundations of visual data analysis. There is a rich tradition of mathematical and computational methods used in visualization, such as topological approaches, feature extraction, numerical sampling and reconstruction methods, numerical integration, differential operators, filtering, dimension reduction, and applications of information theory, partly incorporating uncertainty. While all these methods have a solid mathematical foundation, a careful look at the relation between theories and their role in visual data analysis is needed.

How can it all be organized? What's missing?

Schematic view of Visualization pipeline

interaction loops



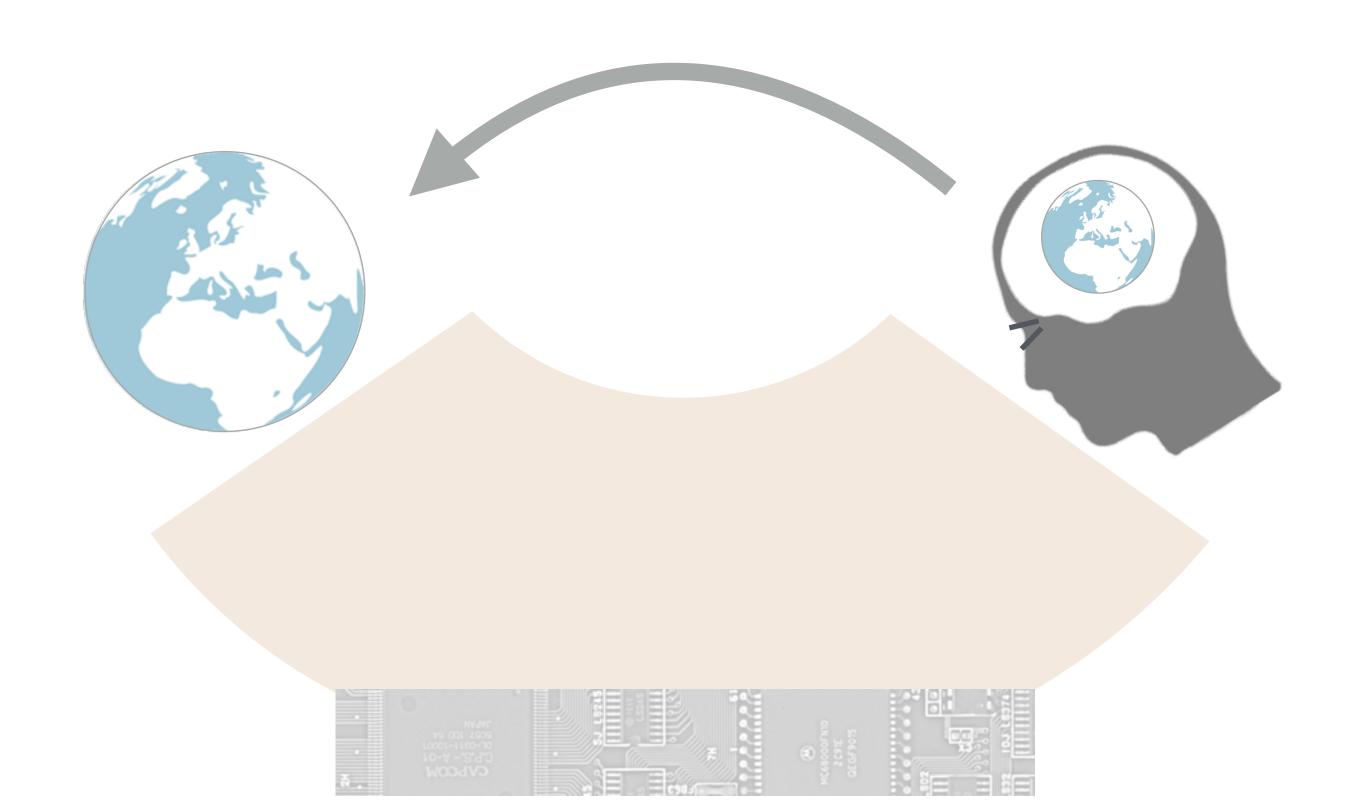


compute hardware

### Why have Math in Vis?

- To **Describe**, to Abstract away specifics, embrace a level of generality
  - ⇒ Usefully Structure Visualization Pedagogy
- To Connect, to Engage with disciplines that already use math
- To Enrich/Solidify vis, by leveraging formalism of mathematics
- To Aspire to or Broadcast Sophistication?

#### Where is Math in Vis?



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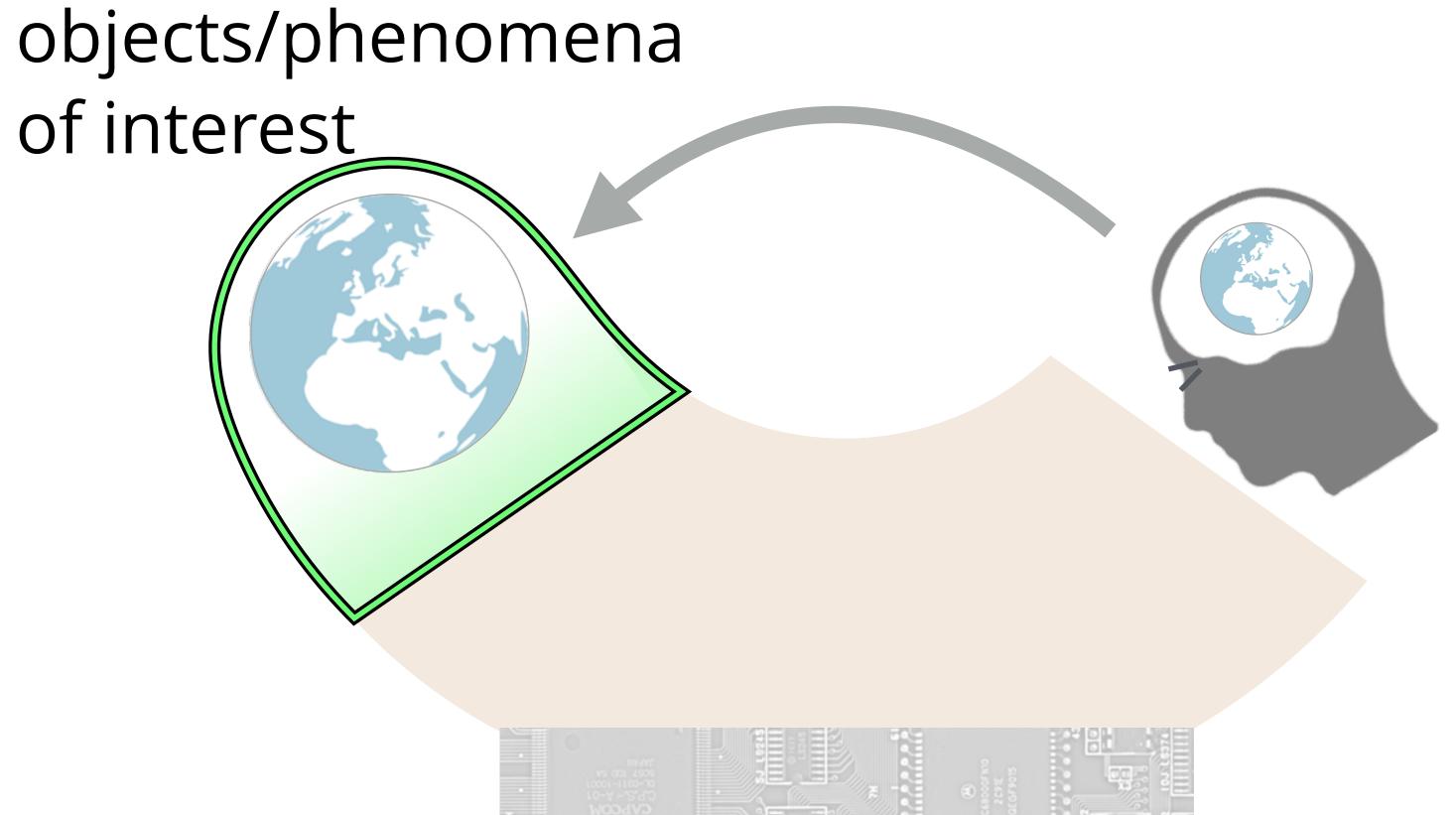


Help!
correct (now)
&
complete (this week)

