LDAV 2011

Analysis of Large-Scale Scalar Data Using Hixels

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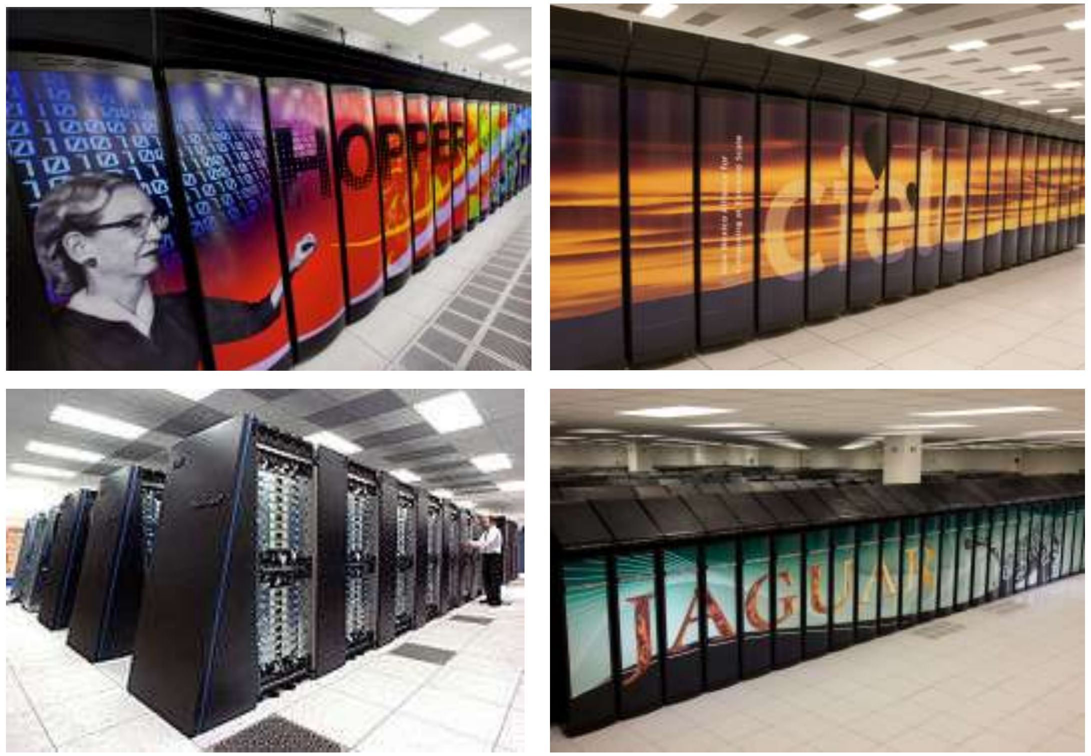
HPC Has Lead to Increases in Both Data Size and Complexity

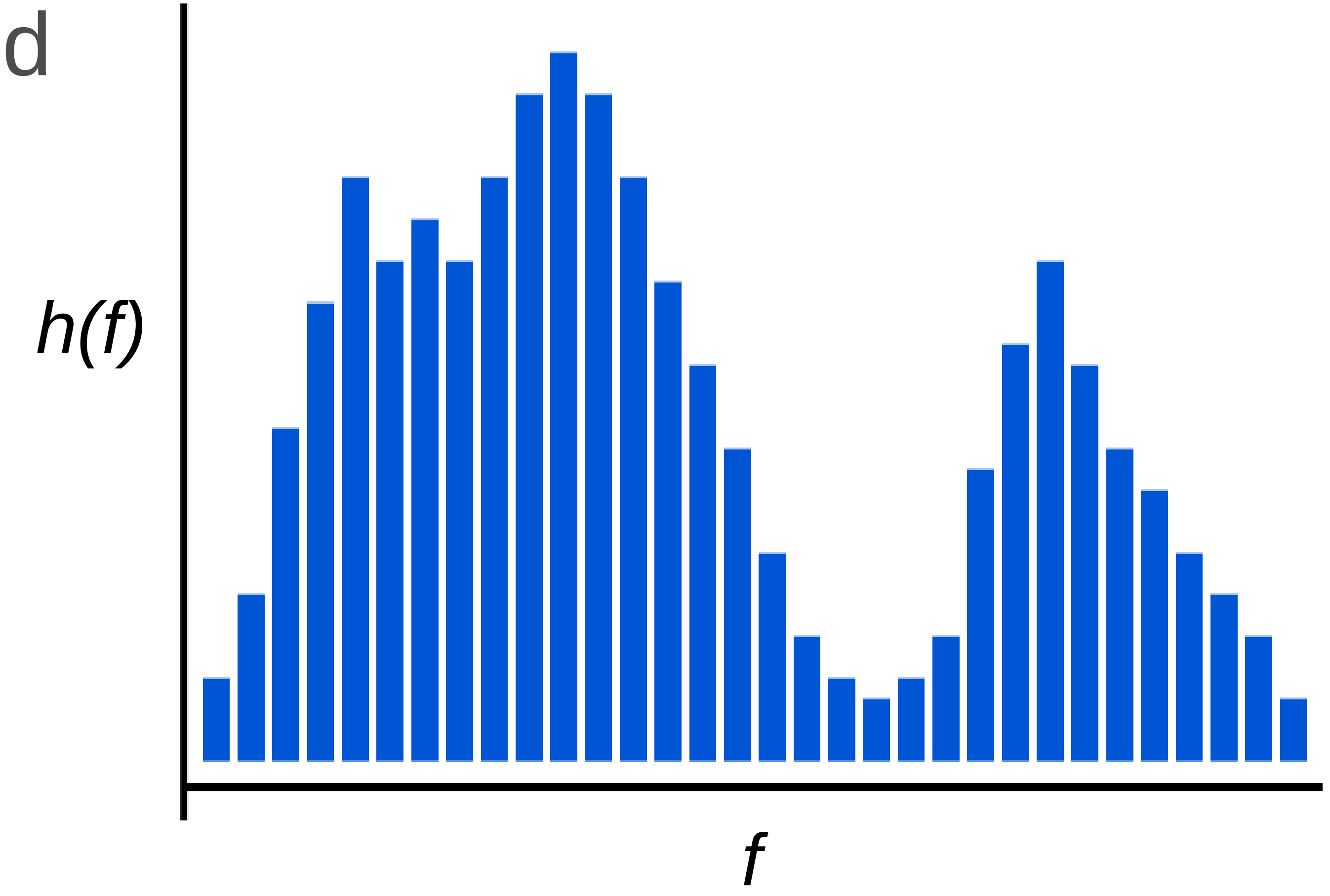
- “Hero” runs
  - Increased spatial resolution
  - Increased number of variables
- Uncertainty Quantification (UQ)
  - Ensembles of runs
  - Polynomial Chaos
  - Stochastic Simulations
- Many analysis methods do not scale with size & complexity of the data



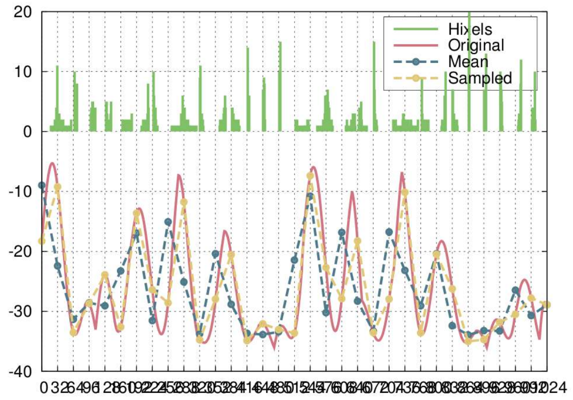
Images courtesy of: National Energy Research Scientific Computing Center, Los Alamos National Laboratory, Argonne National Laboratory, and Oak Ridge Leadership Computing Facility.

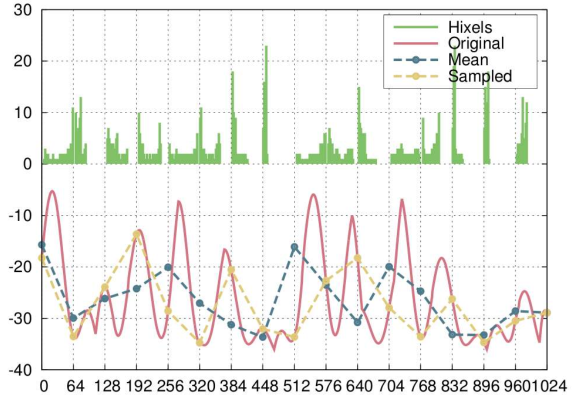
Hixels: A Unified Data Representation

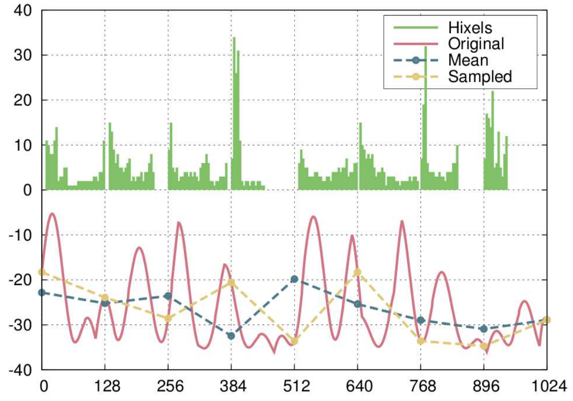
- A **hixel** is a point with an associated histogram of scalar values
- Hixel samples may represent:
  - Spatial down-sampling
  - Ensemble values
  - Random variables
- Trade data size/complexity for uncertainty

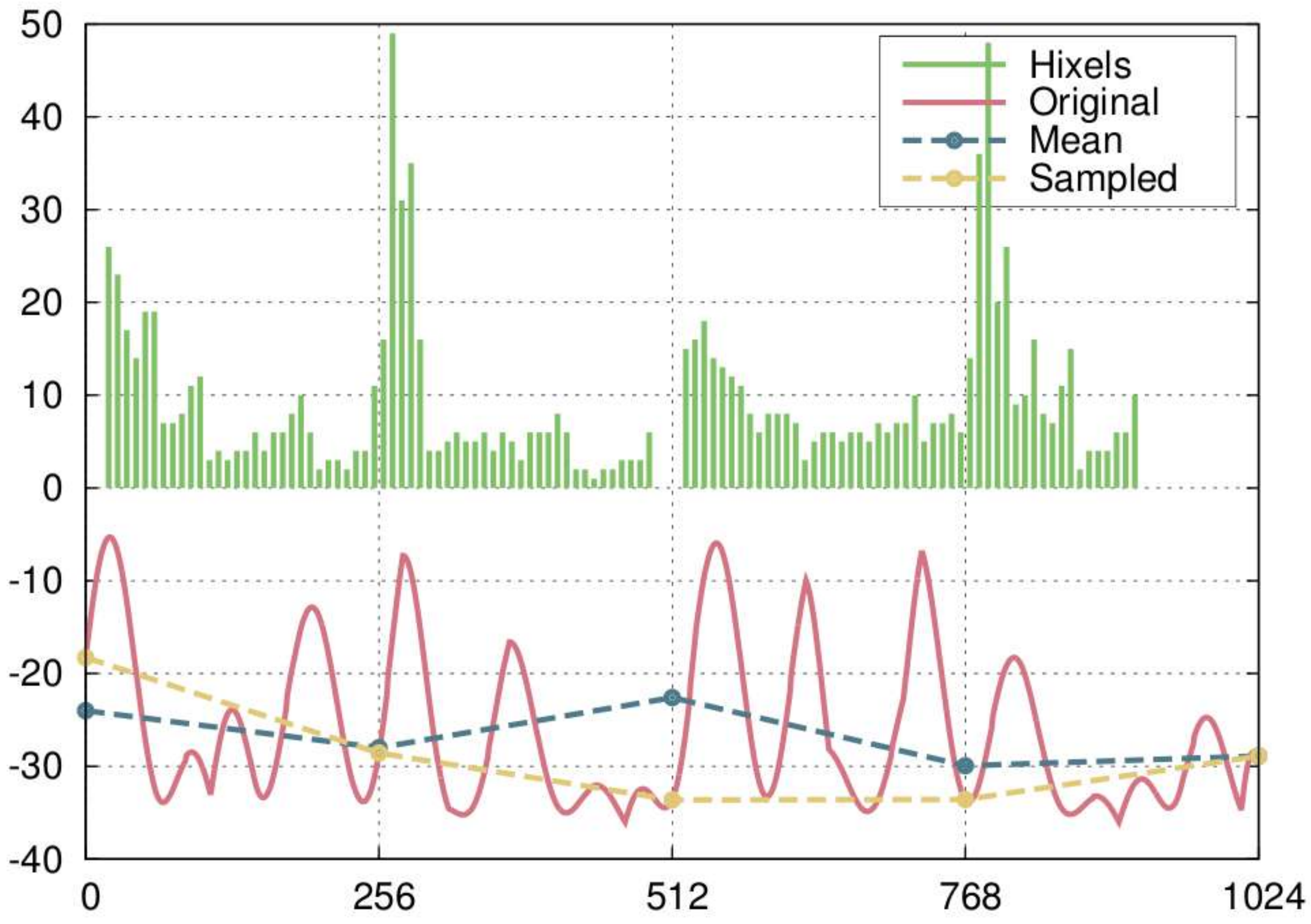


1D Example of Hixels (Block Compression)



