



# Feature-Based Statistical Analysis of Combustion Simulation Data

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# Motivation: state of the art simulations generate large-scale, complex data

- Increases in data size + complexity
  - Spatial resolution
  - Number of variables
  - Number of scales represented
- Our contribution: a feature-based analysis and visualization framework for large-scale data

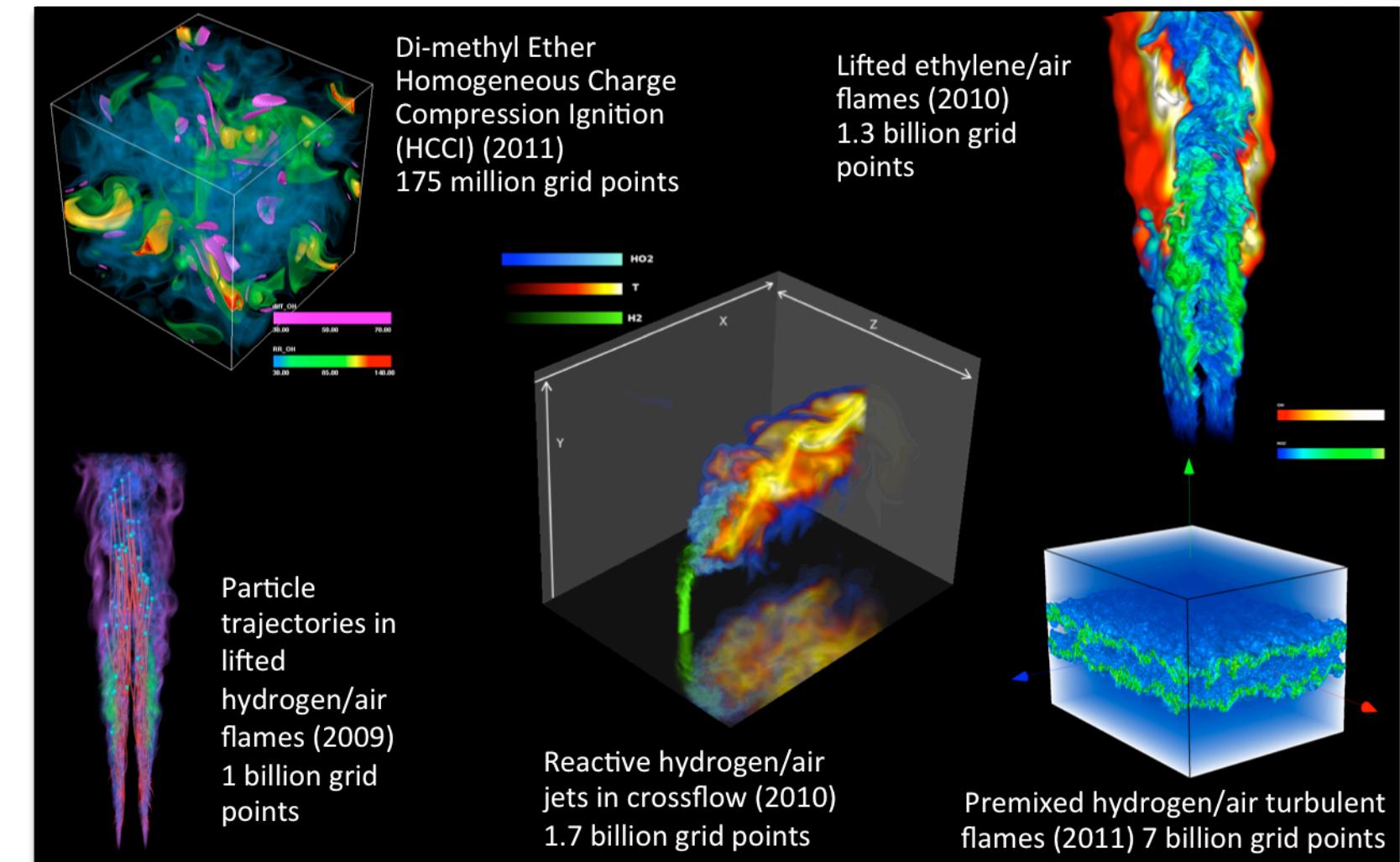


Images courtesy of: National Energy Research Scientific Computing Center, Los Alamos National Laboratory, Argonne National Laboratory, and Oak Ridge Leadership Computing Facility.



# Direct Numerical Simulations (DNS) are used to study fundamental turbulence-chemistry interactions

- DNS data is large and complex
- How do you define features?
  - Thresholds may vary locally
  - Thresholds may not be known *a priori*
- How many features are there?
- What is the behavior of other variables inside the features?



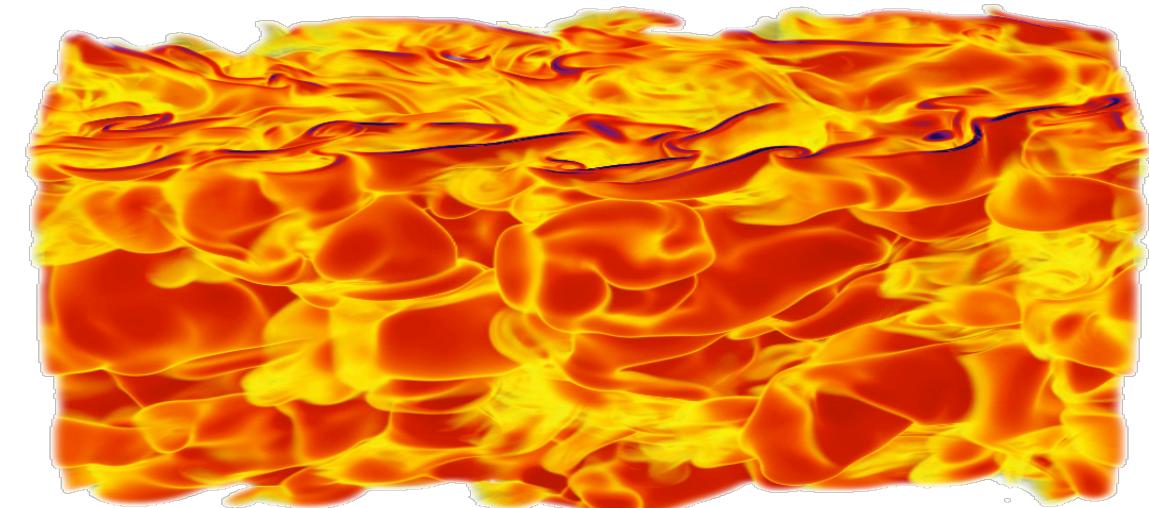
Recent DNS configurations performed using S3D, a DNS code written by Dr. Jacqueline Chen & her research group at the Combustion Research Facility, Sandia National Laboratories



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# Case study: characterizing the relationship between the mean temperature and thickness in regions of high $\chi$