In about 6 different places



(1) in models of objects/phenomena



(1) in models of objects/phenomena of interest

(scientific computing)

Laplace's equation, Poisson's equation

Navier-Stokes, Heat, Advection-Diffusion PDEs

Reflection, Illumination, Energy Transport

Statistics: Ensembles, Uncertainty, Bayesian Methods

(2) in models of human perception and



(Perceptual Psychology)

Stevens Law, WeberFechner Law

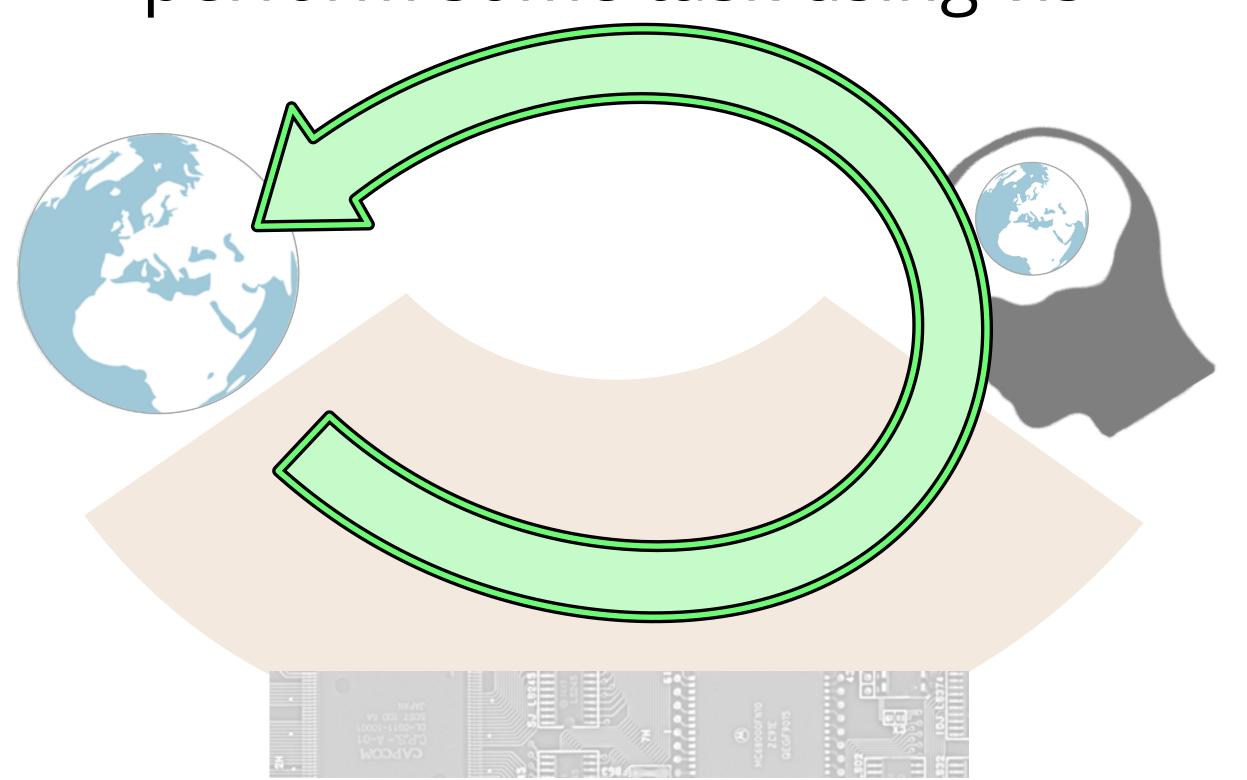
Opponent Color Channels, Color Appearance Models (e.g. CIECAM02)

Gabor Wavelets (perception of scale)

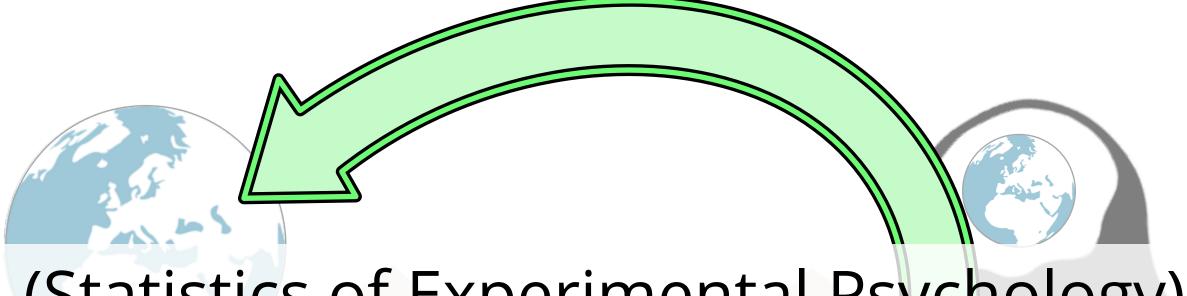
Bayesian Models Of Gestalt [Jäkel-QuantitativeGestalt-VR-2016]

(2) in models of human perception and cognition

(3) in empirical study of how people perform some task using vis



# (3) in empirical study of how people perform some task using vis

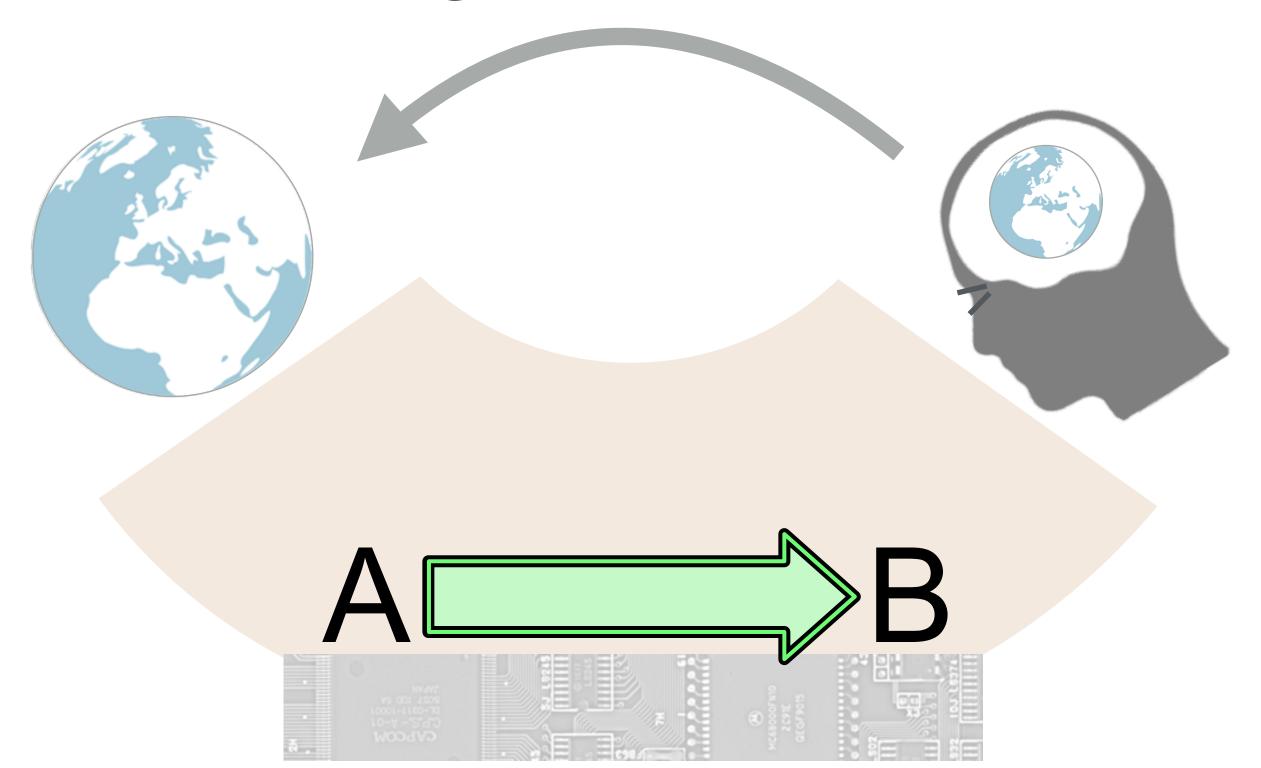


(Statistics of Experimental Psychology)