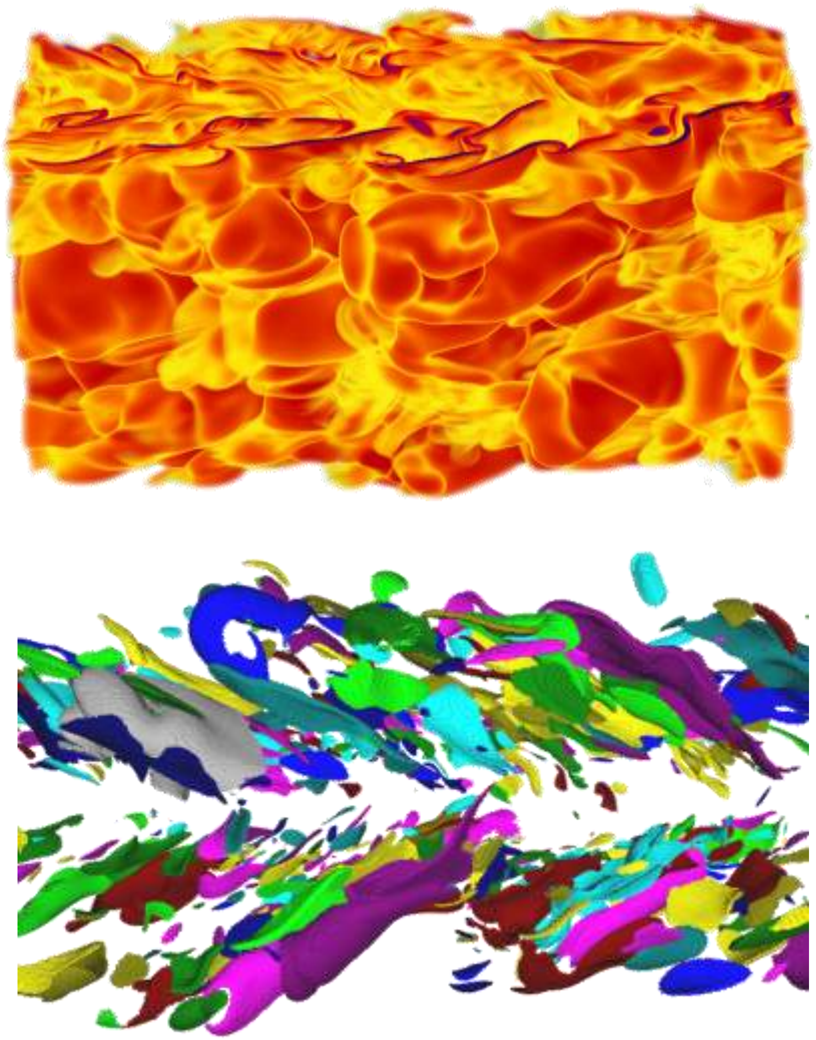






Motivation: Feature-Based Analysis

- Characterize and define features
- Segmentation domain by function behavior
- Answer questions:
  - How many features are there?
  - What is the behavior of other variables within these features?
  - How do you define a good threshold value on which to segment the domain?

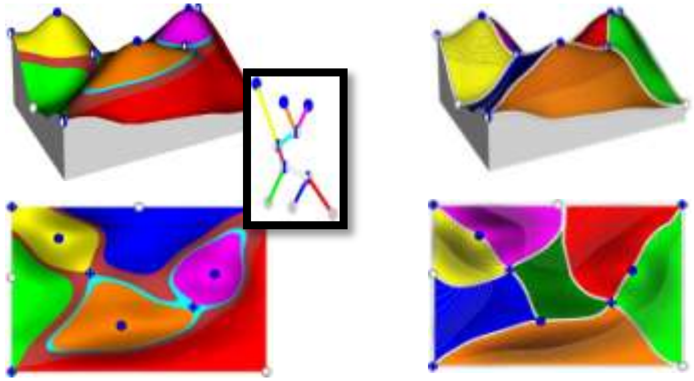


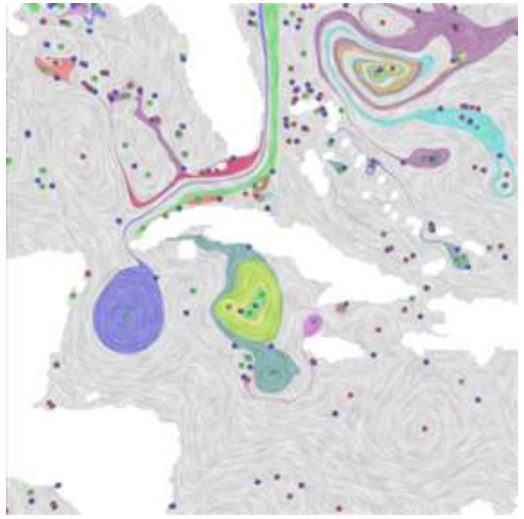
Data courtesy of: Dr. Jacqueline Chen, SNL

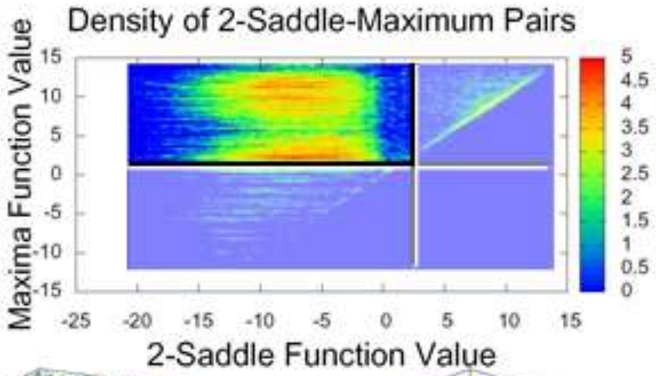
Goal: Extend Topological Methods

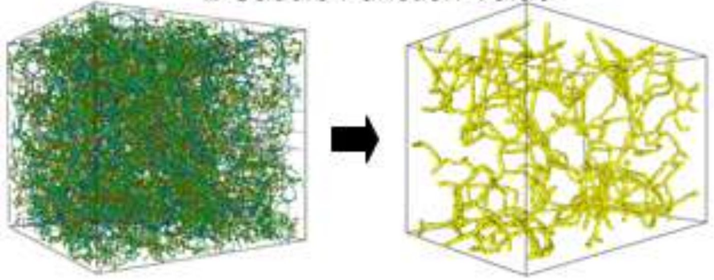
- What structures are present?
- How persistent are they?
- How do we visualize features?

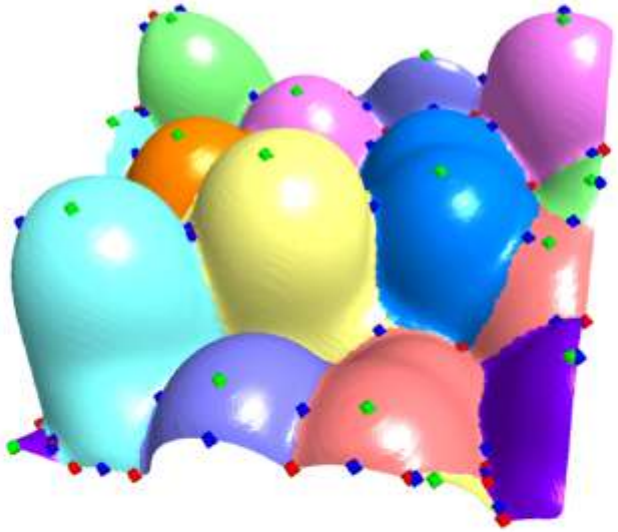
- Our Contributions:
  1. Sampled topology
  2. Topological analysis of statistically associated buckets
  3. Visualizing fuzzy isosurfaces











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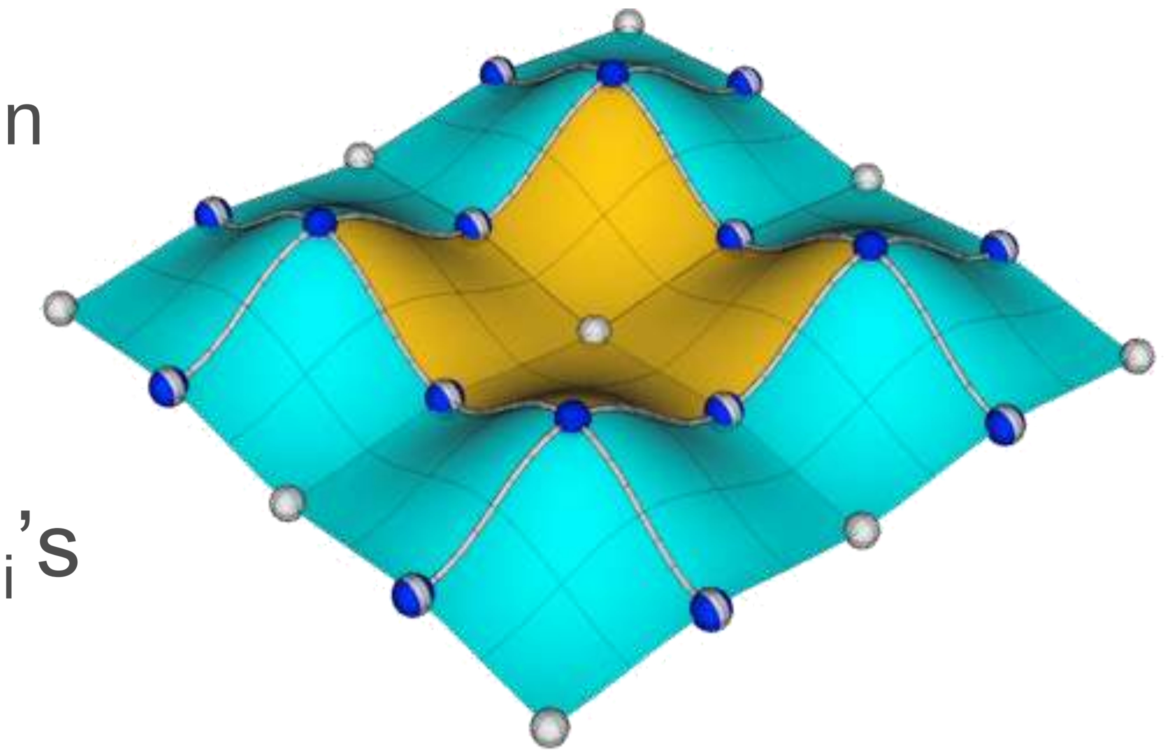
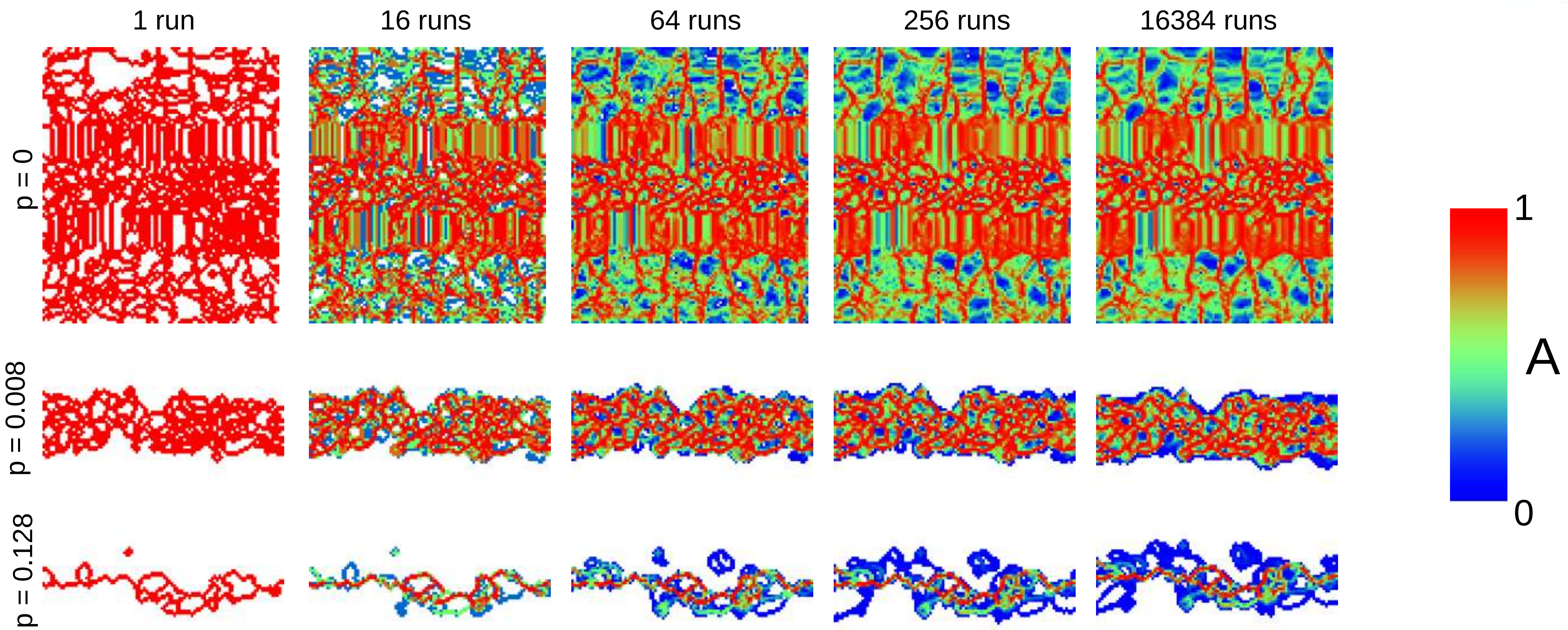
Sampled Topology: Algorithm

1. Sample the hixels to construct a scalar field V_i
2. Compute the Morse complex for V_i
   a) Identify basins around minima & arcs between adjacent basins
   b) Encode arc locations in a binary field C_i
      - Boundaries = 1, Rest = 0
3. Construct aggregate A as mean of the C_i's
4. Visualize variability of arc locations