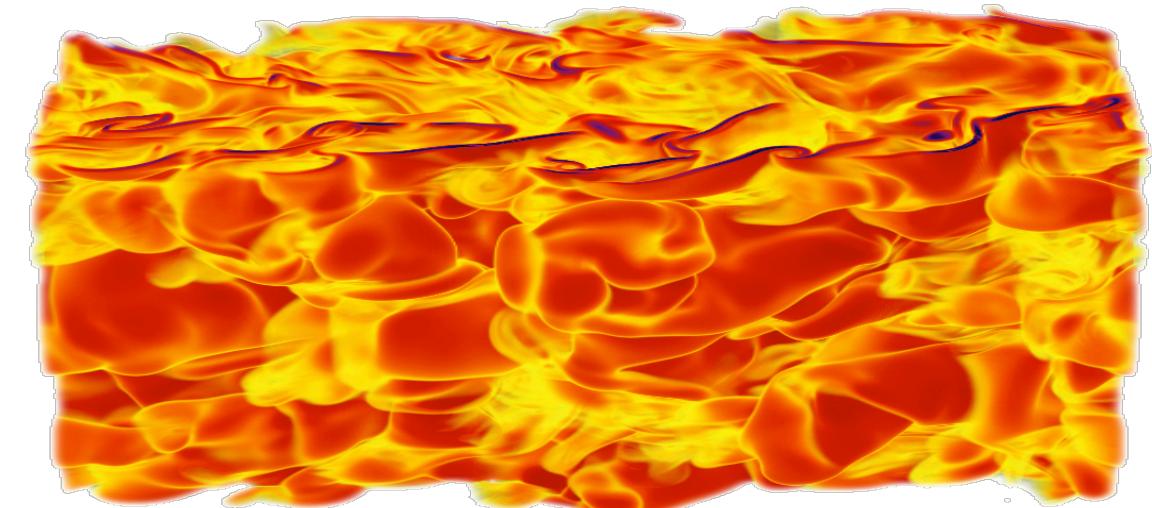
- Scalar dissipation rate,  $\chi$ : rate of molecular mixing
- Goals:
  - Study relationship between mechanical strains & chemical processes
  - Compute feature-based statistical summaries



# Case study: characterizing the relationship between the mean temperature and thickness in regions of high $\chi$

## Challenges:

- $\chi$  structures are defined by locally varying isovales
- Sub-selection based on other criteria is important
- Visual feedback of the effect of parameter choices is desired
- Large data complicates matters



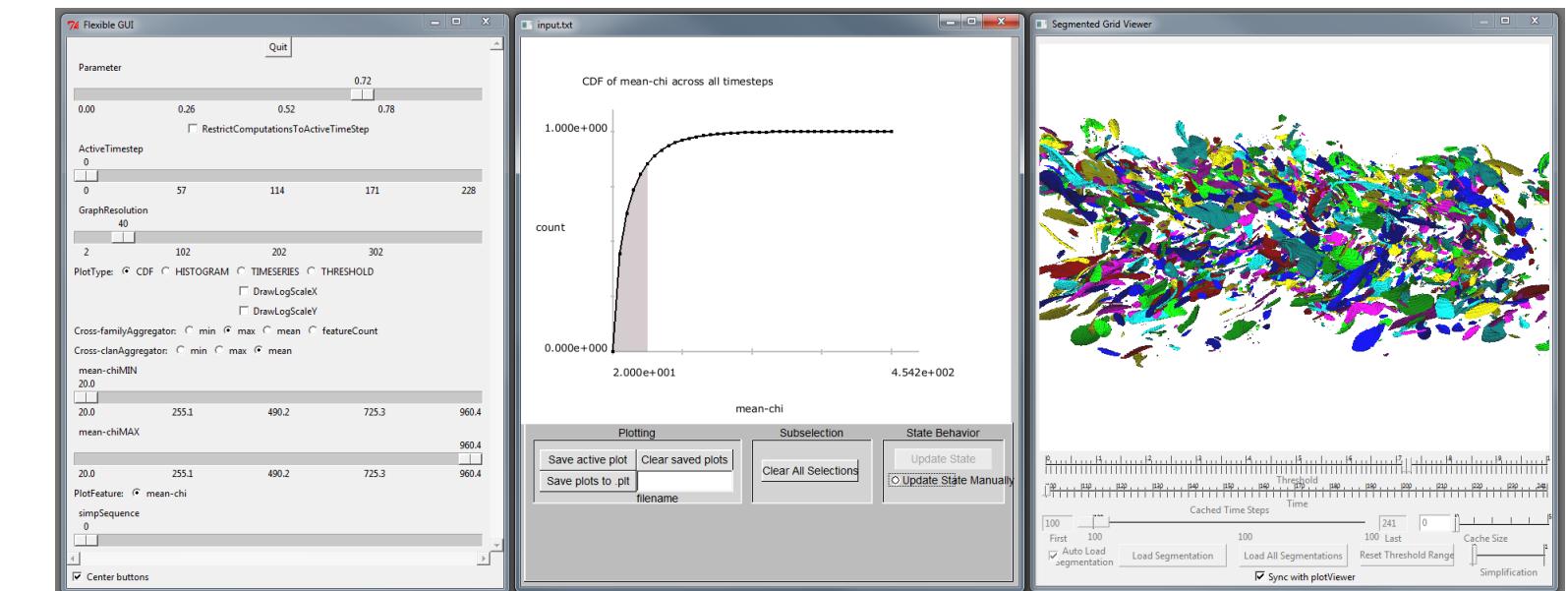
# Related Work

- Conditional statistics
- Data warehouse technologies: *e.g.* FastBit [Wu, *et al.*]
  - + Extracts and aggregates pre-computed information
  - + Uses compressed bit map indices to provide efficient sub-selections
  - Regions cannot always be defined by range queries
  - Feature parameter thresholds not always known *a priori*
- Feature hierarchies
  - Merge Trees [Carr *et al.*, Pascucci *et al.*],
  - Morse-Smale Complex [Laney *et al.*, Bremer *et al.*, Gyulassy *et al.*]
  - Clustering methods [Hartigan]



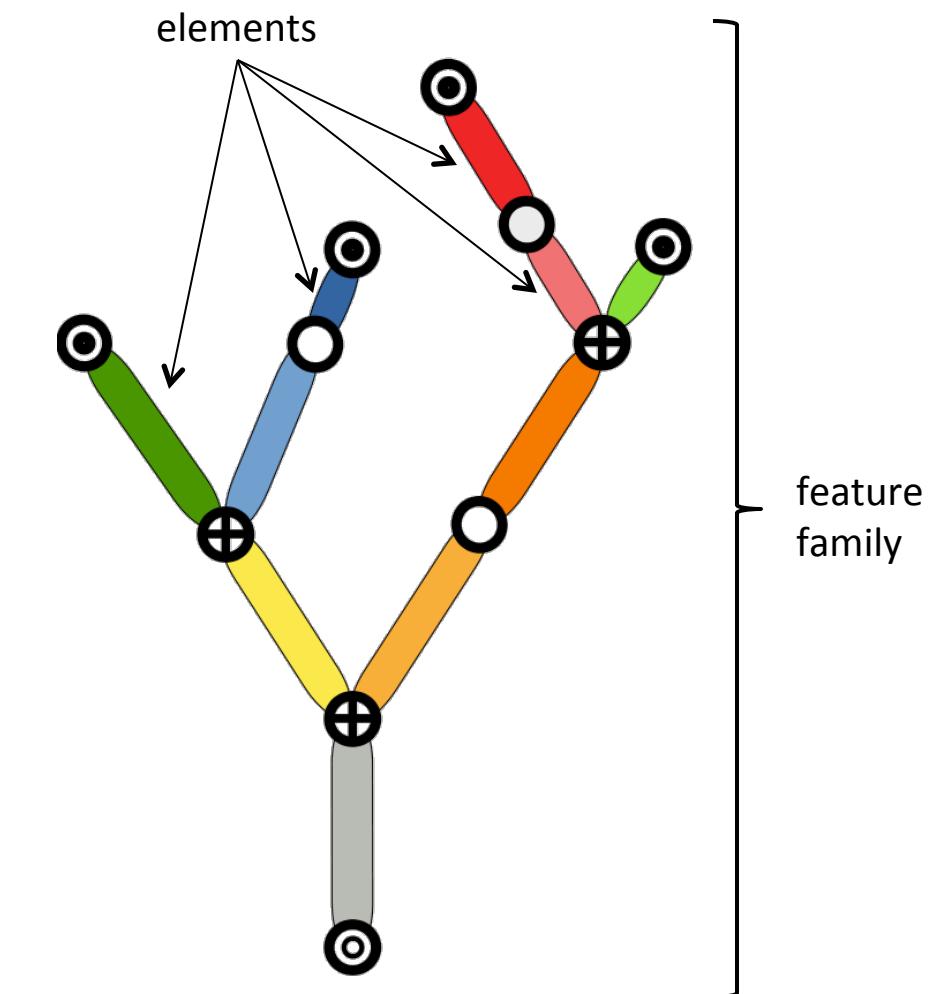
# We have developed an integrated feature-based analysis & visualization framework to study large scientific data