Randomization, Counterbalancing Significance levels, P-values, ANOVA

[Forsell-IntroEvalVis-HHCV-2014]

# (4) in definitions of essential overall goal of vis method



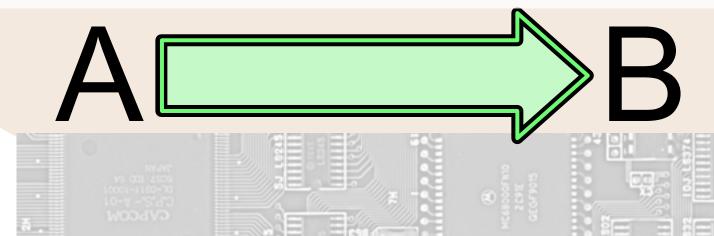
# (4) in definitions of essential overall goal of vis method

**Feature Extraction**: Isocontours, Parallel Vectors Operator, Ridges and Valleys, Vortex Cores

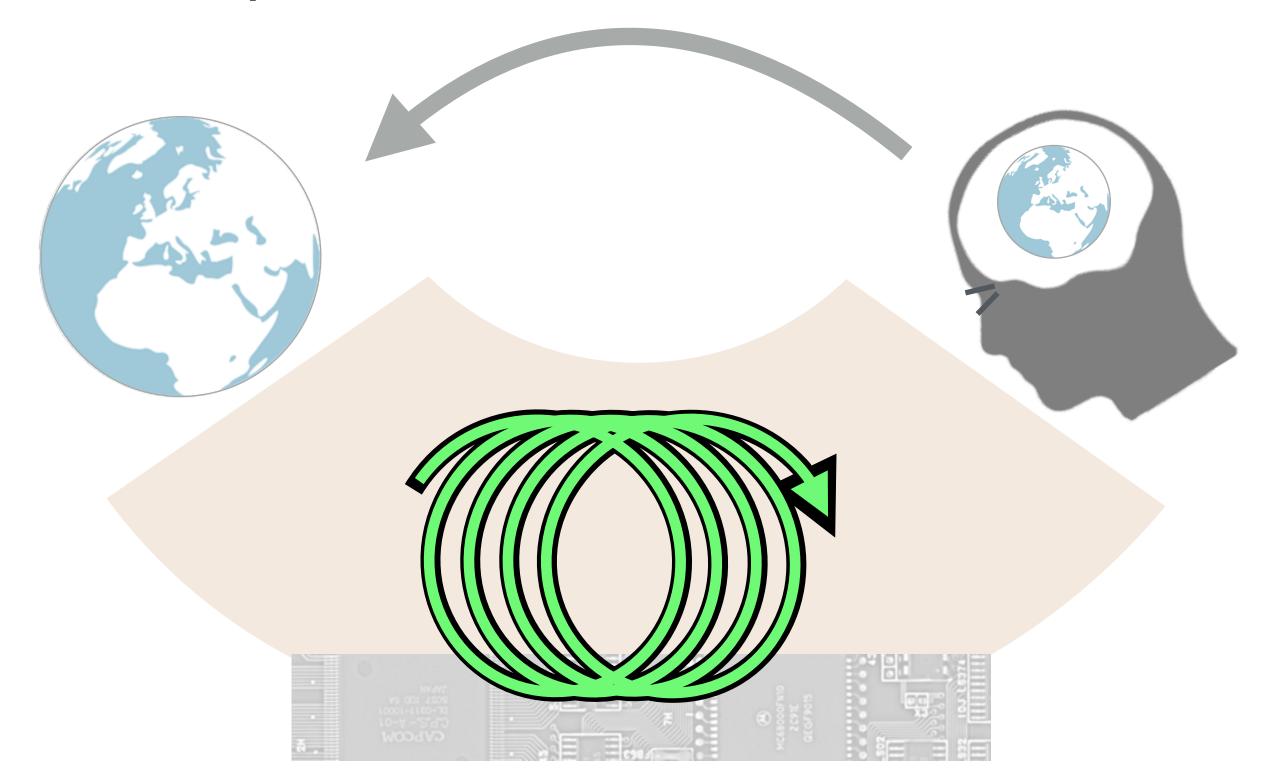
Topological methods: Morse-Smale Complex, Reeb Graph

Points & Graphs: Principal Component Analysis, Spectral Clustering, Dimensionality Reduction, Graph Drawing

Solving PDEs with Finite Elements: Dirichlet/Neumann boundary conditions, Galerkin Method, Linear/Spectral Elements



# (5) to implement low-level parts of overall method

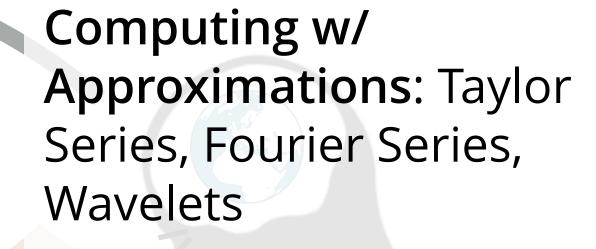


# (5) to implement low-level parts of overall method

Linear algebra: LU decomposition, eigensolve

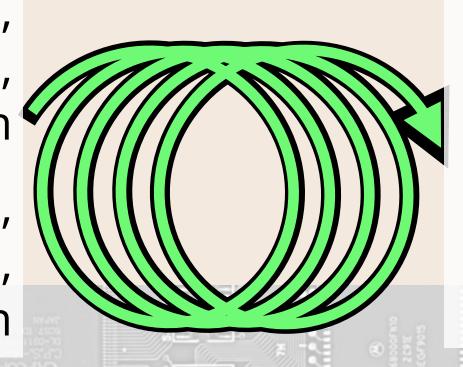
Numeric Methods: Euler/ Runge-Kutta Integration, Streamlines, Tractography, Newton root finding, Newton optimization, Kahan summation