Assumption: hixels are independent

Aggregate Segmentation on Temporal Jet



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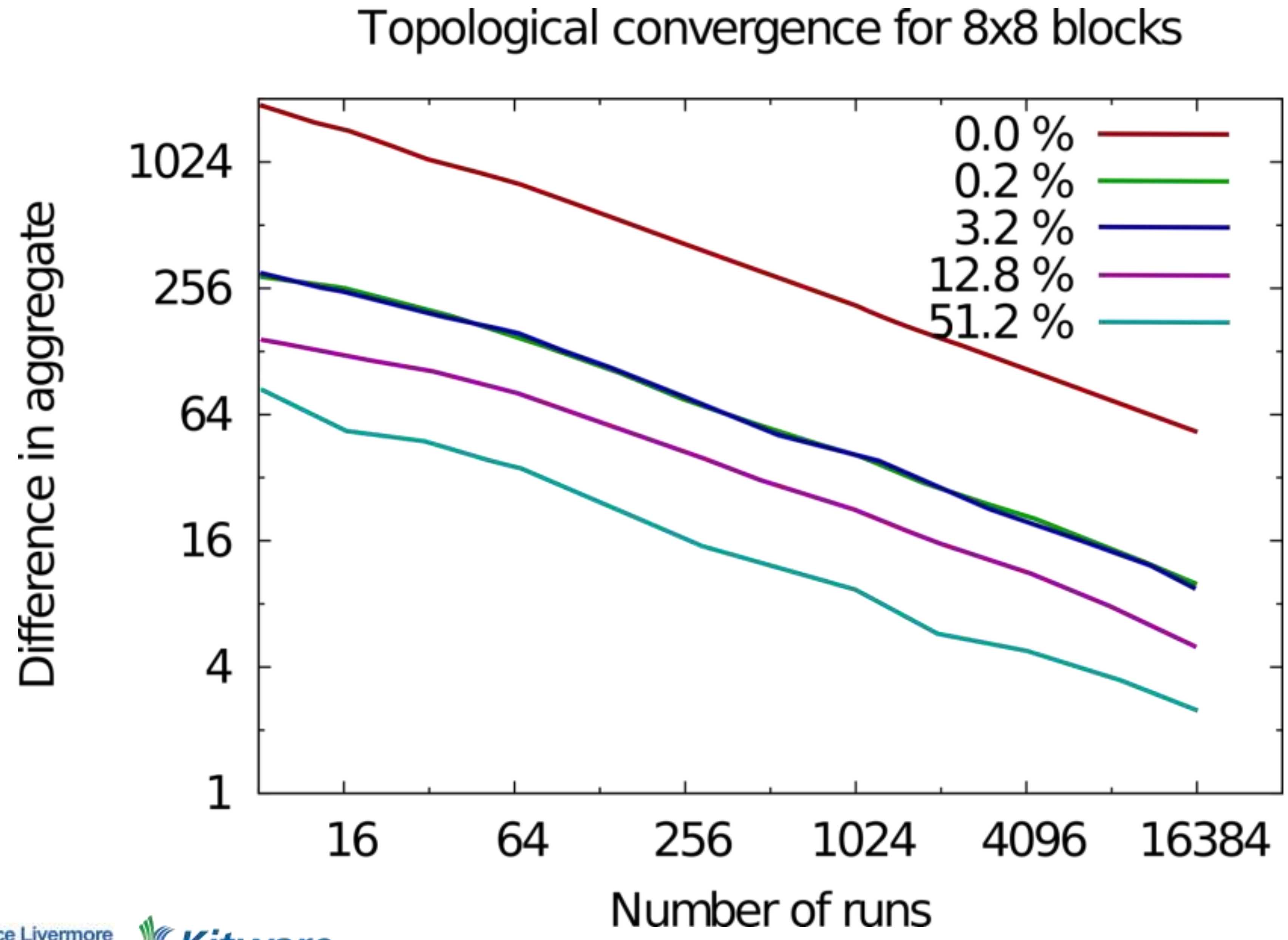
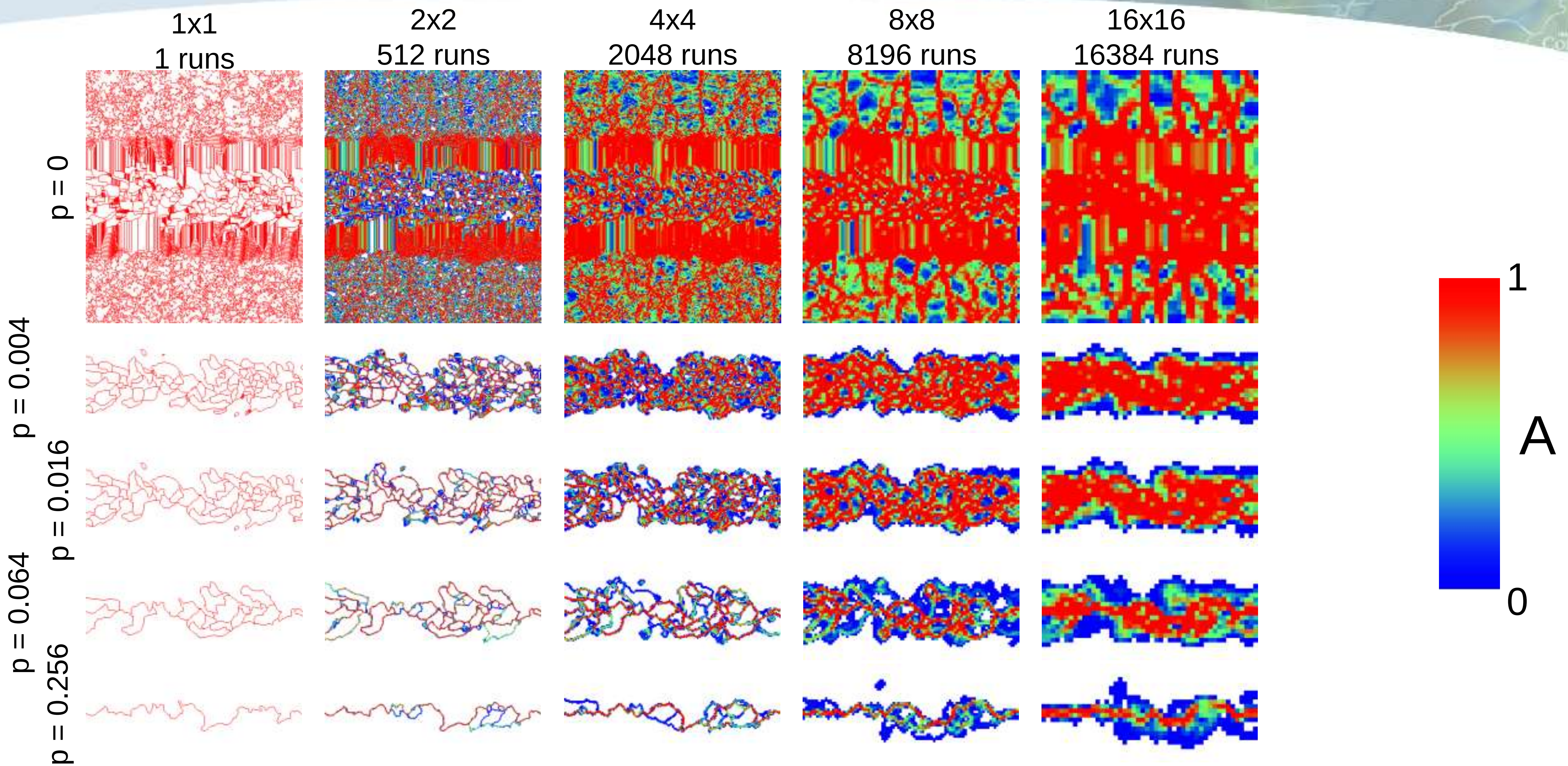
Convergence of Sampled Topology



Varying Block Size & Persistence



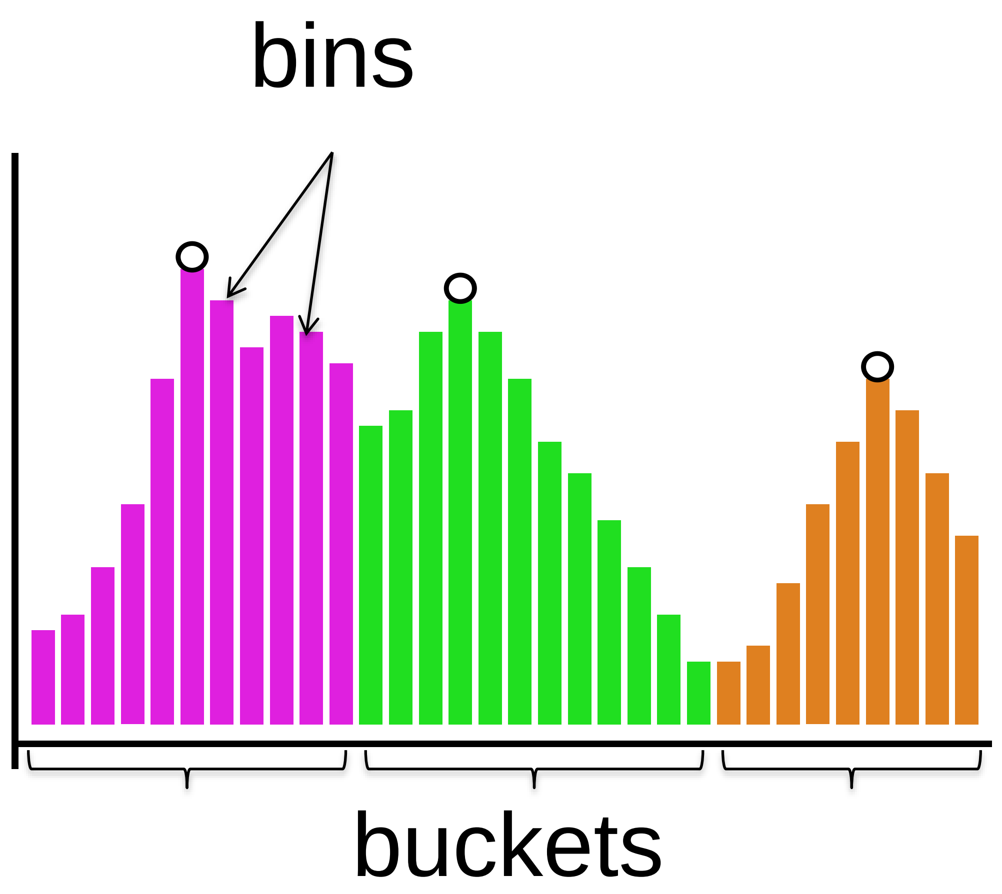
Topological Analysis of Statistically Associated Buckets: Algorithm

- Aimed at recovering prominent features from ensemble data
  - Exploit dependencies between runs
  - Identify regions in space & scalar values consistent with positive association
  - Perform topological segmentation on these regions individually

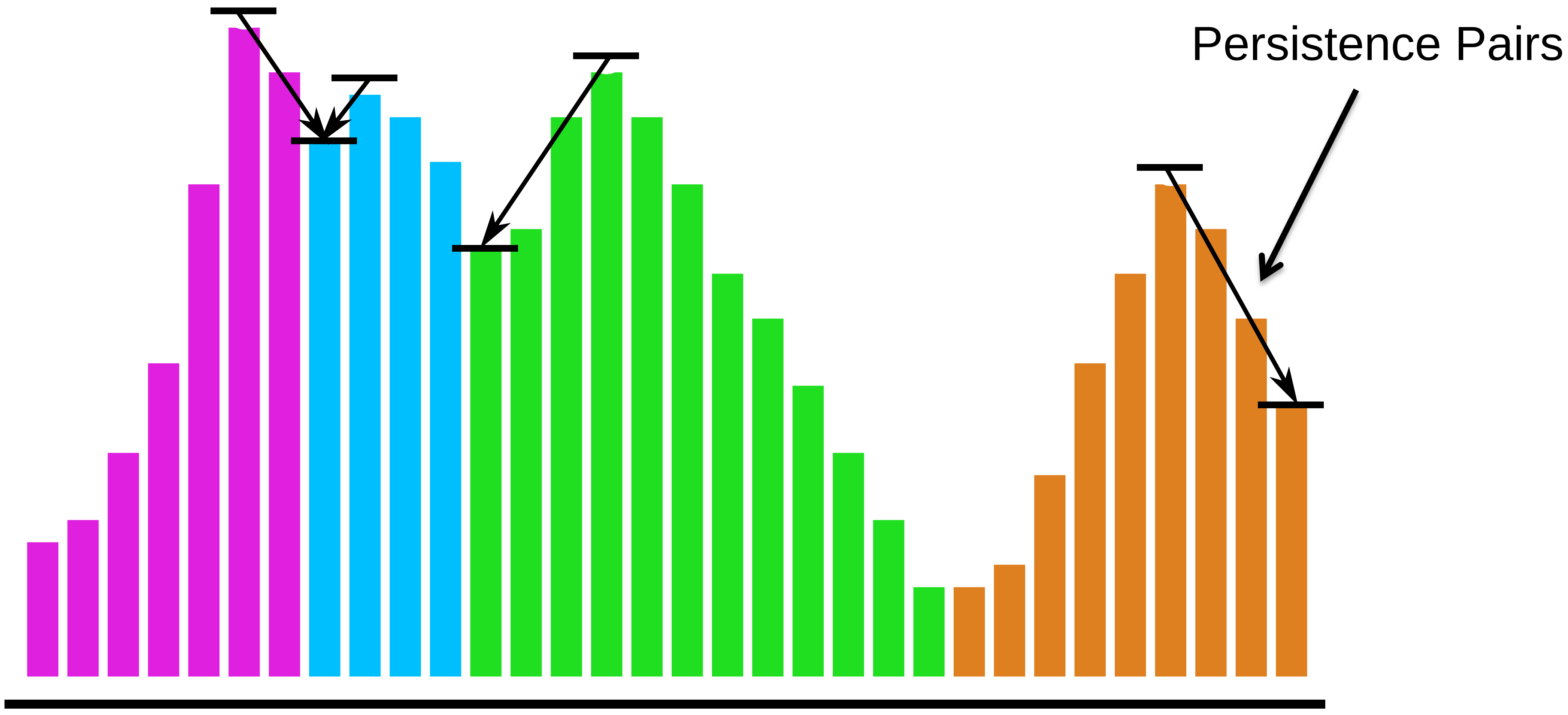
1. Compute buckets
2. Compute contingency statistics
3. Identify sheets
4. Perform topological analysis on individual sheets

Computing Buckets

- Values of high probability associated with peaks in the histogram
- Identify peaks + range of function values around that peak
- Topological segmentation on histogram
  - Use areal (hypervolume) persistence
  - Weight of interval = area of the histogram
  - Merge until the probability of smallest bucket is above a particular threshold