- Pre-compute meta-data
  - Efficient encoding for multi-resolution hierarchies & statistics
  - Drastic data reduction
  - Preserves moments
- Interactive exploration
  - On the fly aggregation of feature-based spatial & temporal statistics
  - Creation of spatial & temporal statistical summaries
  - Linked view display of statistics & features



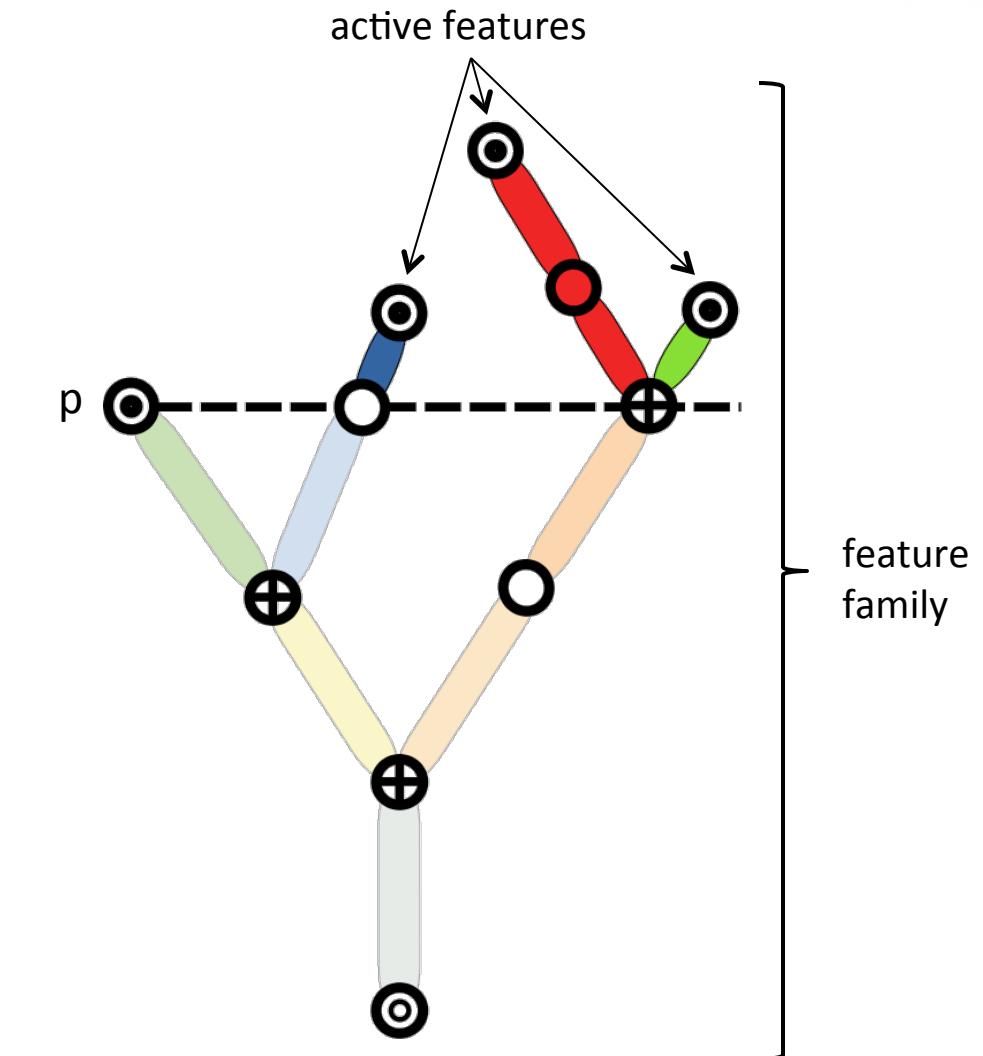
# Augmented feature families form a compact data representation

- Element: spatial region of the input domain
  - Life span information
  - Parent/child information
  - Optional associated statistics
- Feature: collection of elements
- Feature Family: one-parameter family of features
  - Active features are identified by specifying a parameter value
- Clan: collection of feature families
  - *e.g.* across time steps