> Derivatives: Gradient, Jacobian, Laplacian, Hessian

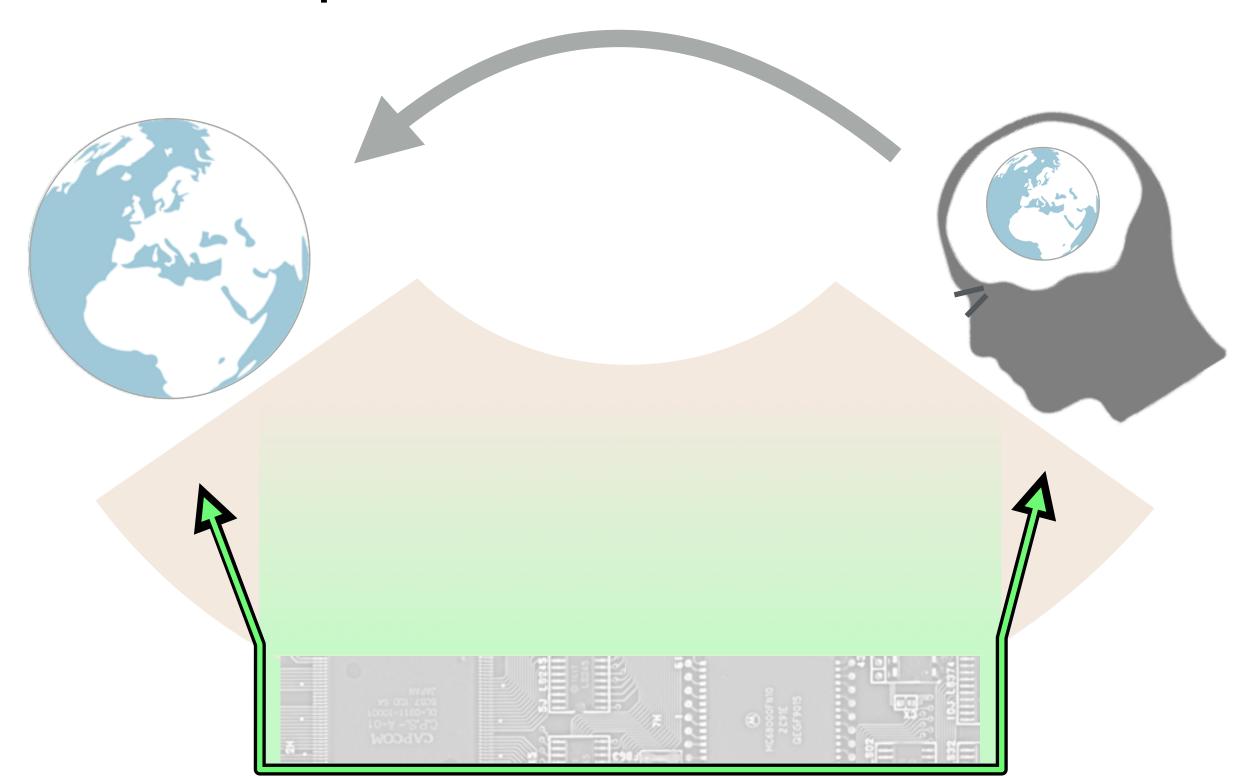


Signal processing: Nyquist Sampling, Reconstruction by Convolution

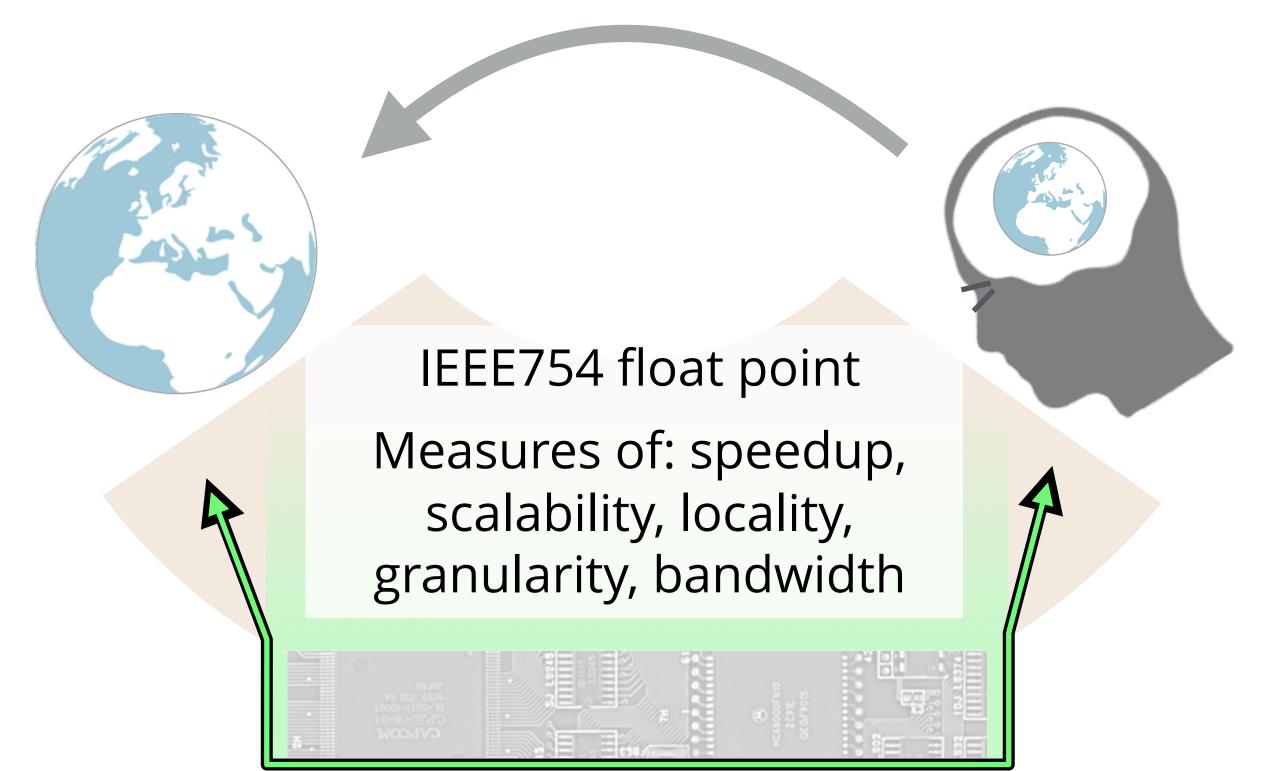
Sequence Data: matching, searching, Smith-Waterman alignment