Persistence Simplification of Buckets



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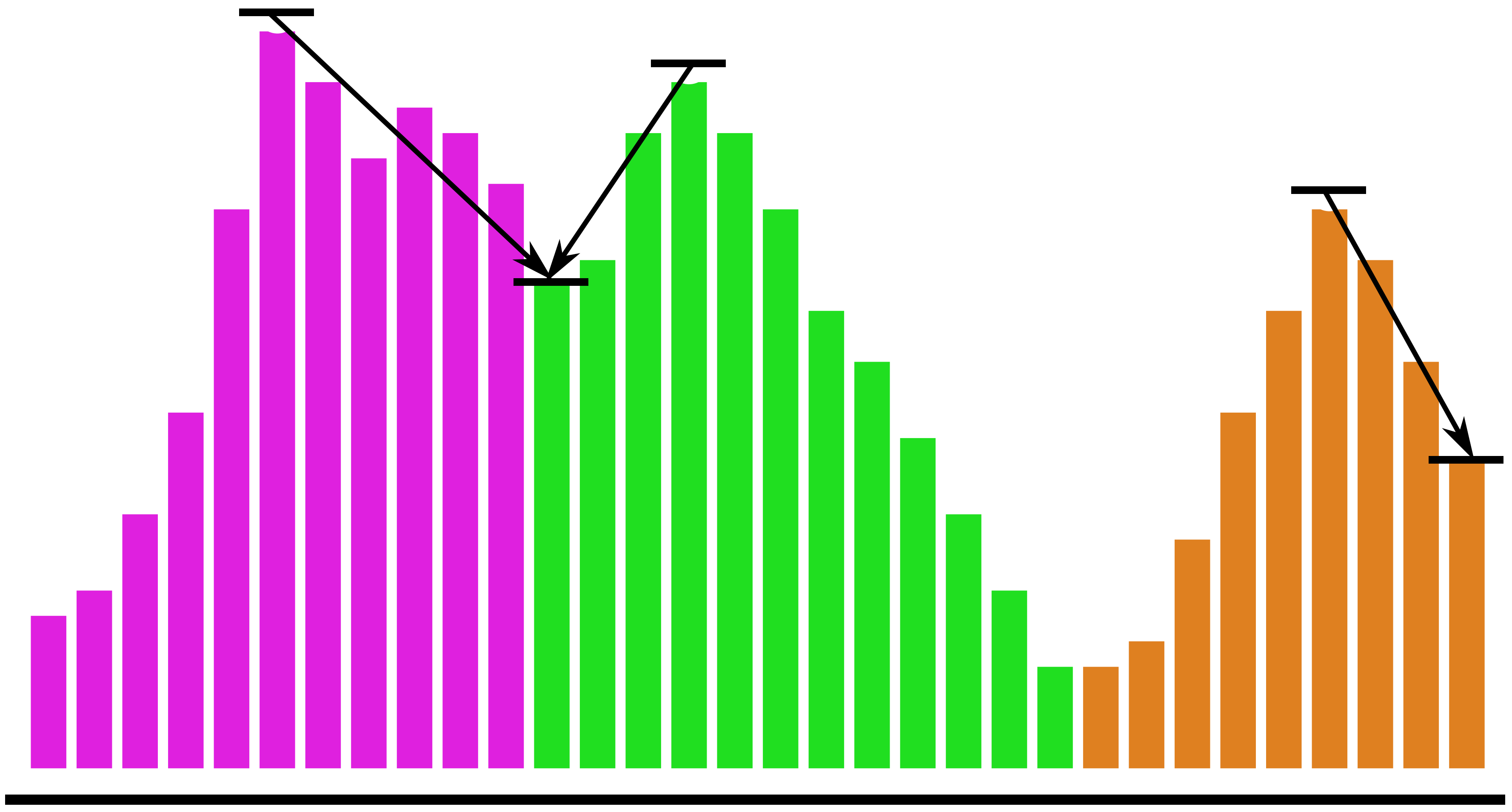

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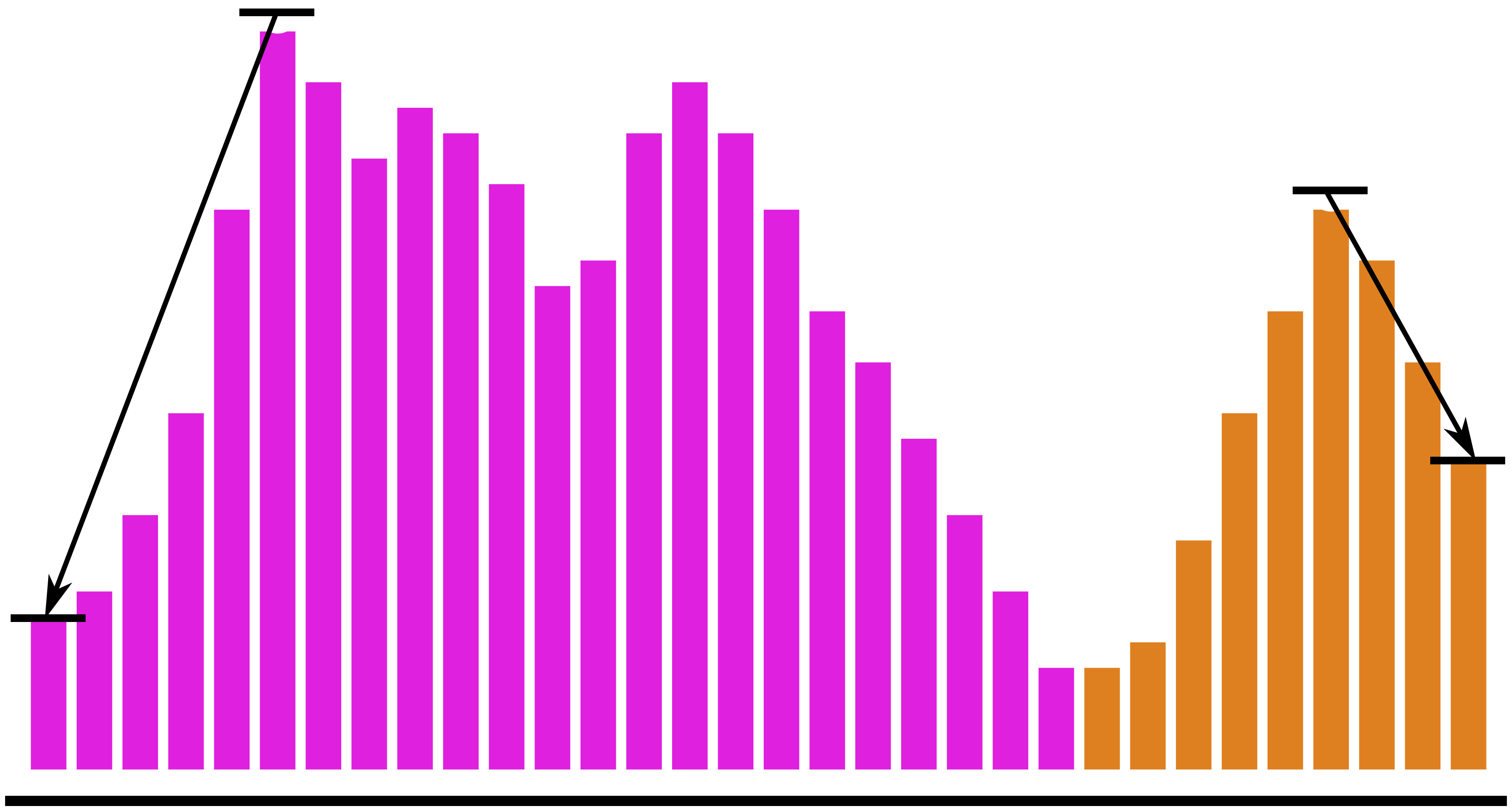
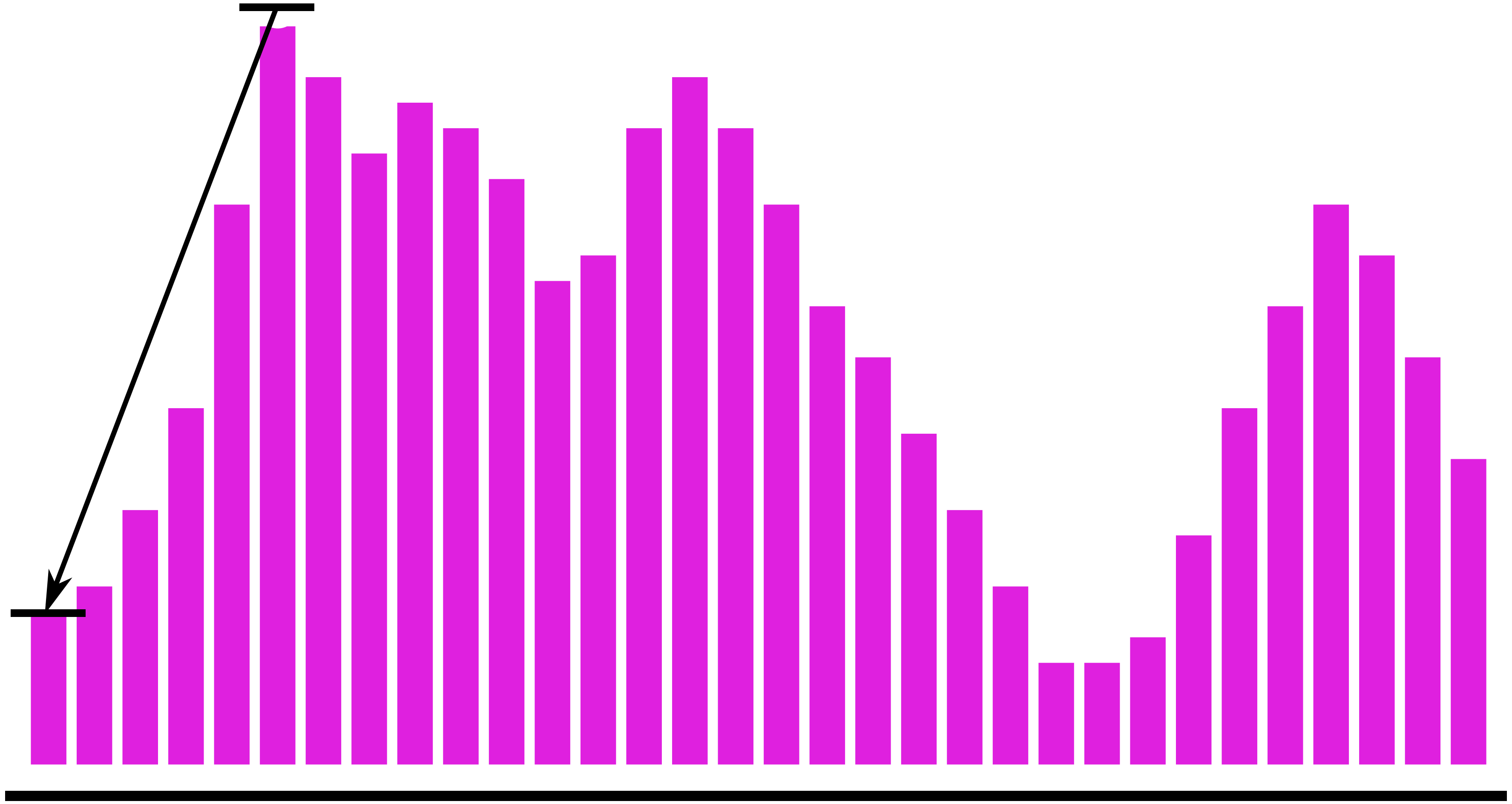
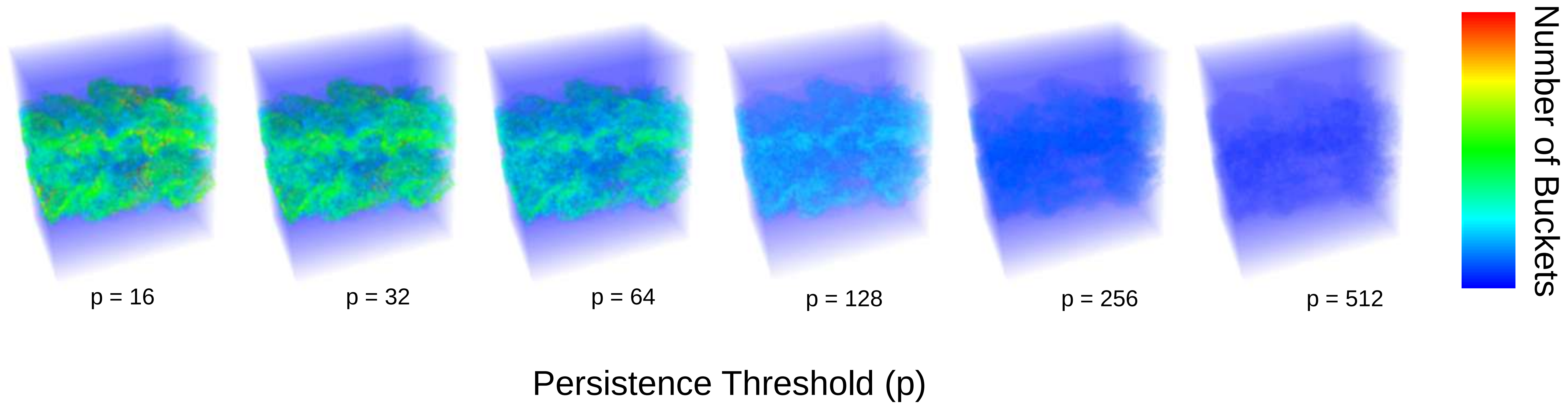