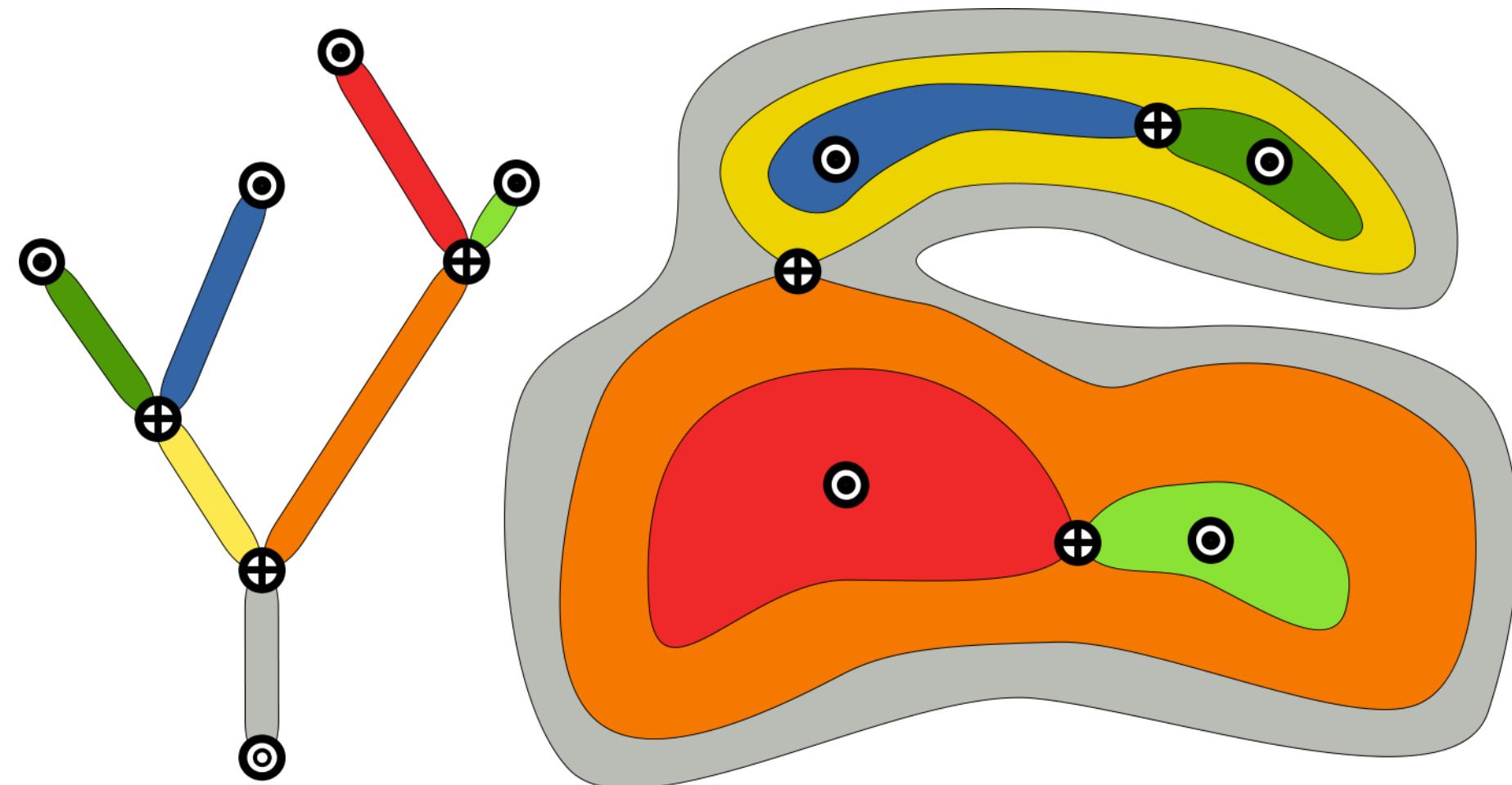


# Augmented feature families form a compact data representation

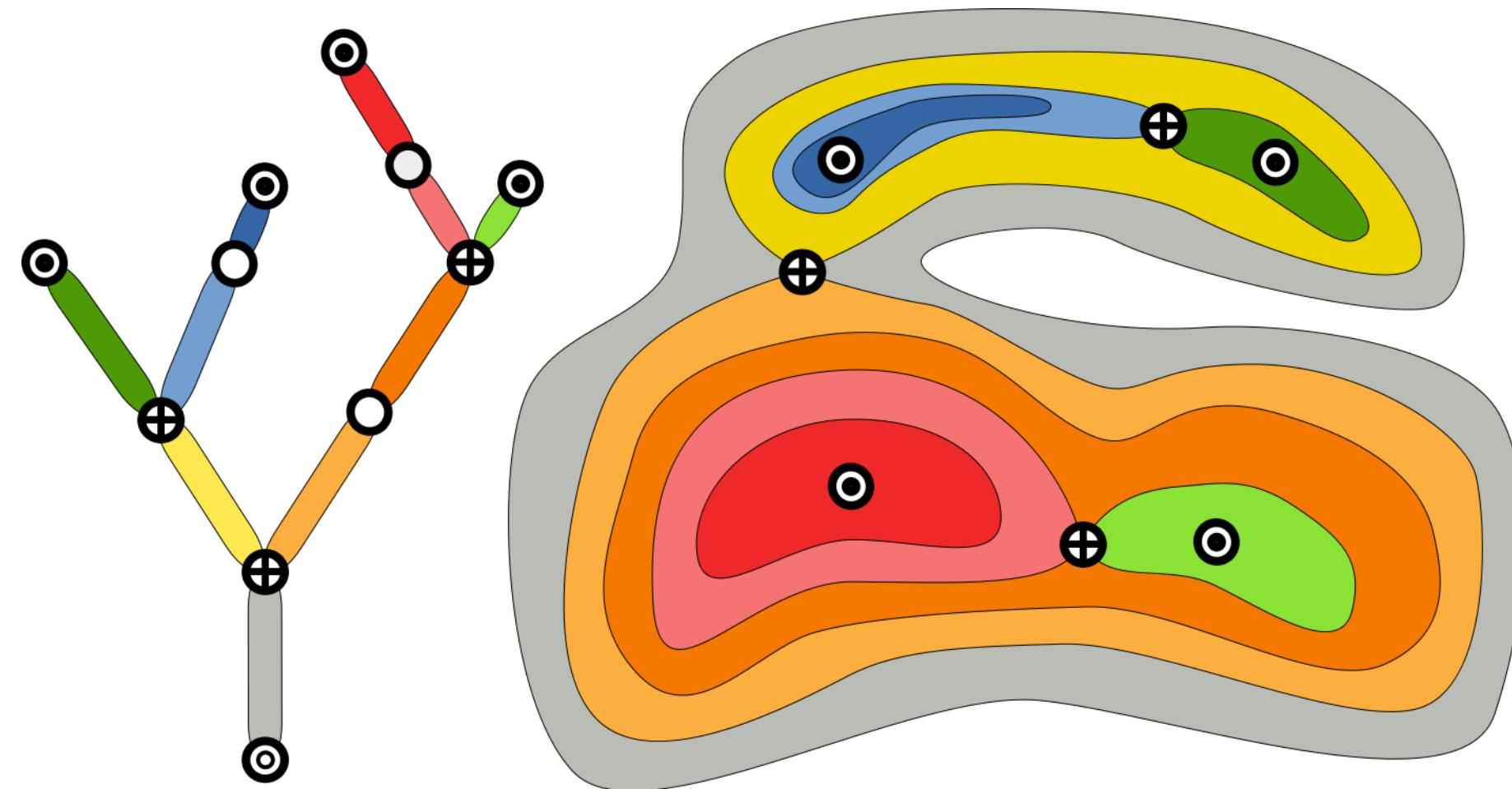
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# The merge tree segments a domain according to a function's level-set behavior