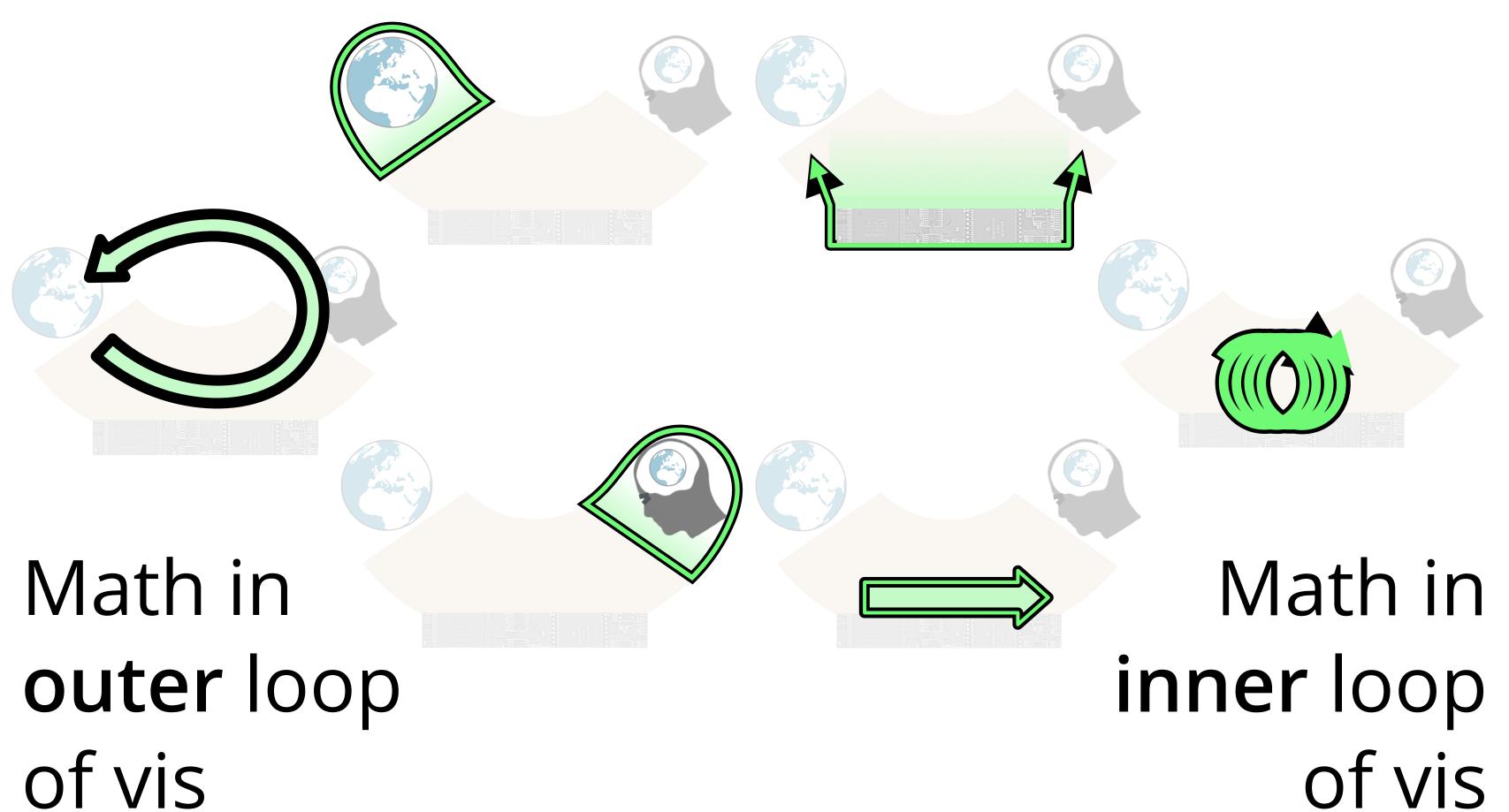


# (6) to characterize performance of compute hardware for task



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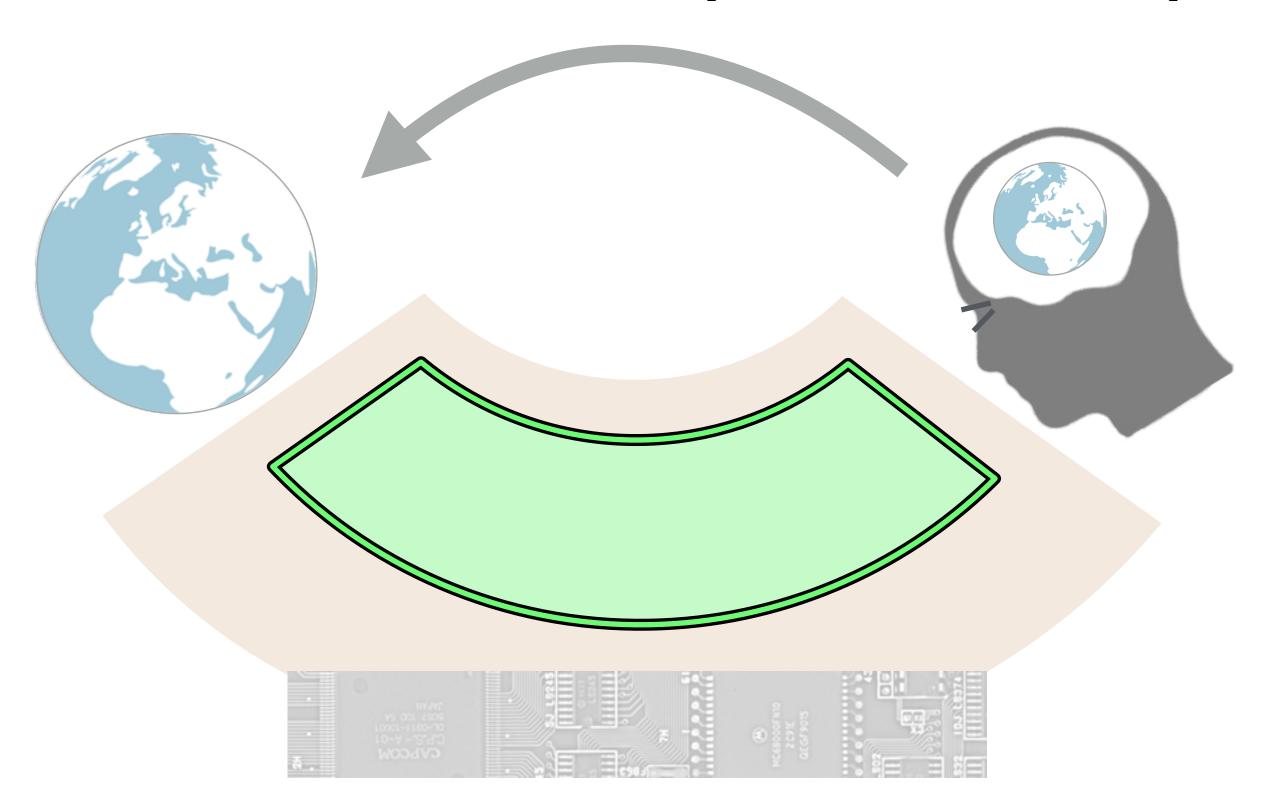