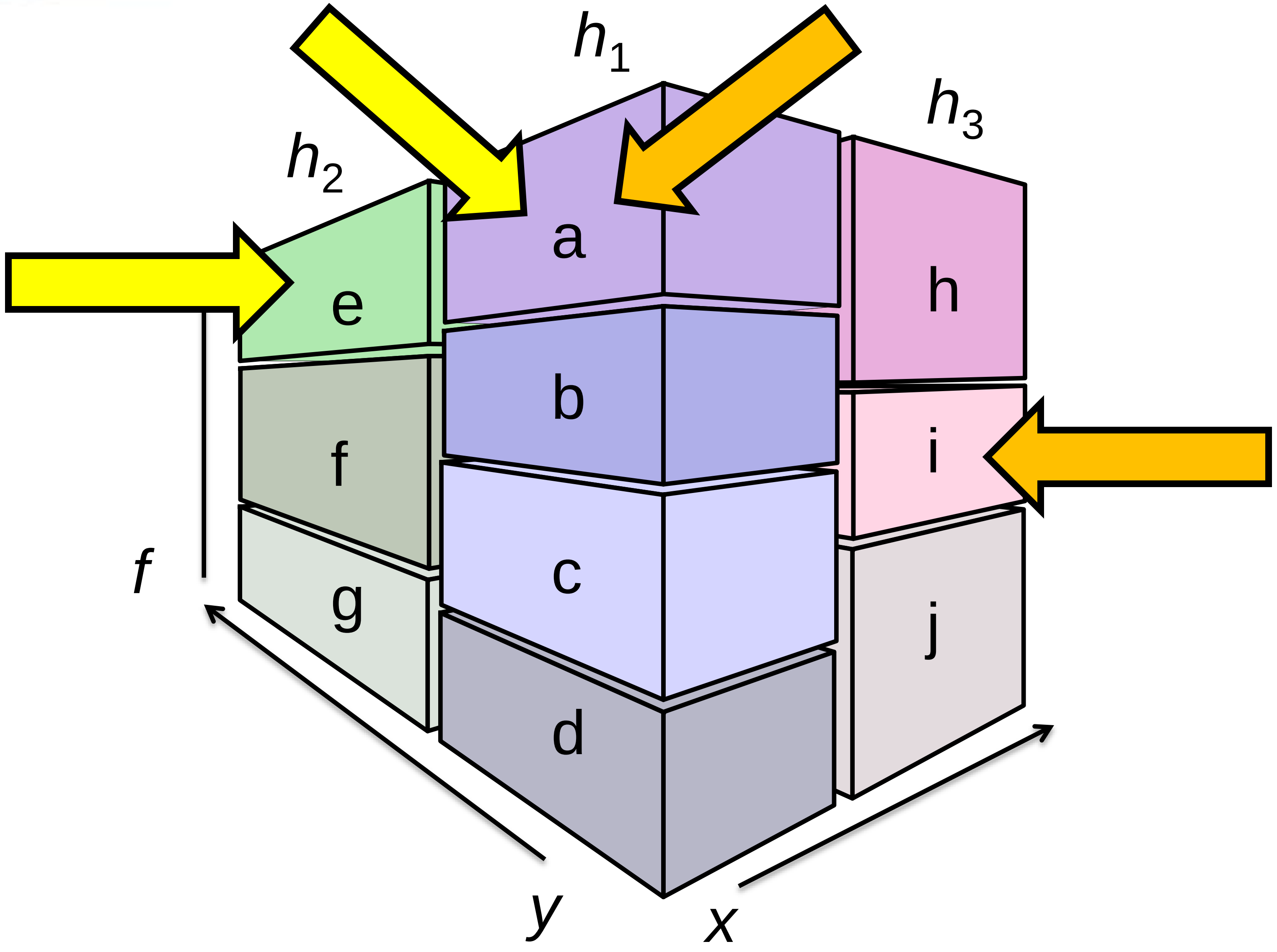
Persistence Simplification of Buckets



Effect of Persistence on Bucket Count



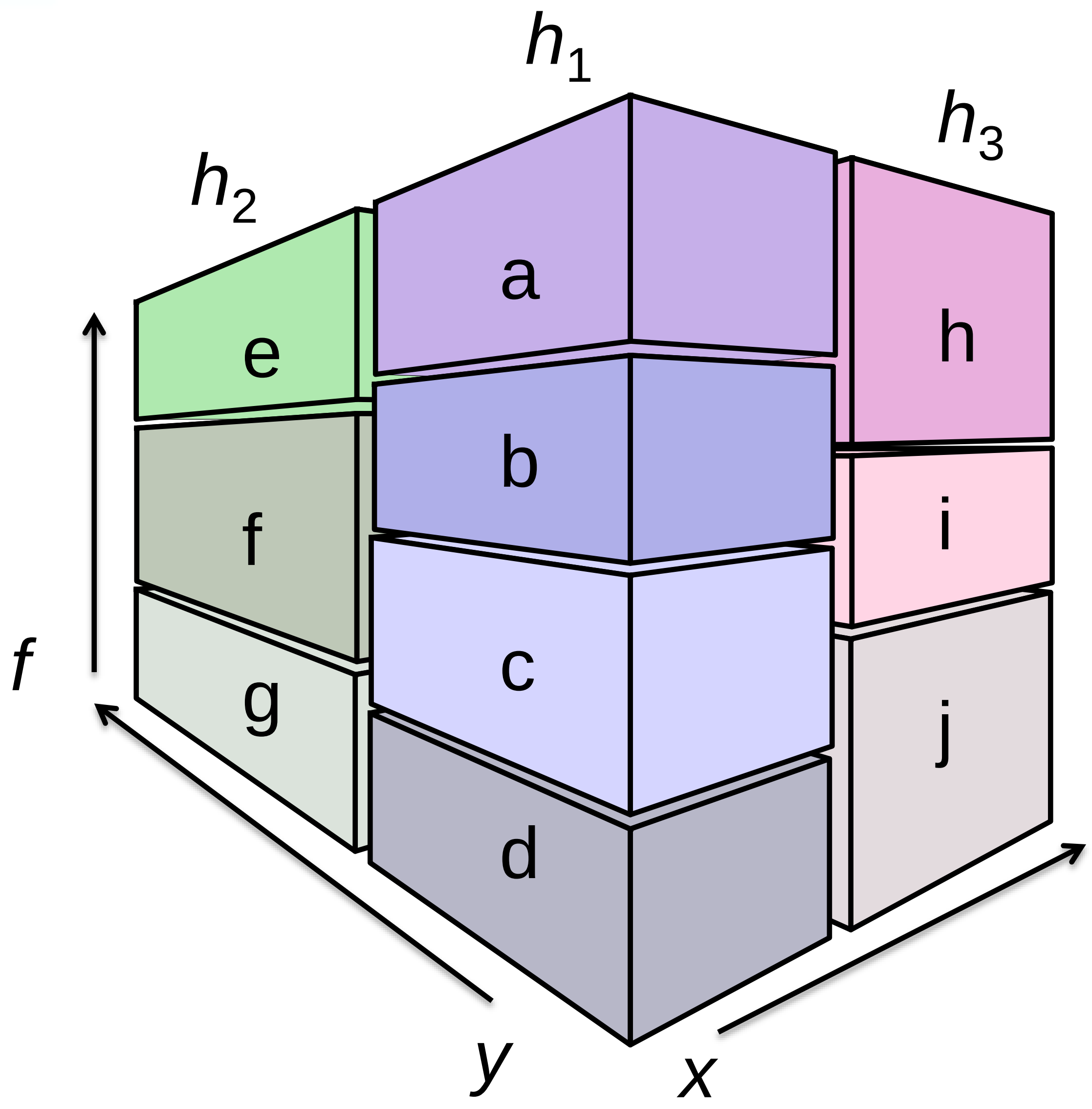
Contingency Tables on Bucketed Hixels



h_1-h_2	e	f	g
a	4	2	0
b	2	3	1
c	0	5	1
d	6	0	

h_1-h_3	h	i	j
a	5	1	0
b	1	4	1
c	2	4	0
d	0	1	5

Pointwise Mutual Information (PMI) Encodes Association Between Hixels

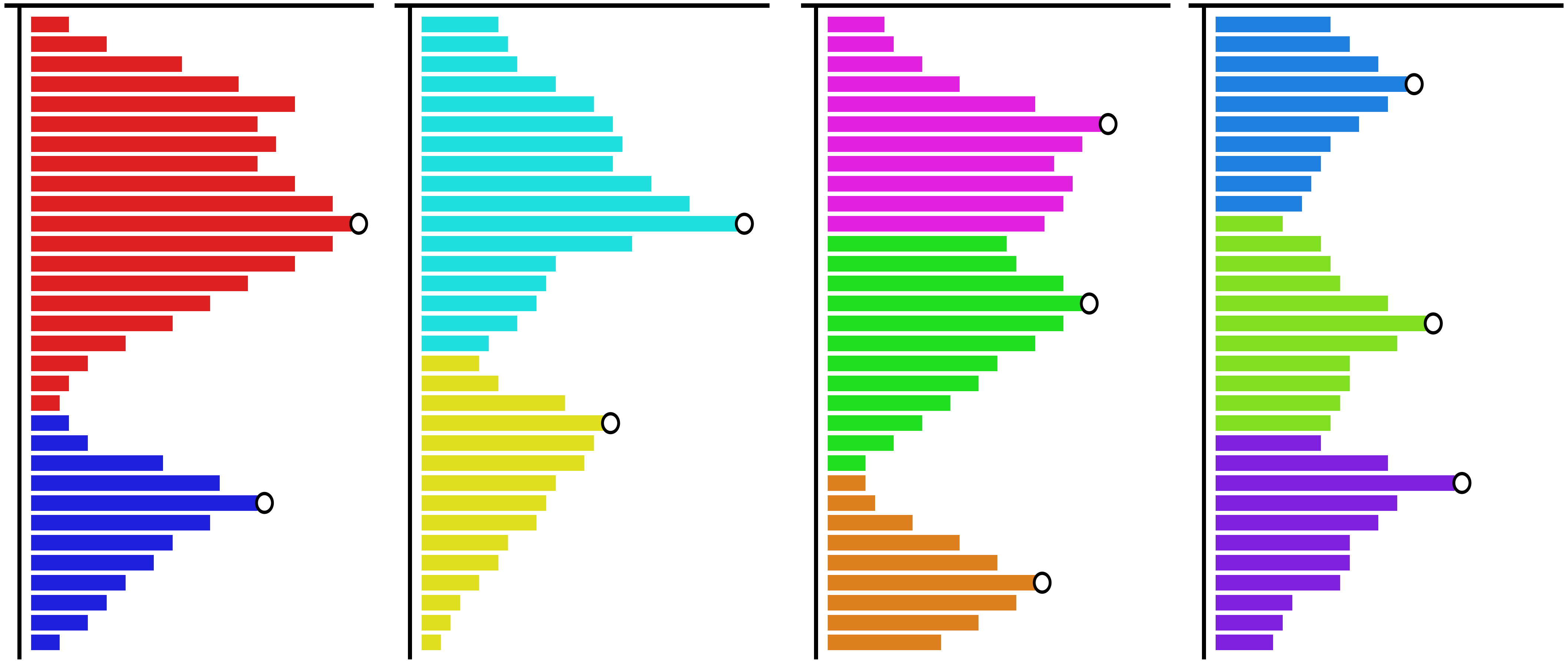


Goal: Identify buckets that co-occur more frequently than if statistically independent

$$\mathrm{pmi}(x,y) := \log\left(\frac{p_{(X,Y)}(x,y)}{p_X(x)\,p_Y(y)}\right)$$

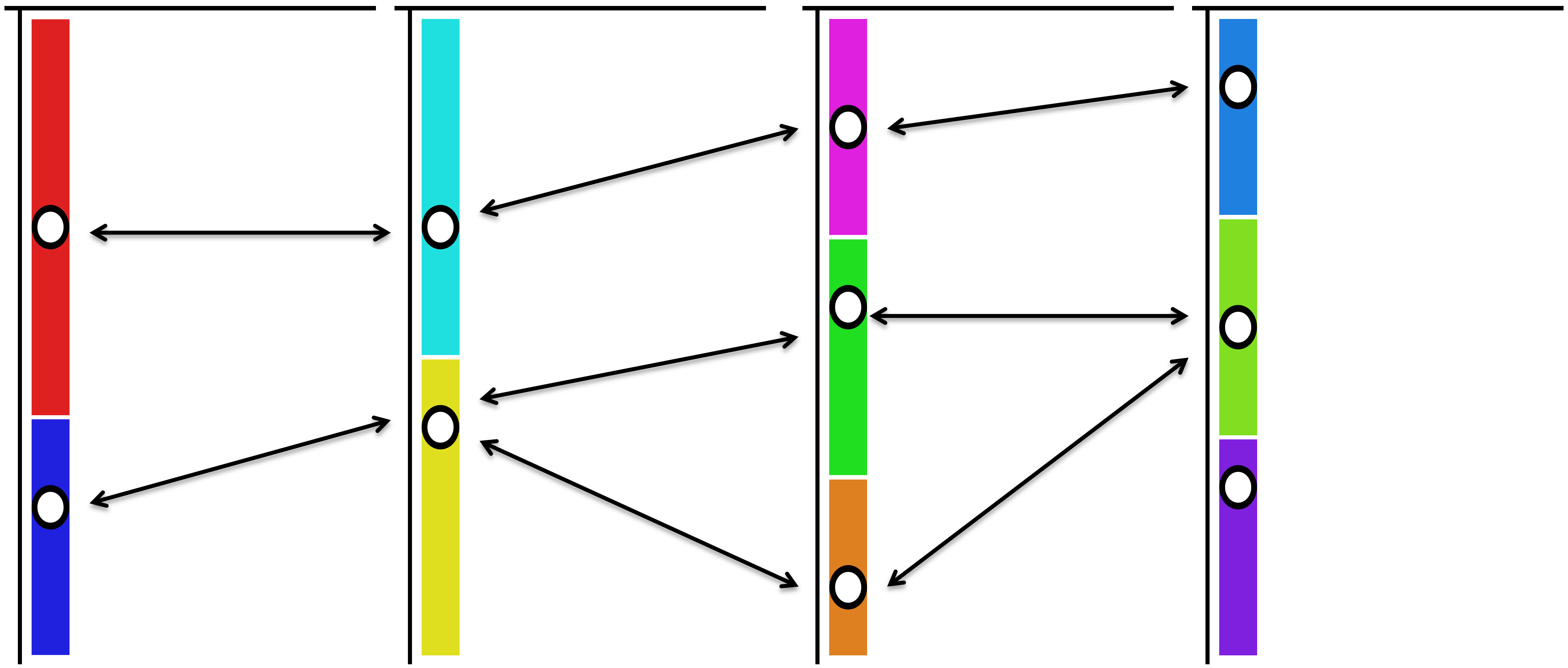
pmi(x,y)=0 => x independent y

Positive PMI Constructs Sheets of Statistically Associated Buckets



Before: Bucketed Hixels

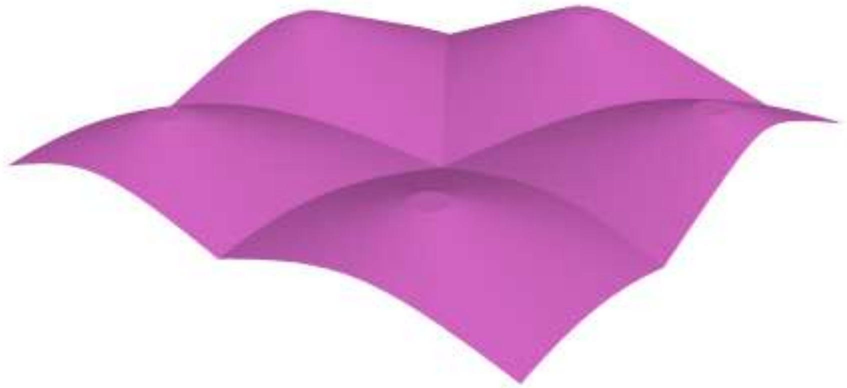
Positive PMI Constructs Sheets of Statistically Associated Buckets