# The resolution of the parameter space is increased by splitting long branches

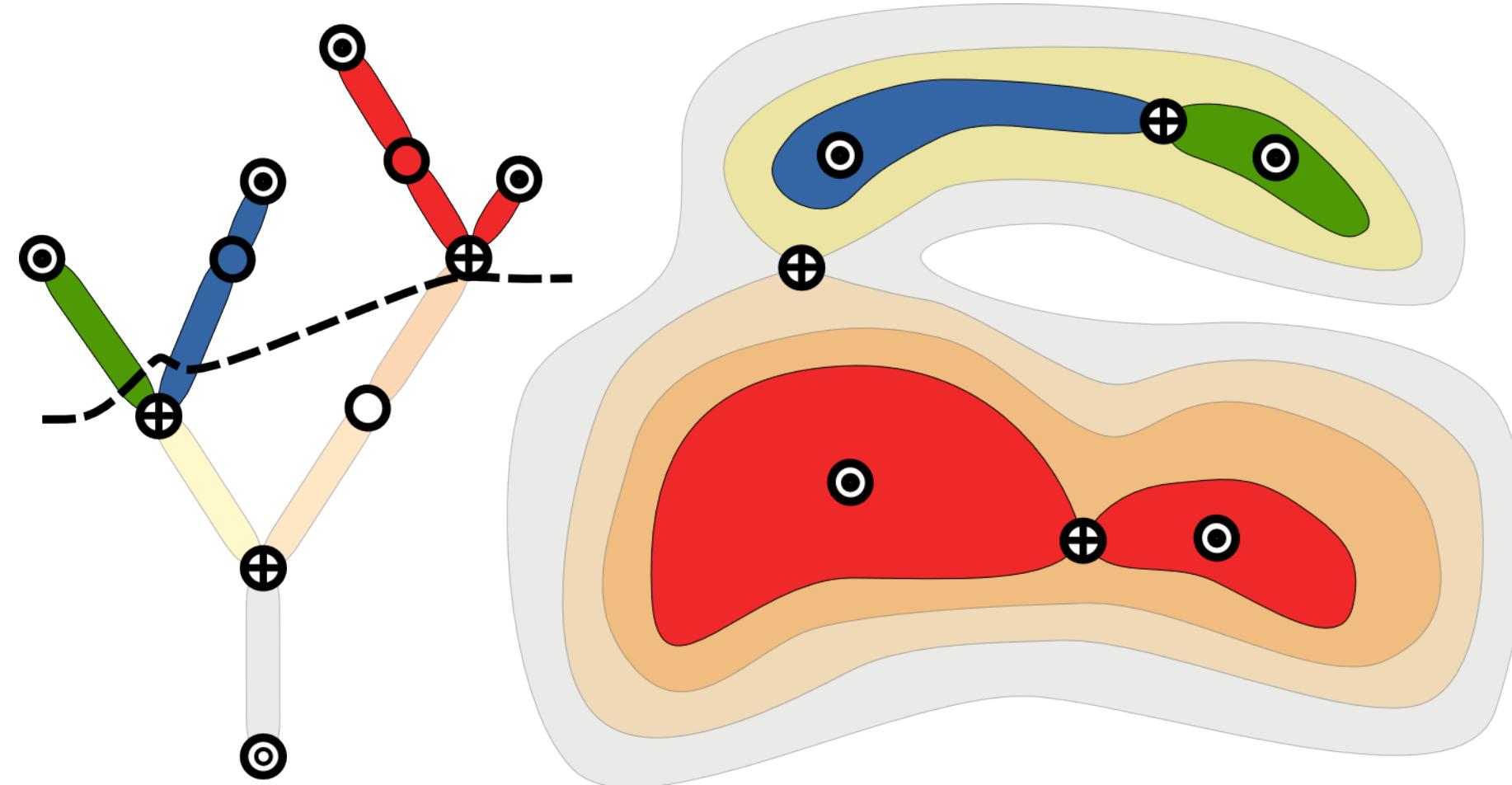


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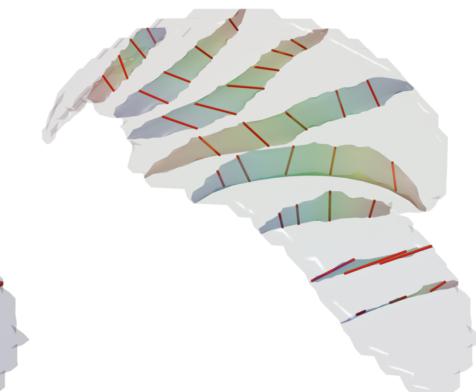
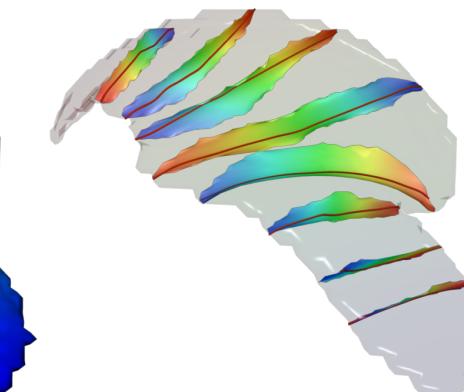
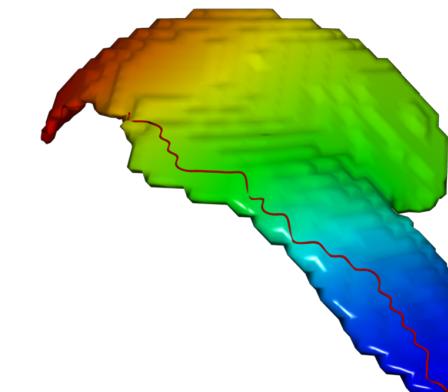
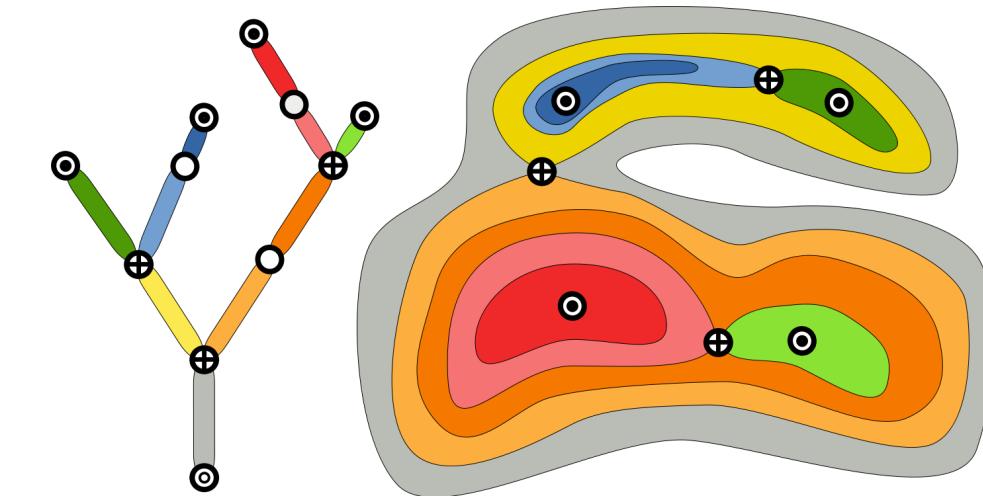
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# A relevance-based persistence measure is used to explore the augmented feature family