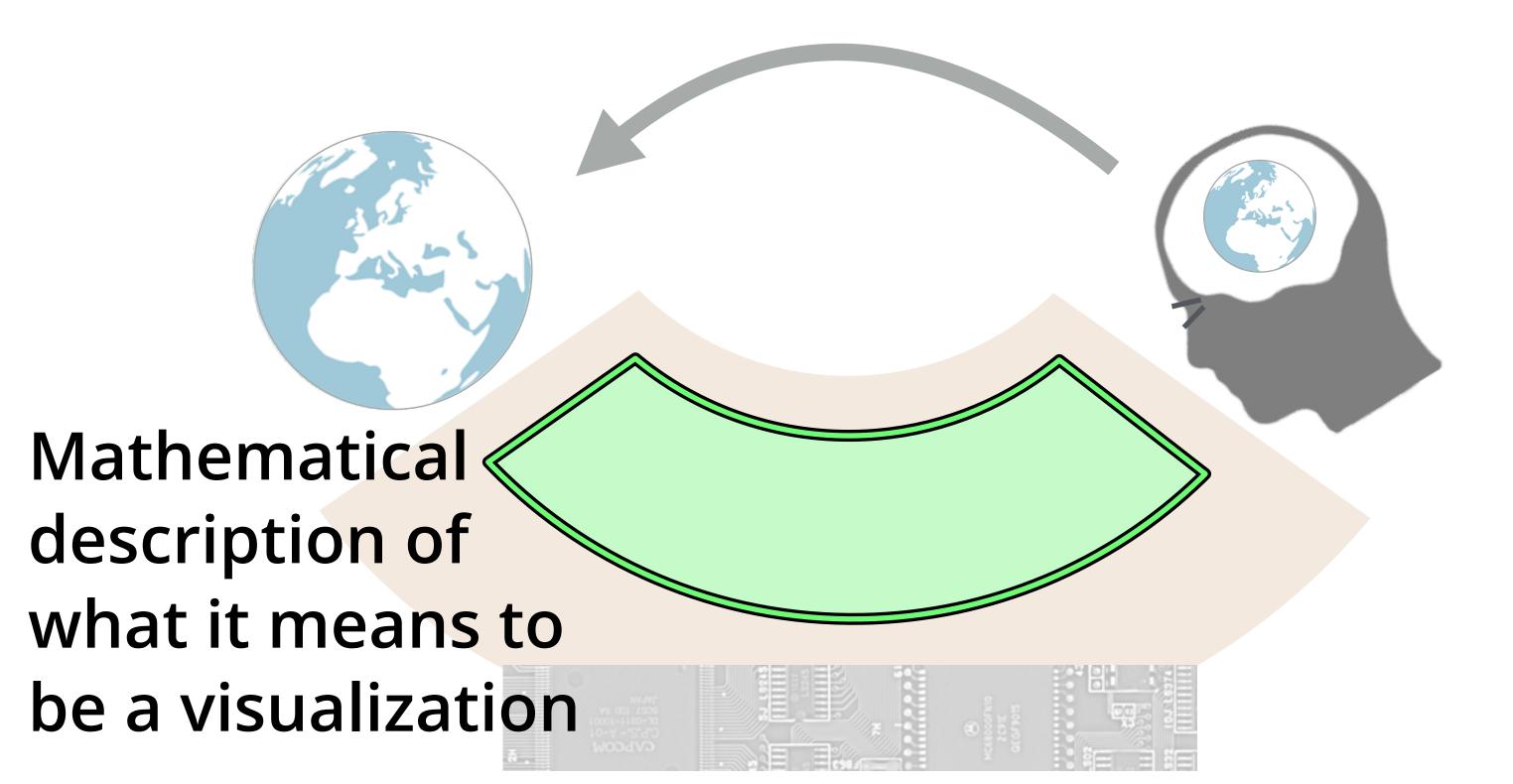
Math in outer loop of vis

Math in inner loop of vis

### Math of vis (not in vis)



### Math of vis (not in vis)



#### William Hibbard [Hibbard-StructuresOfData-DIDV-1995]

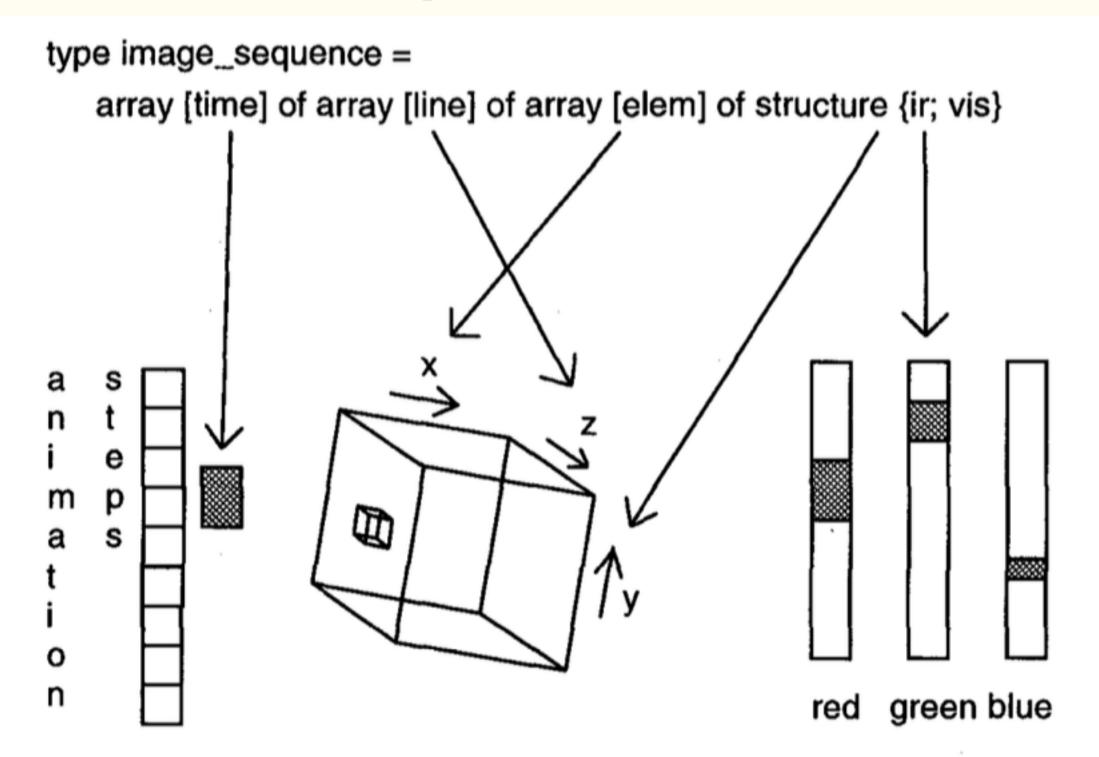


Figure 3. A mapping from a data aggregate to a display aggregate is decomposed into mappings from data primitives to display primitives.

#### William Hibbard [Hibbard-StructuresOfData-DIDV-1995]

type image\_sequence =

array [time] of array [line] of array [elem] of structure {ir; vis}

We have briefly investigated how mathematical structures on data can be used to define conditions on the visualization mapping from data to displays. The first three conditions that we discussed are that  $D: U \to V$  map:

The algebraic structure of U to the algebraic structure of V (i.e., D is linear). The metric structure of U to the metric structure of V (i.e., D is isometric). The lattice structure of U to the lattice structure of V (i.e., D is a lattice isomorphism).

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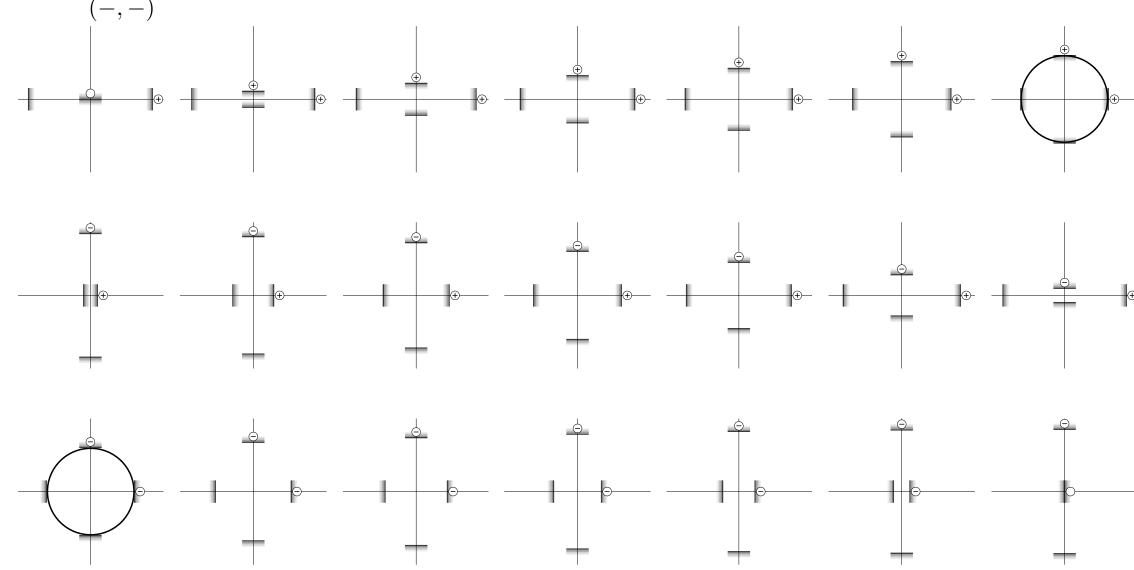
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[Demiralp-VisualEmbedding-CGnA-2014]

Dagstuhl Seminar 09251 Scientific Visualization (July 2009)

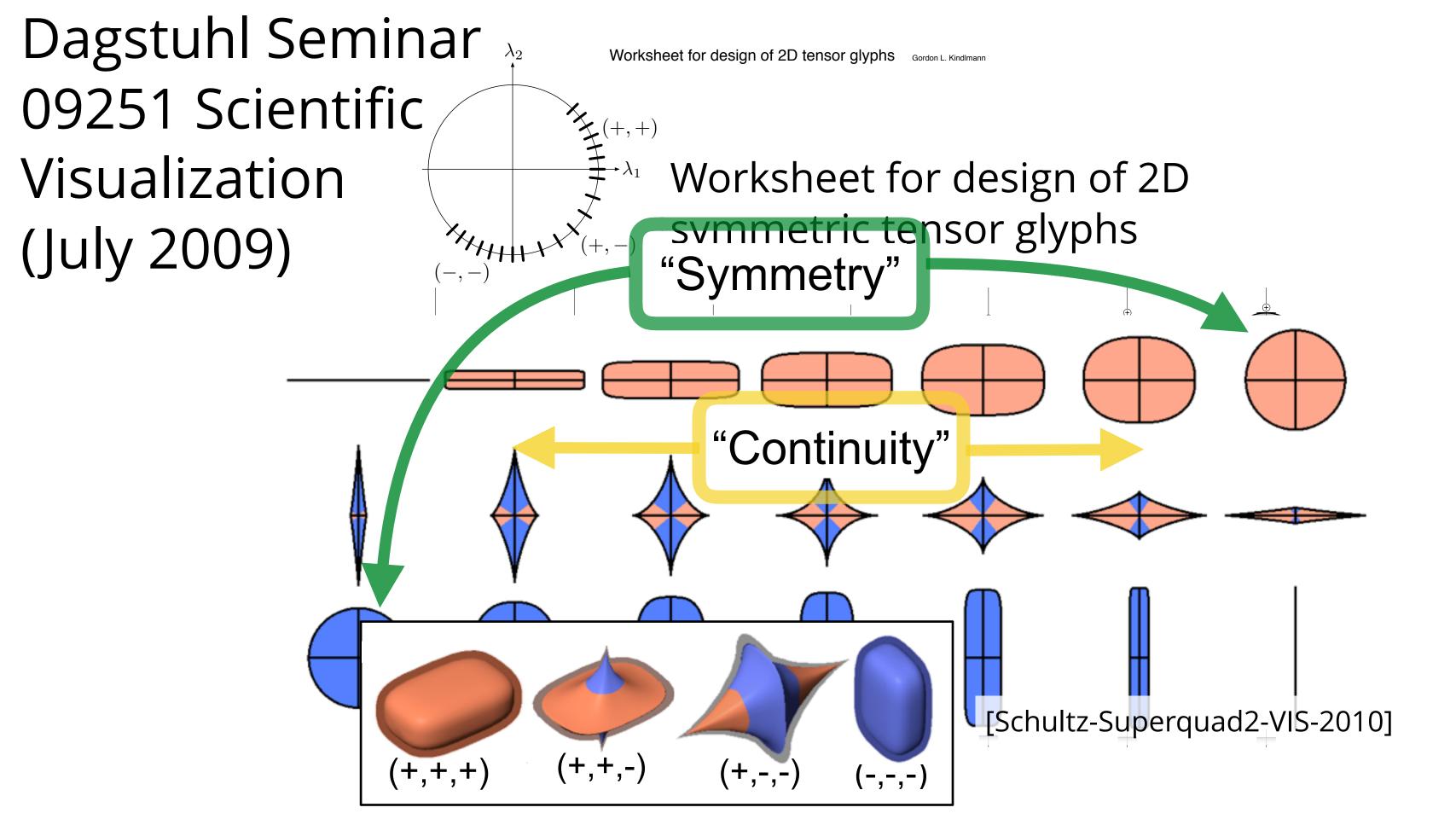
Worksheet for design of 2D tensor glyphs Gordon L. Kindlmann  $\lambda_2$  Worksheet for design of 2D  $\lambda_1$  Worksheet for design of 2D symmetric tensor glyphs

