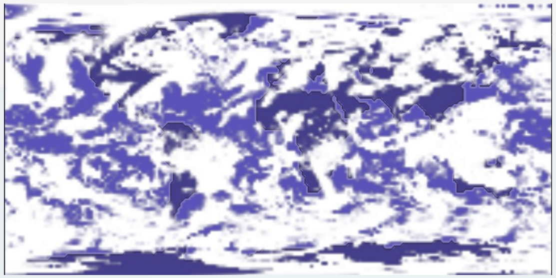
VisWeek 09

VIS • INFOVIS • VAST

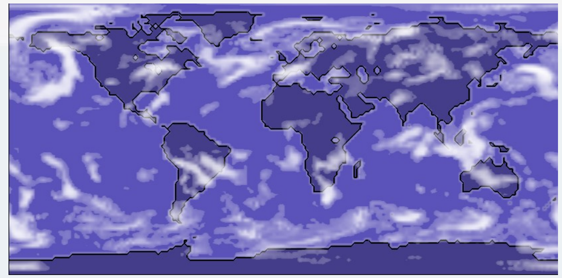
Information-theoretic Methods for the Visual Analysis of Climate and Flow Data

Heike Jänicke – Swansea University, UK

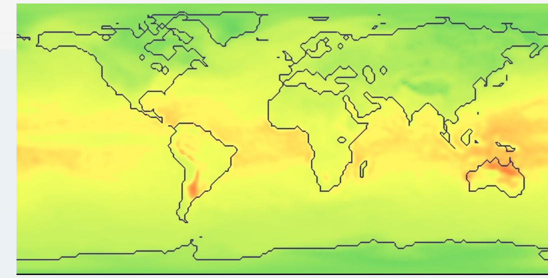
Weather simulation



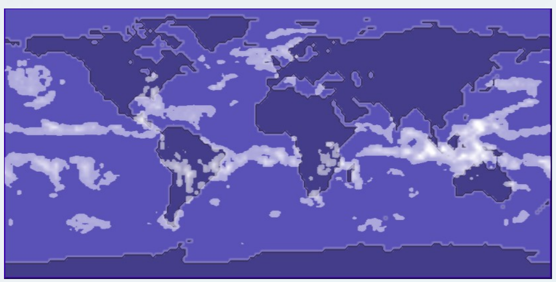
Cloud cover



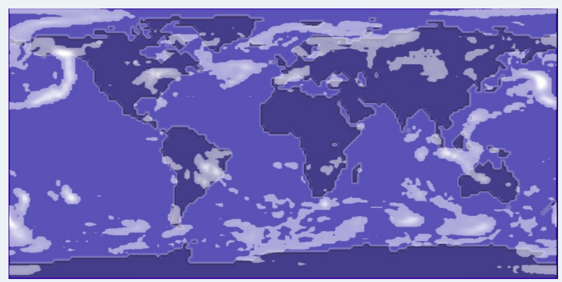
Cloud ice



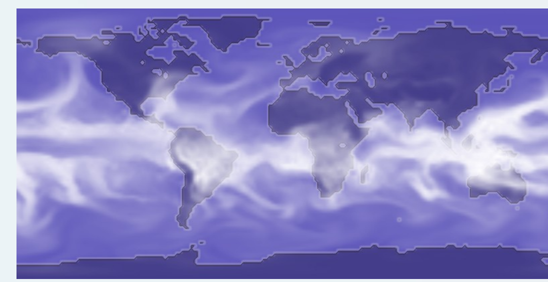
2m temperature



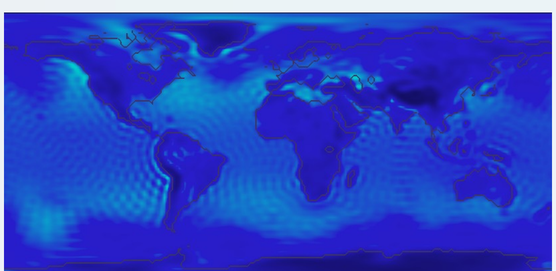