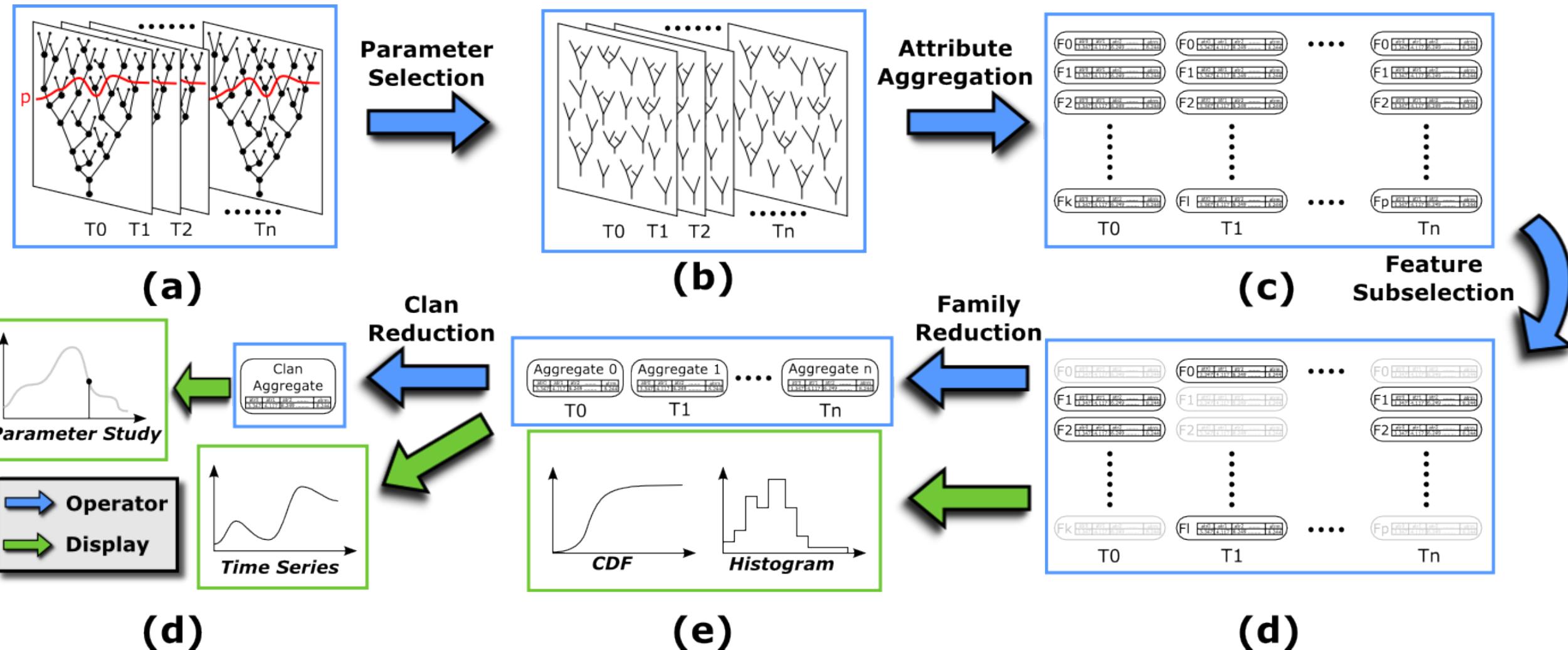


# We aggregate feature-based statistics of interest & encode meta-data in a modular, extendable file format

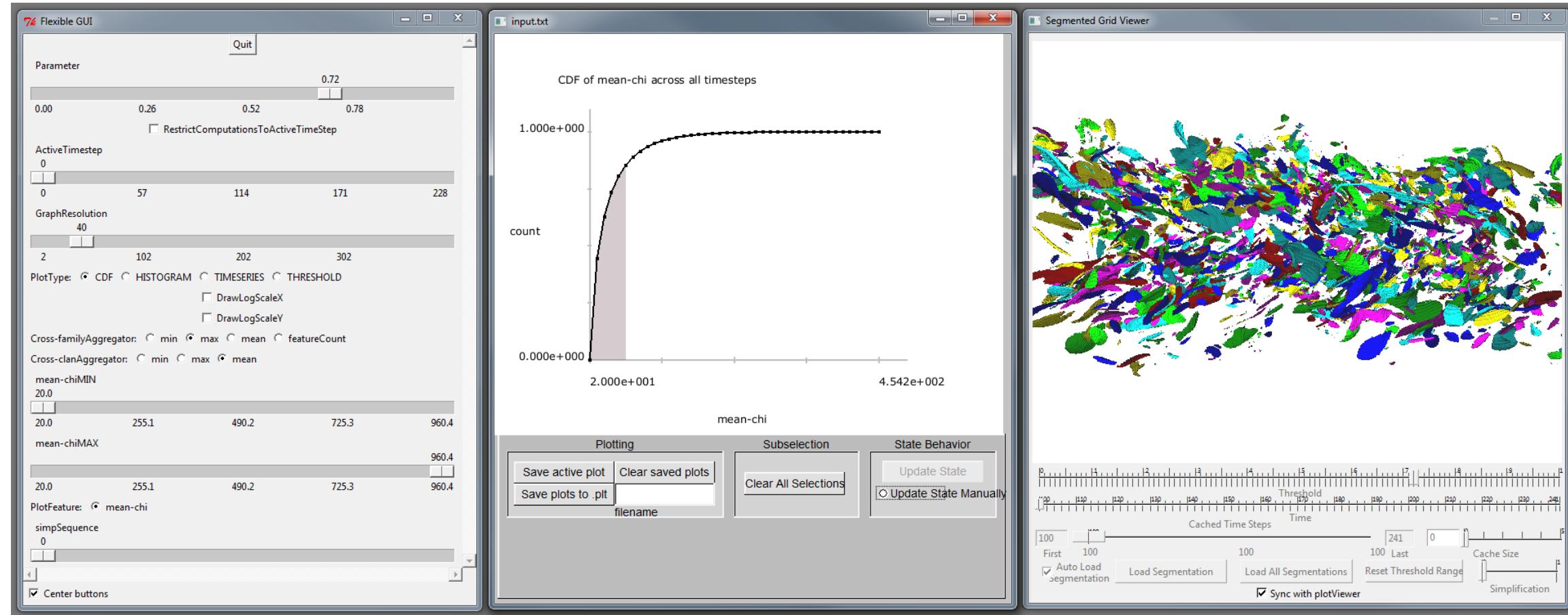
- Descriptive statistics
  - Min/max
  - 1<sup>st</sup>-4<sup>th</sup> order moments
  - Sums
- Various length scales
  - Computed via a spectral technique



# Our exploratory pipeline lets the user quickly explore a variety of statistical summaries



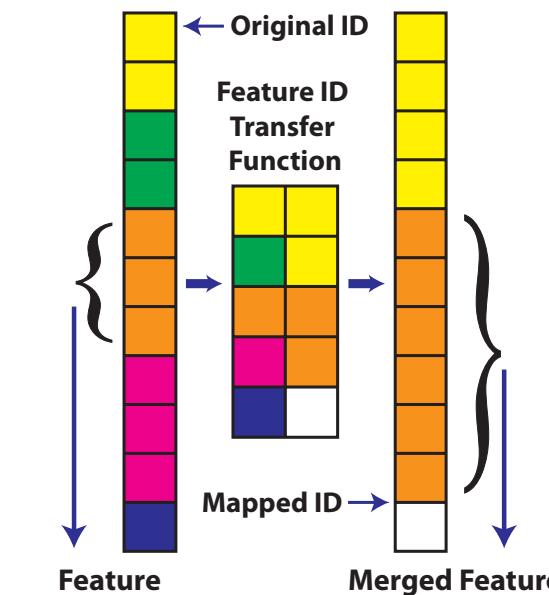
# Cross-linked statistics & feature viewers provide insight into the effects of parameter selections



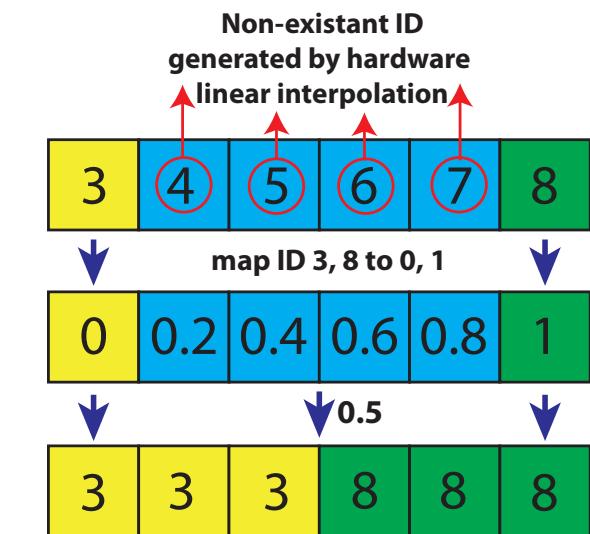
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# Visualizing a dynamic feature hierarchy poses challenges

- Feature: collection of elements
  - Elements store ids into regular grid
  - Binary segmented data
- Challenges
  - Identifying color of dynamically changing feature elements
  - Interpolation to smooth and light features in GPU
  - Features are dynamic