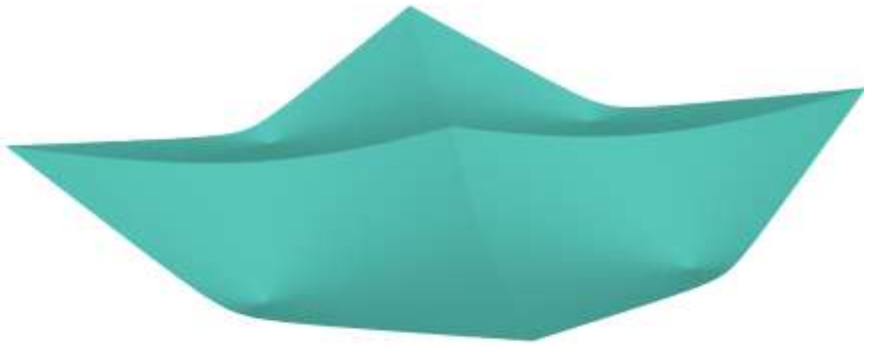
After: Sheets Connecting Buckets

An Ensemble of Mixed Distributions

- 512 x 512 hixels, 128 bins each
- 3200 samples from Poisson distribution
  - λ is a 100 at 5 source points in a circle
  - λ decreases to 12 $\propto$ distance from source points
- 9600 samples from a Gaussian distribution
  - μ & σ are min & max at 4 points in a circle
  - μ & σ vary μ distance from source points

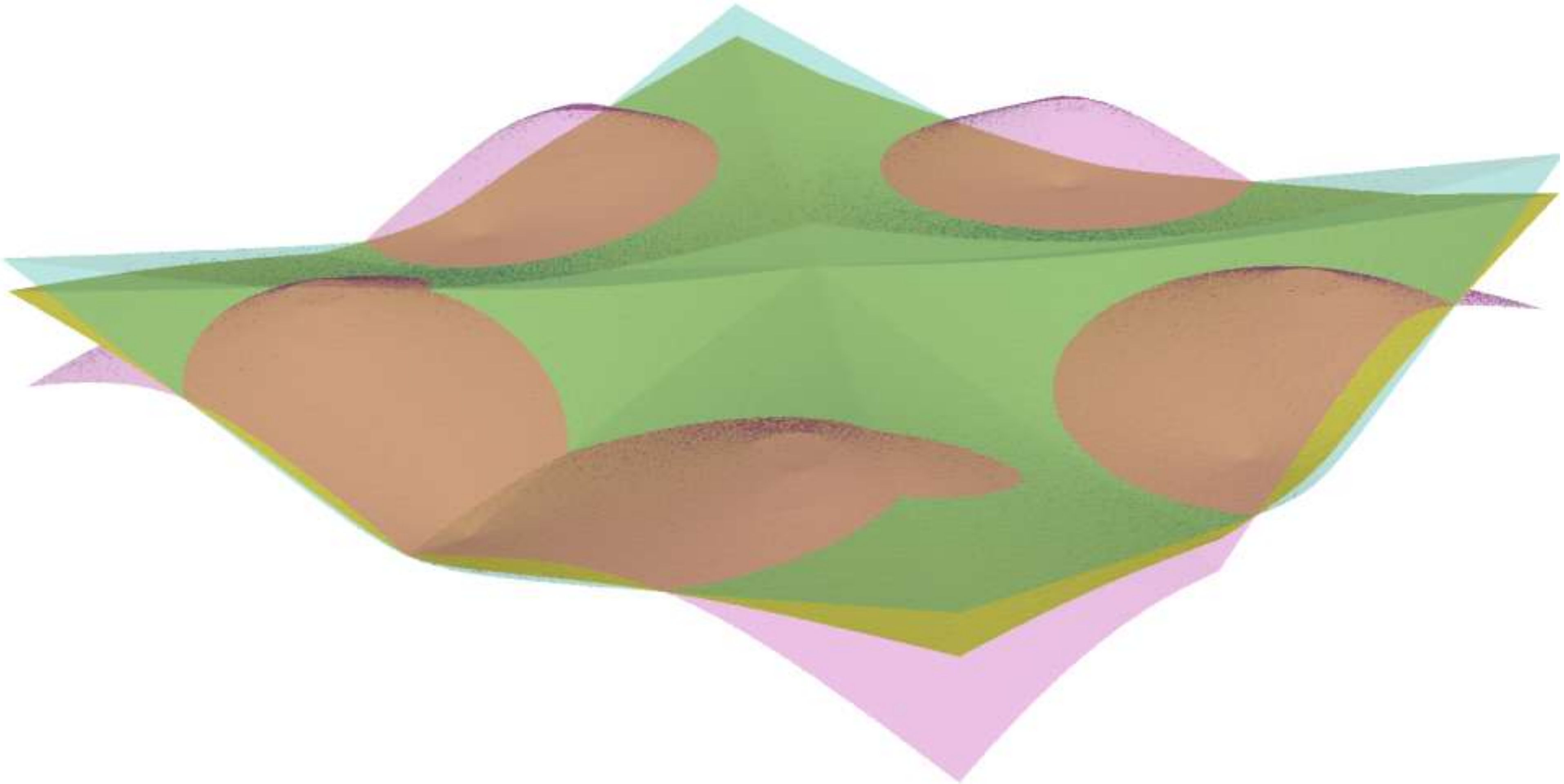


Mean Poisson Surface

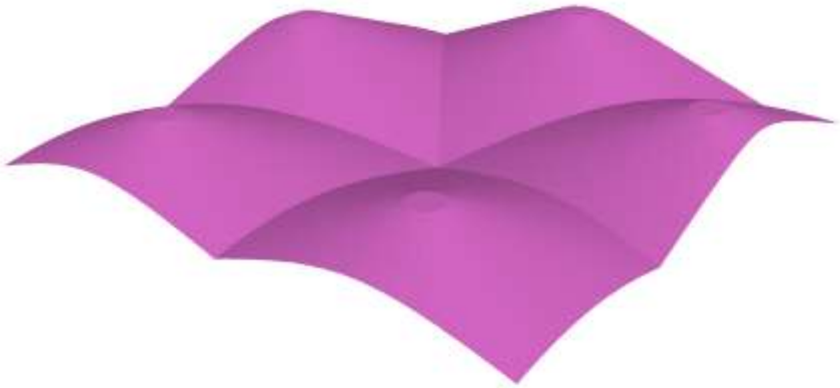


Mean Gaussian Surface

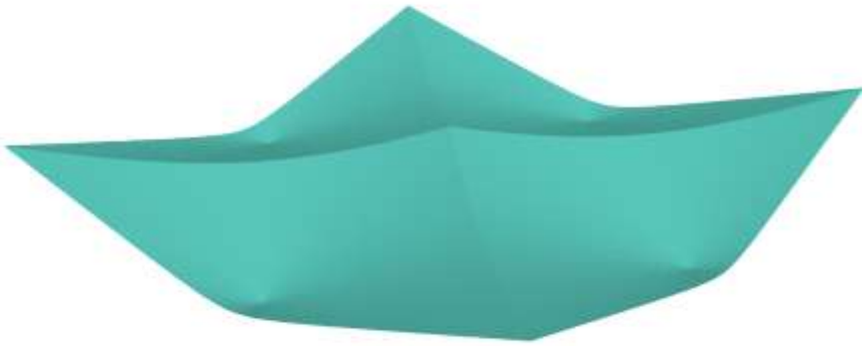
An Ensemble of Mixed Distributions



Mean Surface (Yellow) for Combined Samples



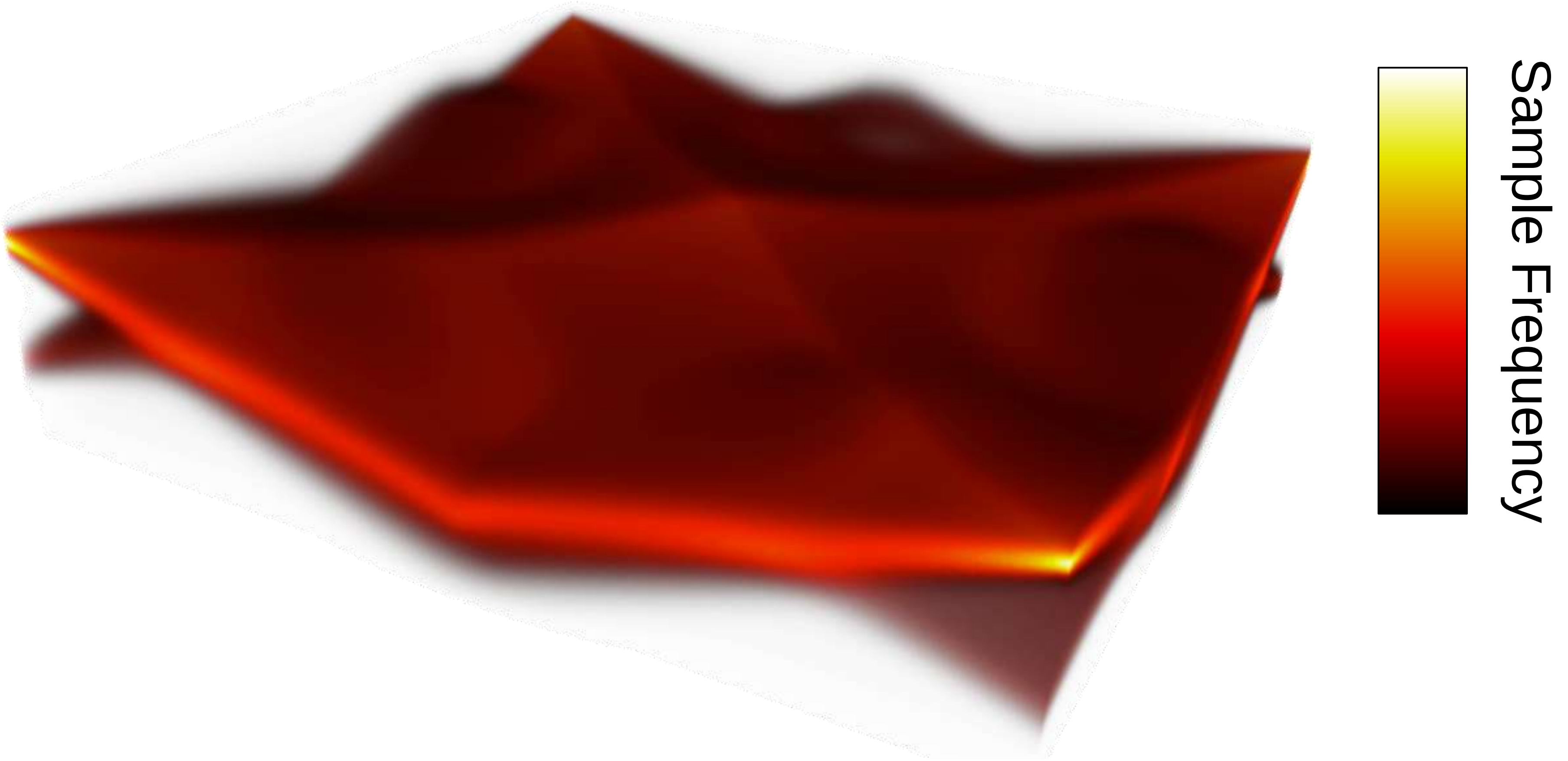
Mean Poisson Surface



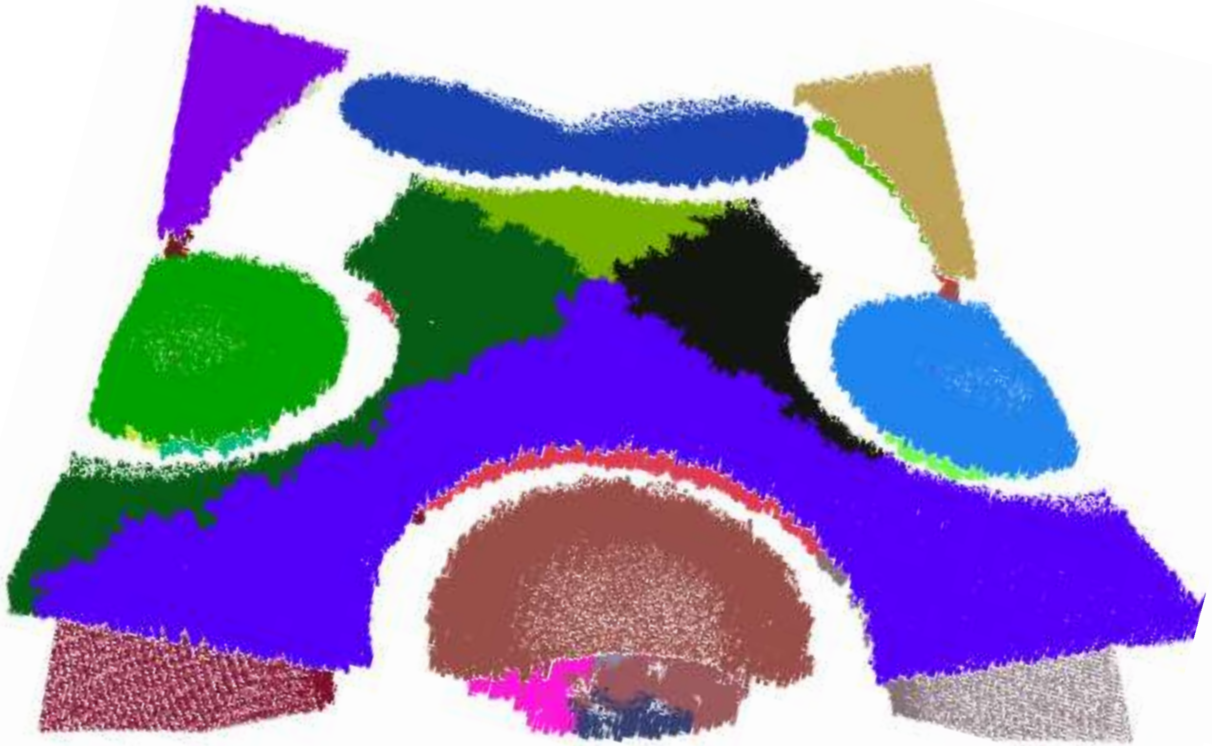
Mean Gaussian Surface

“Simple” Topological Tests Fail!