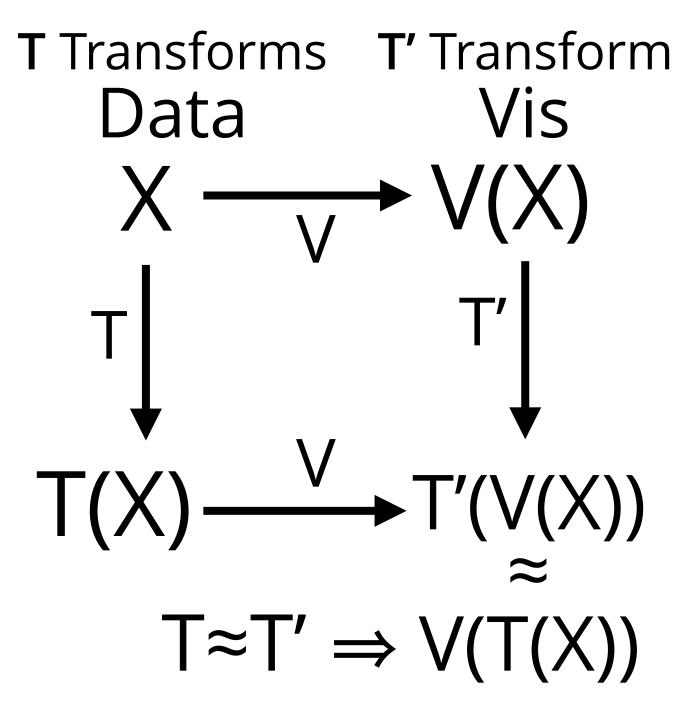


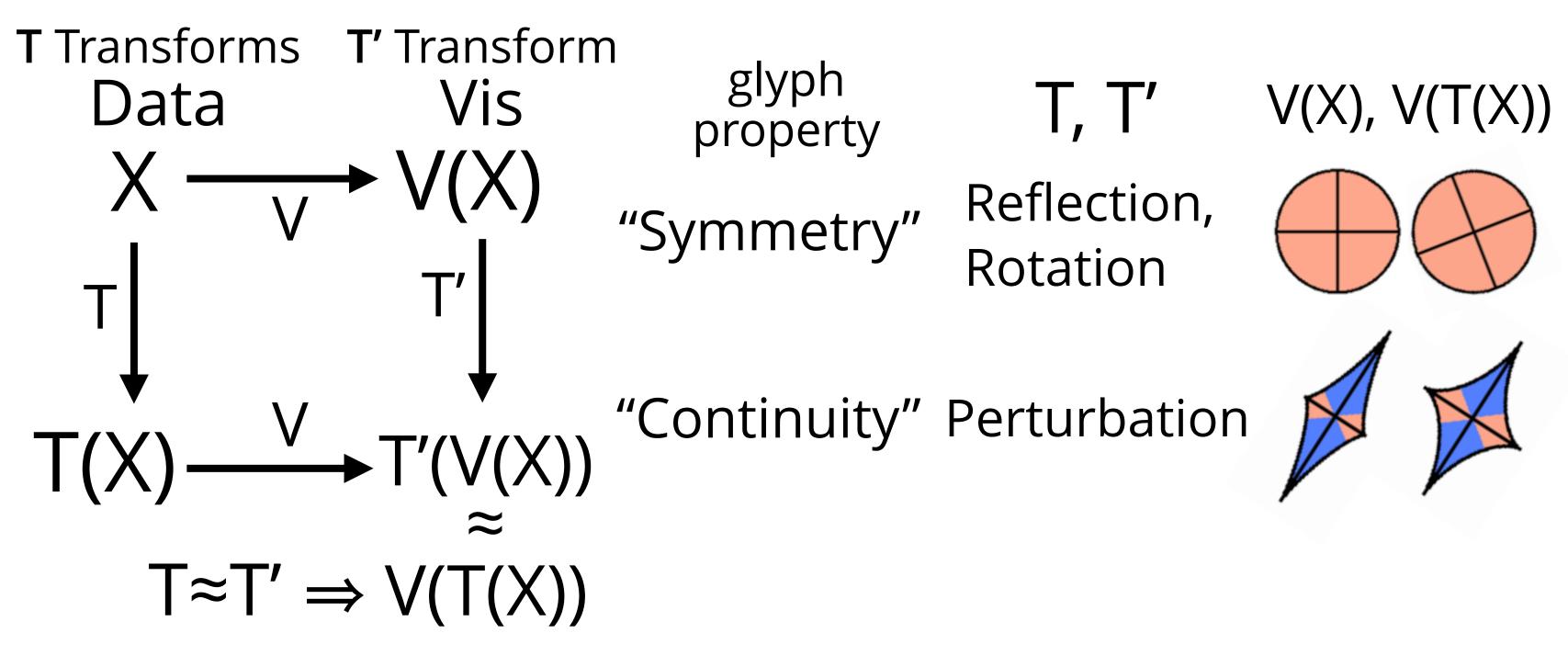
Dagstuhl Seminar Worksheet for design of 2D tensor glyphs Gordon L. Kindlmann 09251 Scientific Visualization Worksheet for design of 2D symmetric tensor glyphs (July 2009) "Symmetry"