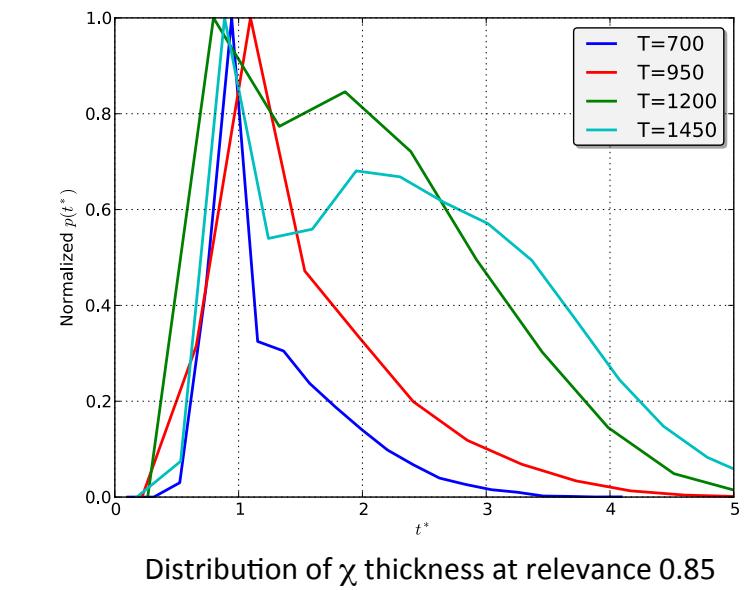
Feature transfer function mitigates cost of reloading feature id volume into GPU.



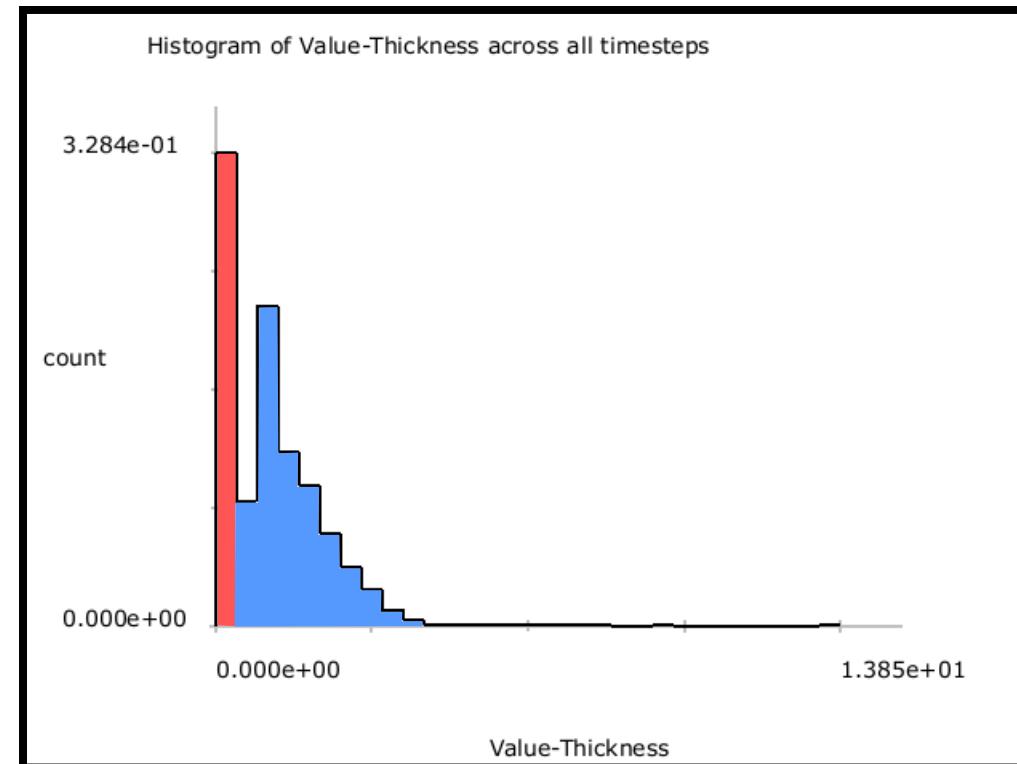
A 0-1 mapping approach [Hadwiger *et. al*] is used to address hardware linear interpolation issues.

# Case study results: efficient exploration of large-scale simulation data on commodity hardware

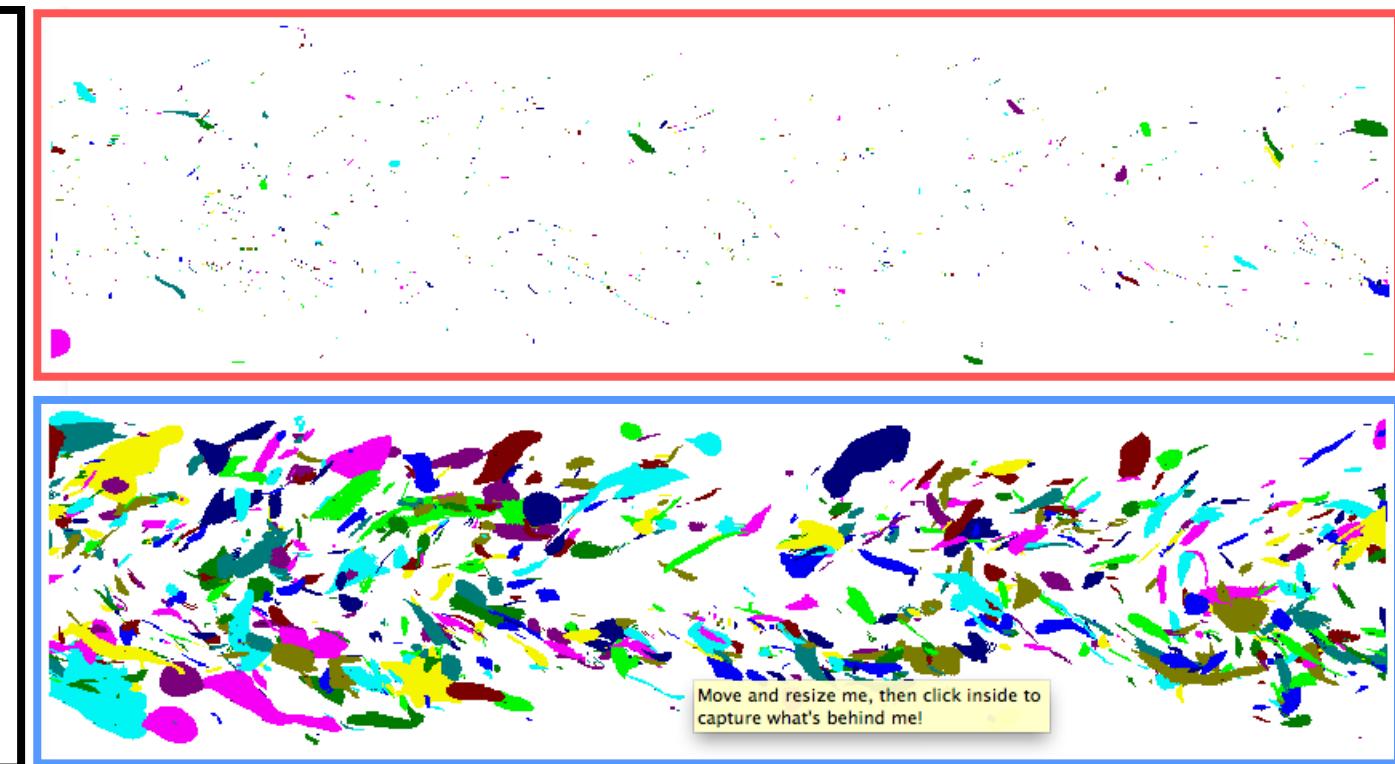
- Simulation has 0.5 billion grid points & 230 time steps
- Data reduction  $O(1 \text{ TB}) \rightarrow O(14\text{GB})$
- Building data:
  - In parallel on Lens: 32 node Linux cluster at Oak Ridge National Lab
  - Building merge tree & computing statistics:  $O(5 \text{ min})/\text{time step}$
  - Length scales:  $O(90 \text{ minutes})/\text{time step}$
- Exploring data:
  - Commodity hardware
  - Species distribution plots/time series:  $O(1 \text{ second})$
  - Parameter studies:  $O(35 \text{ seconds})$
  - Feature browser 12-25 frames/second