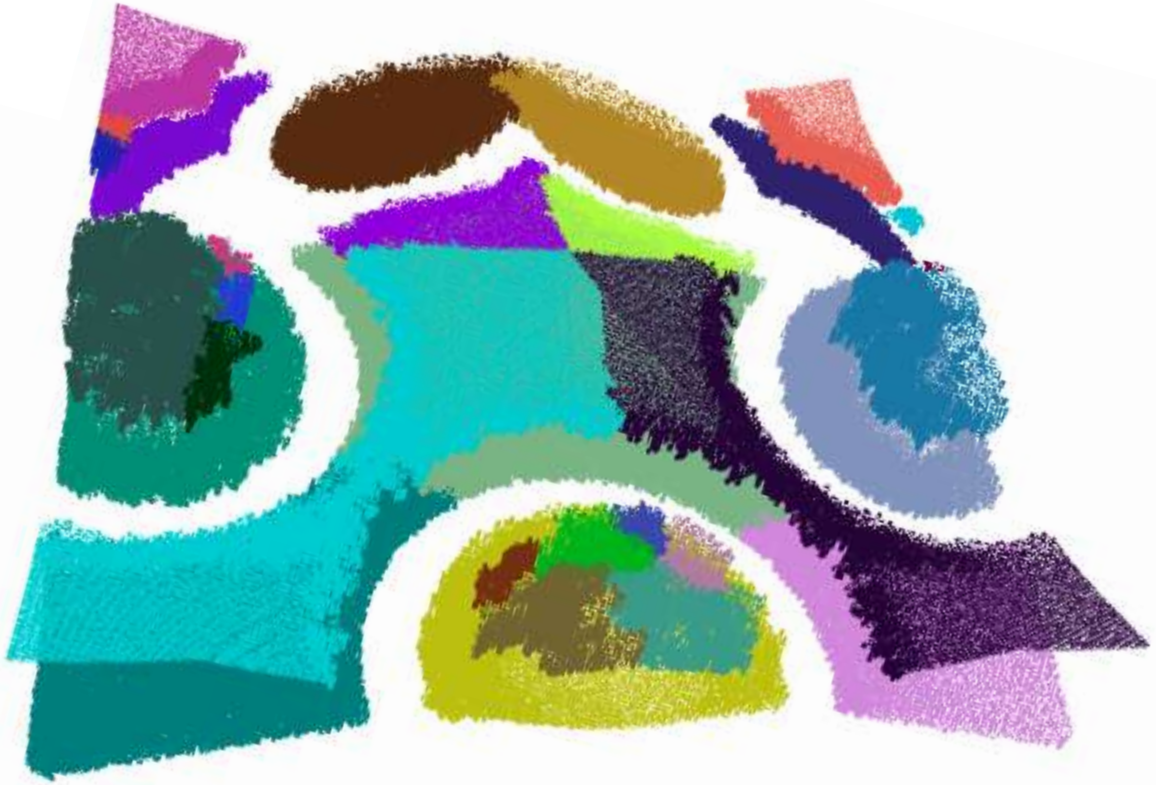
- Probability that each hixel corresponds to
  - Minimum ~ 20%
  - Maximum ~ 20%
  - Saddle ~ 7%
  - Regular point ~ 53%