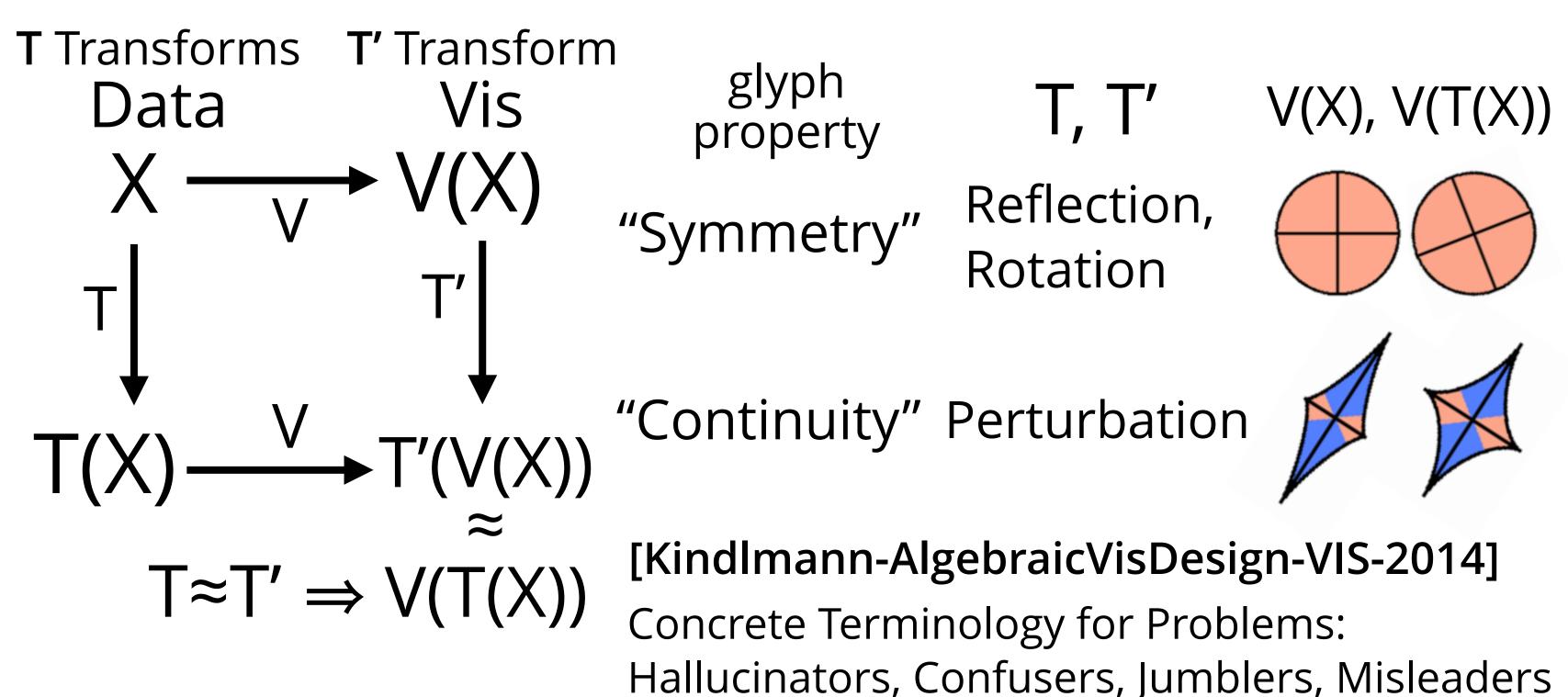
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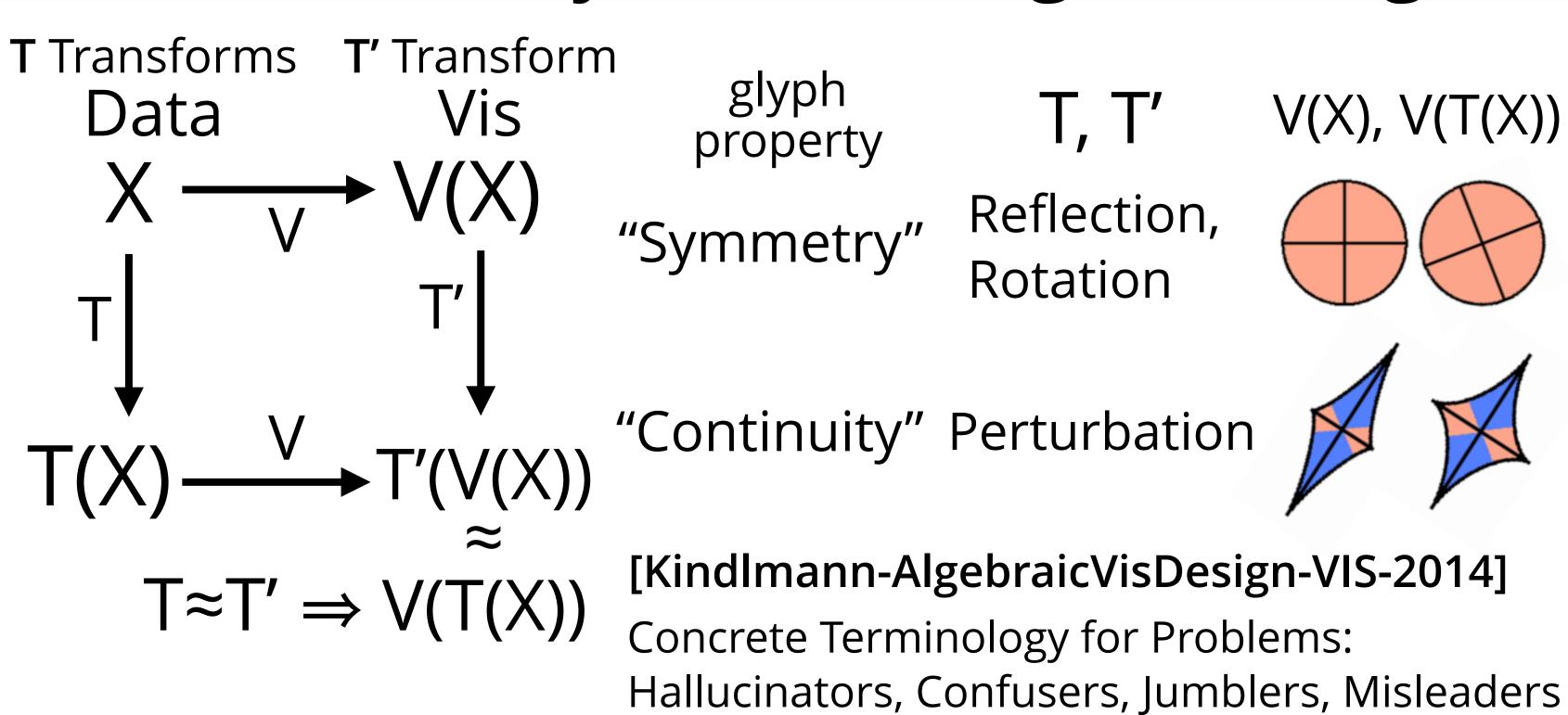
Dagstuhl Seminar Worksheet for design of 2D tensor glyphs 09251 Scientific £(+,+) Visualization Worksheet for design of 2D symmetric tensor glyphs (-,-) (July 2009) "Symmetry" "Continuity" [Schultz-Superquad2-VIS-2010]







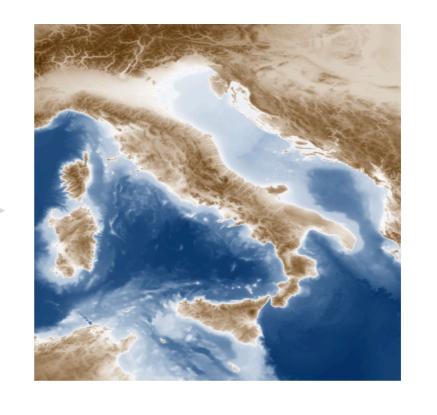




complements [Chen-InfoTheory-TVCG-2010]

#### Correspondence example: elevation colormap

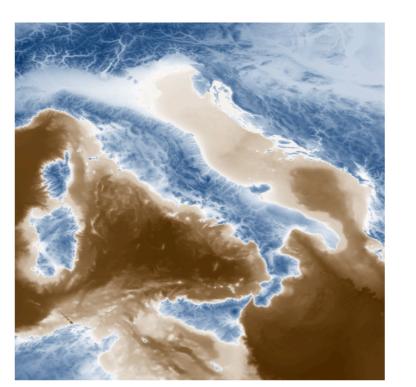
Data: signed elevation relative to sea level  $\mathcal{T}$ 



diverging colormap

 $\alpha(e) = -e$ 

 $D^{-v}$ 



 $\omega$ : negate hue

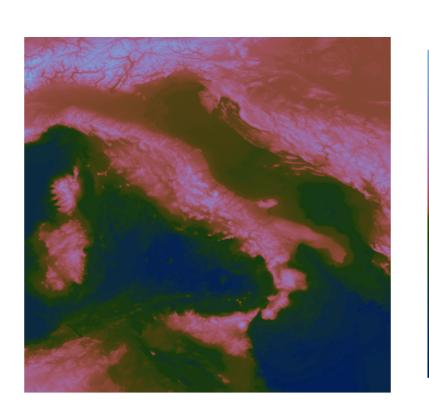
-v(e) ≈ v(-e) colormapping commutes with negation

#### Correspondence example: elevation colormap

Data: signed elevation relative to sea level  $\mathcal{T}$ 

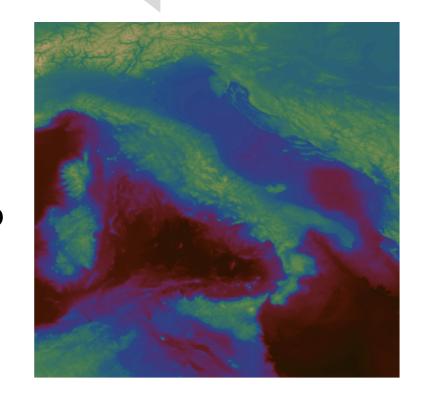
$$\alpha(e) = -e$$

 $D^{-v}$ 





 $\omega$  = negate hue



meaningful  $\alpha$  not matched with perception: "jumbler"

Mathematical foundations of visual data analysis. There is a rich tradition of mathematical and computational methods used in visualization, such as topological approaches, feature extraction, numerical sampling and reconstruction methods, numerical integration, differential operators, filtering, dimension reduction, and applications of information theory, partly incorporating uncertainty. While all these methods have a solid mathematical foundation, a careful look at the relation between theories and their role in visual data analysis is needed.

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Anything else missing? Better way to organize?

#### Conclusions

Short of unifying "theory of vis", need accounting of math in vis (please help) Why: principles empower vis students (more than a craft taught by apprenticeship) Math of vis essential for Theory of vis

⇒ Either way, Vis needs Math

#### References

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- [Schultz-Superquad2-VIS-2010] Superquadric Glyphs for Symmetric Second-Order Tensors. T Schultz and GL Kindlmann. IEEE Transactions on Visualization and Computer Graphics (Proceedings of VisWeek 2010), 16(6):1595–1604, November–December 2010.