# Using our framework scientists can quickly diagnose issues with their analysis



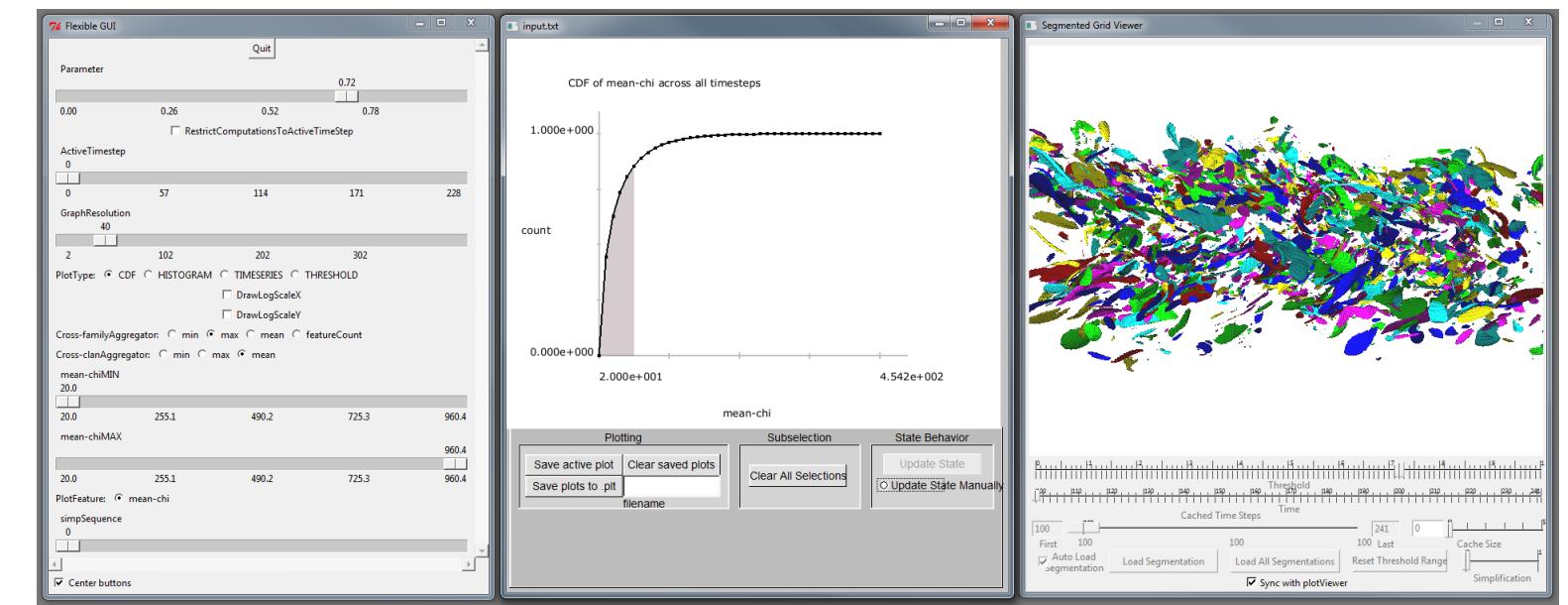
(a)



(b)

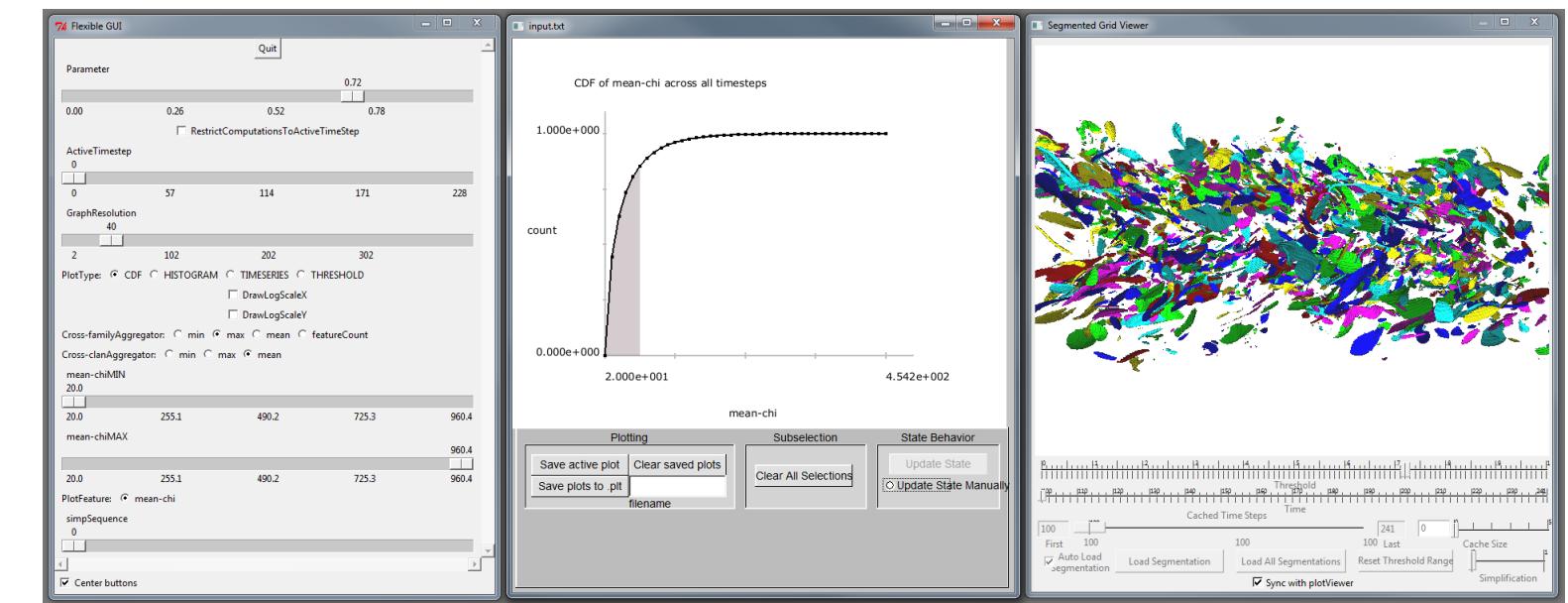
# Conclusion

- Compact meta-data
  - Drastic data reductions
  - Maintains statistics of interest
  - Feature thresholds need not be known *a priori*
- Interactive linked view data exploration
  - Picking & highlighting
  - Runs on commodity hardware



# Future Work

- Parallelize to support extreme-scale data
- Support additional reduction operators
- Support for alternate hierarchies



# Questions?

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