Sheets Isolate Prominent Features

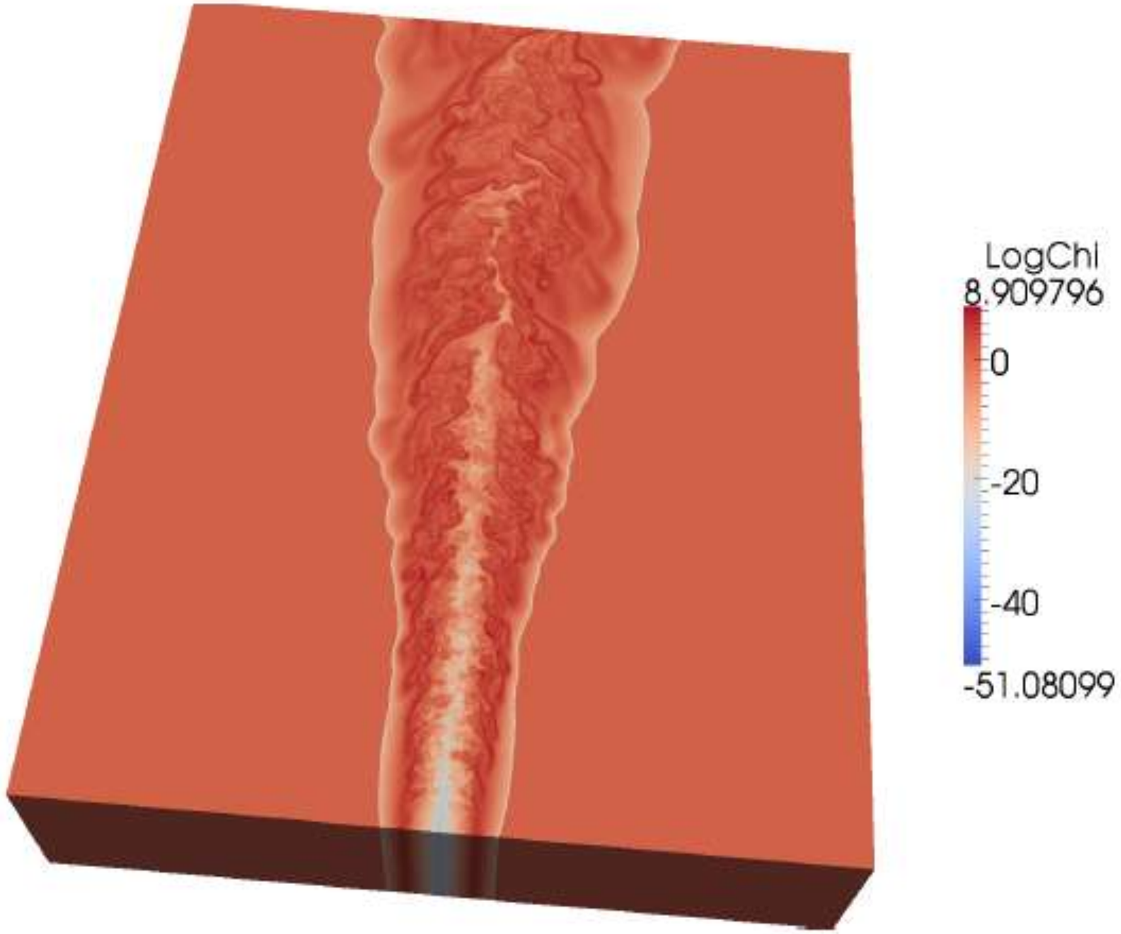


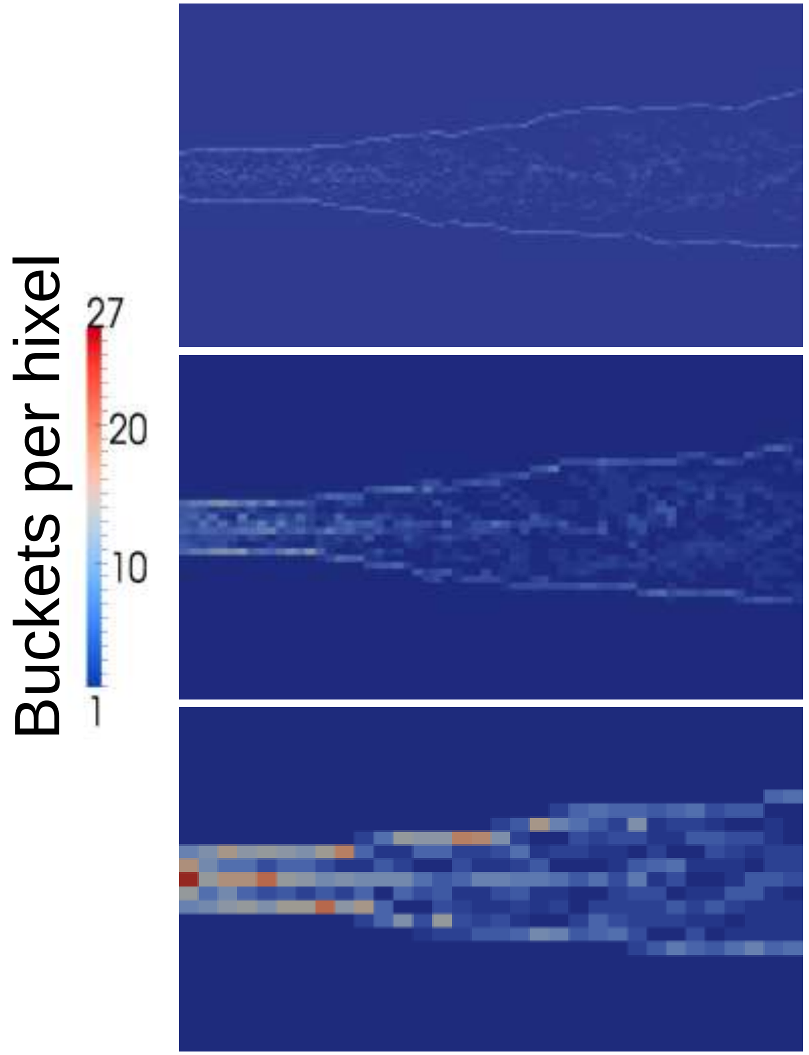
Basins of Minima

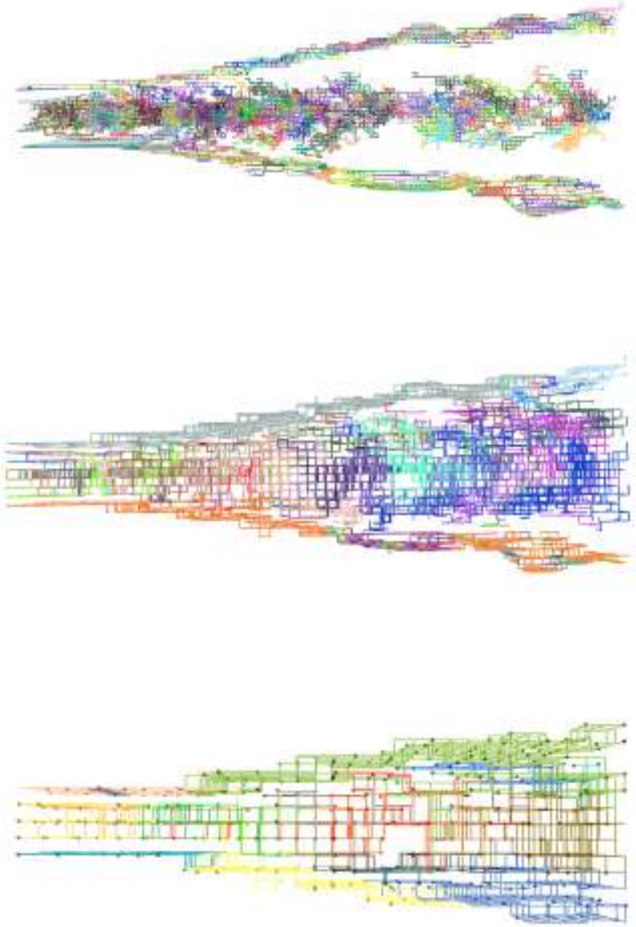


Basins of Maxima

Sheets for Lifted Ethylene Jet





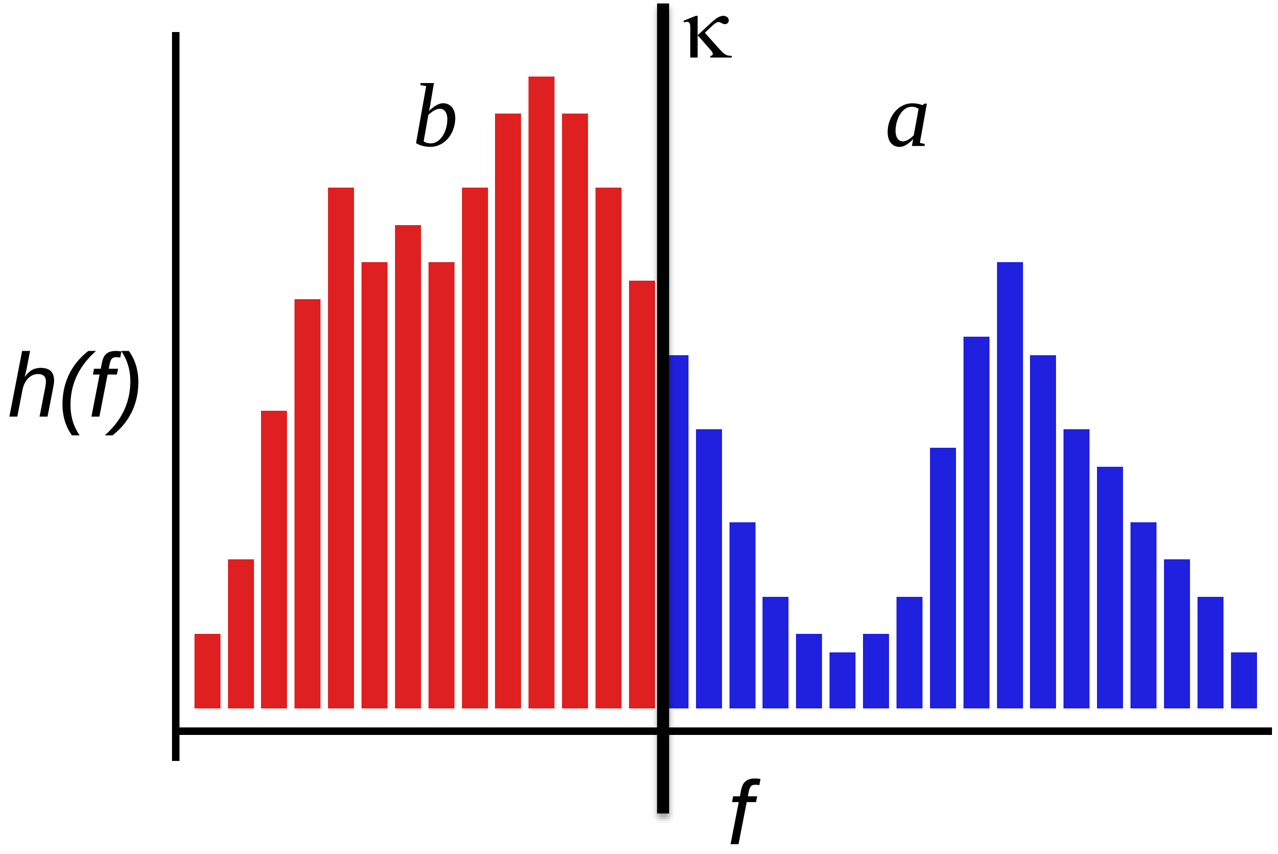


Visualizing Fuzzy Isosurfaces: Algorithm

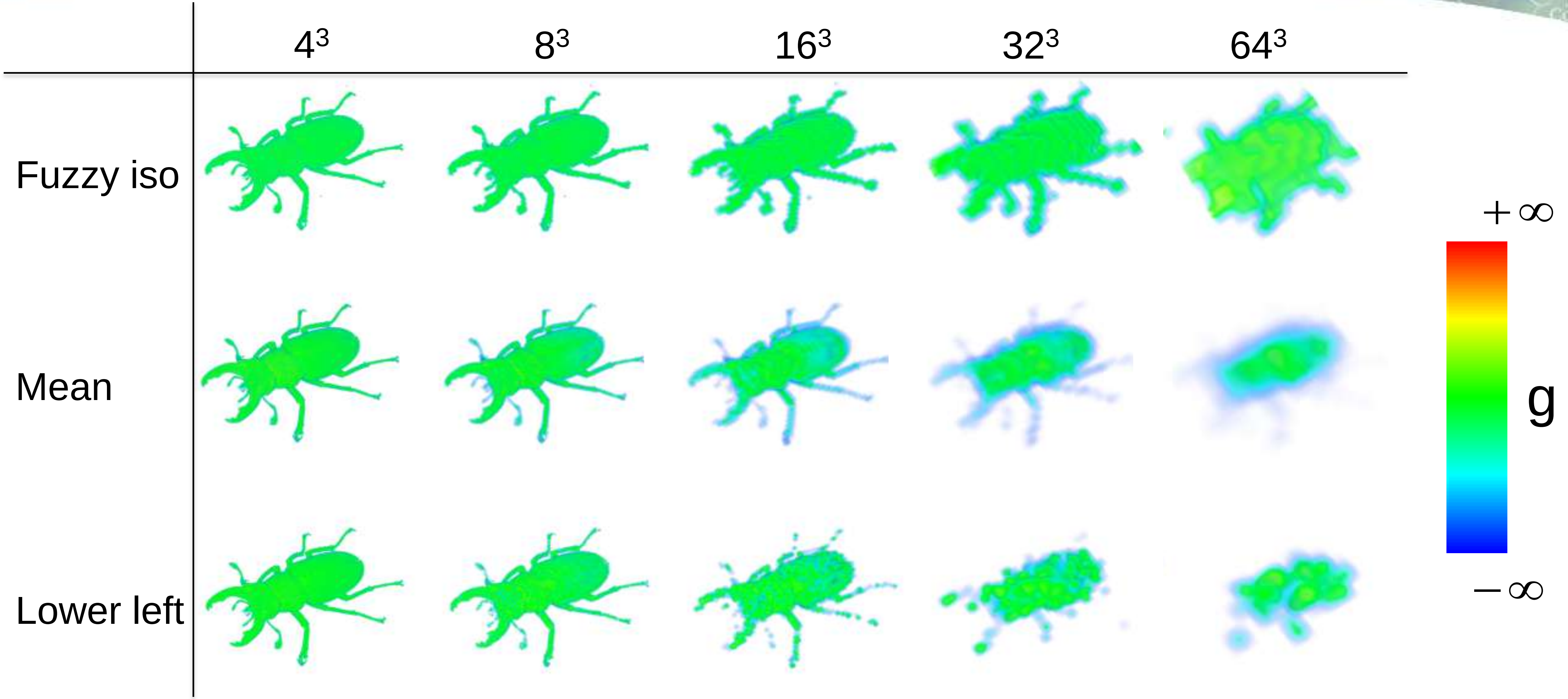
1. Compute likelihood function g

$$g = \begin{cases} a, & b = 0 \\ -b, & a = 0 \\ \dfrac{a}{b} - \dfrac{b}{a}, & \text{otherwise} \end{cases}$$

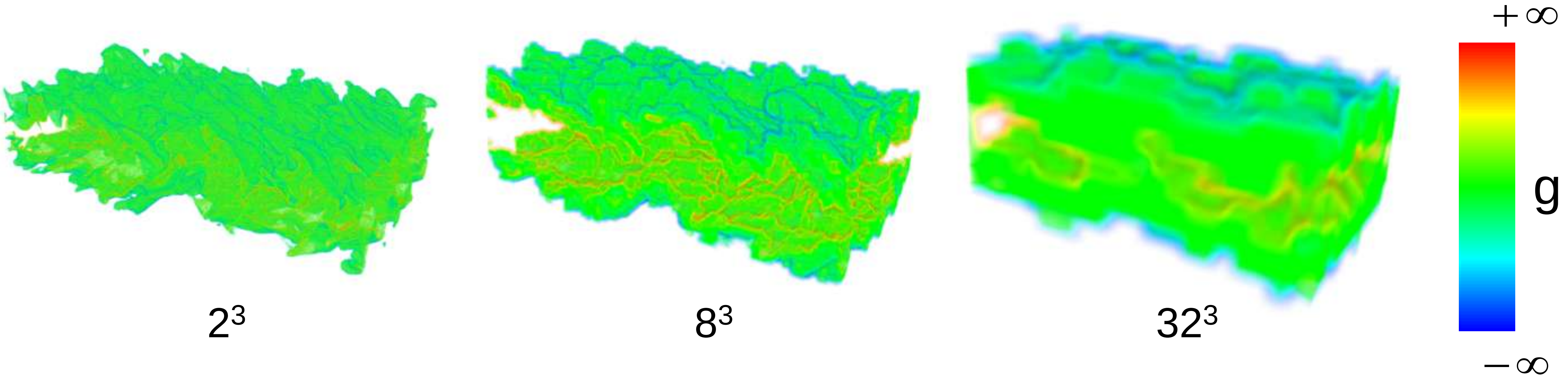
2. Volume render g
   - Provides a fuzzy description of the likelihood of where an isosurface exists



Comparison to Downsampling



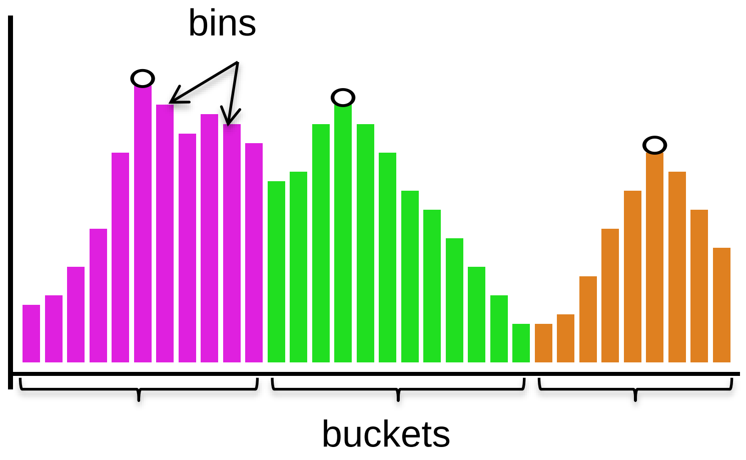
Fuzzy Isosurface of Temporal Jet

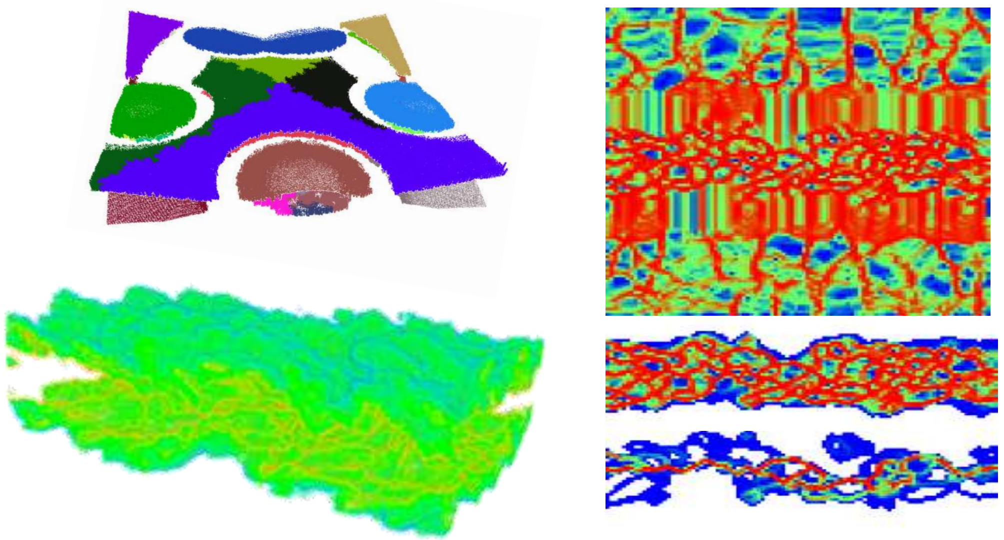


Likelihood that isovalue $\kappa = 0.506$ passes through a hixel

Conclusions and Summary

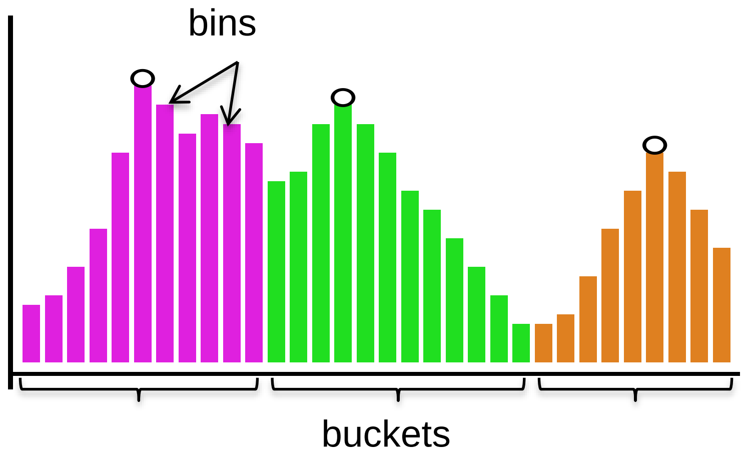
- Unified representations of large scalar fields from various modalities
- 3 proof of concept applications
  - Sampled topology
  - Topological analysis of statistically associated buckets
  - Visualizing fuzzy isosurfaces

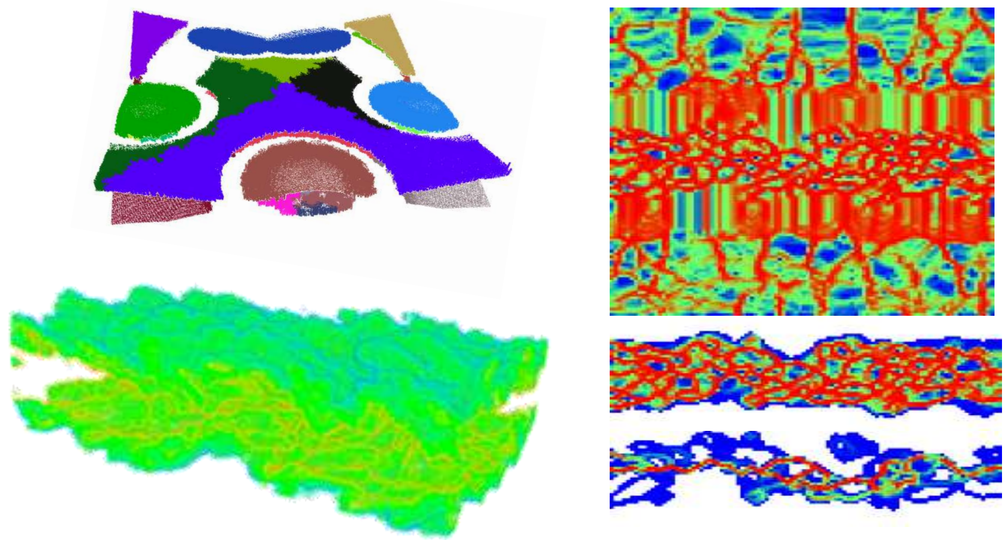




Future Work

- Larger ensembles/larger data
- Performance/scaling
- Infer sheets from multivariate hixels
- Issues to study
  - What is preserved by hixels vs. resolution loss
  - Identify appropriate number of bins/hixel
  - Persistence thresholds for bucketing algorithm
  - Balance data storage vs. feature preservation
  - What topological features can/cannot be preserved by hixelation





Acknowledgement

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