Convective precipitation



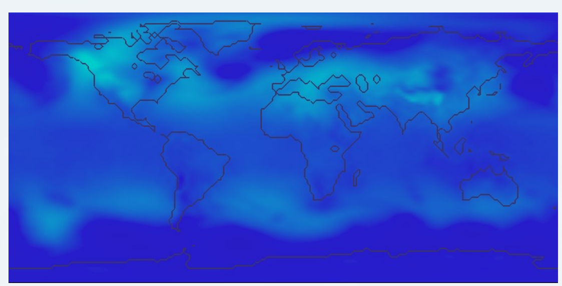
Precipitation



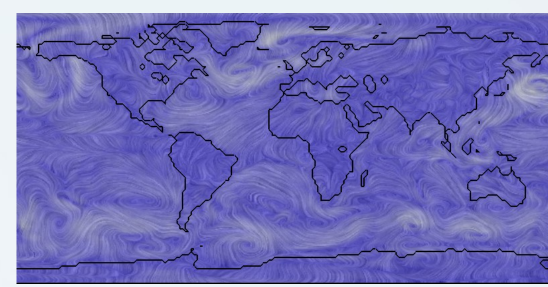
Evaporation



Surface pressure

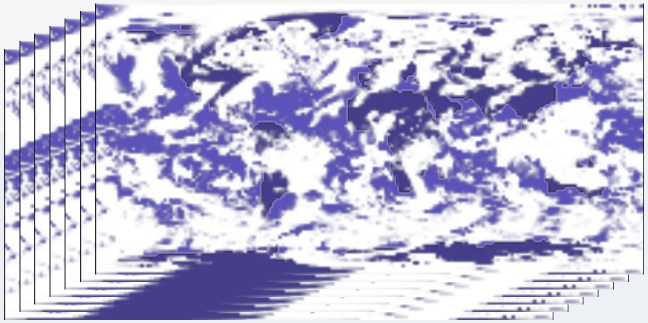


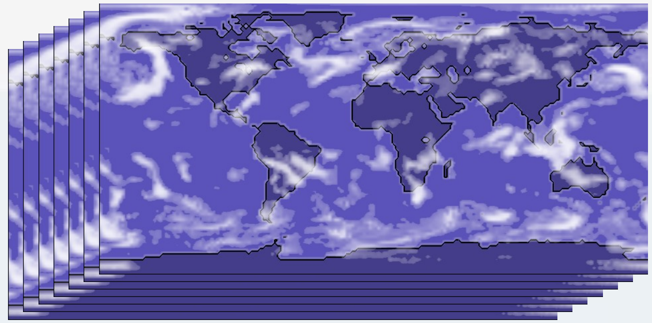
0m pressure

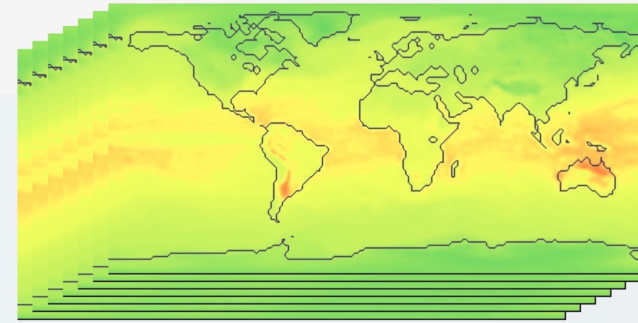


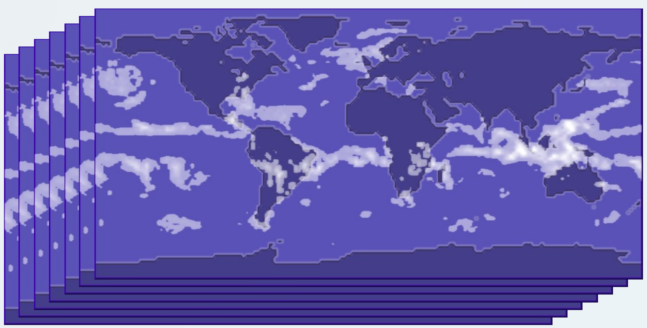
Wind

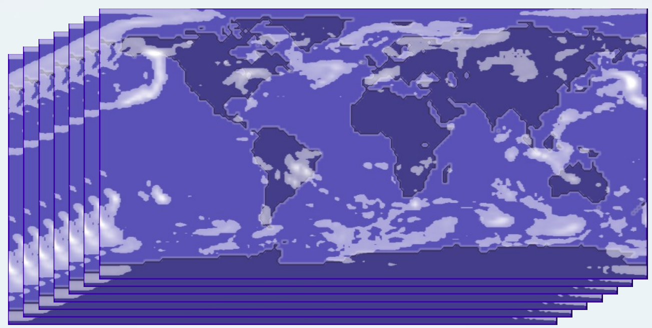
Weather simulation

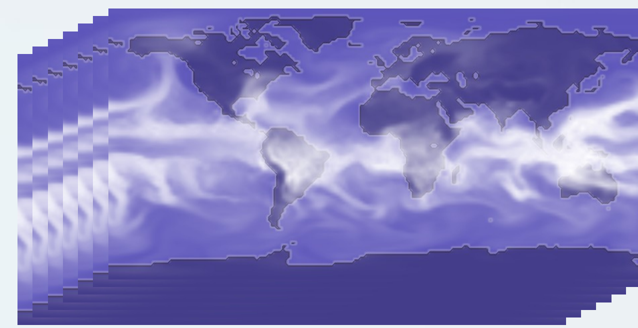

Cloud cover

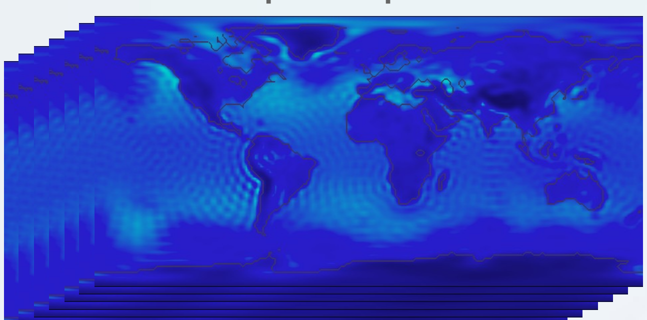

Cloud ice

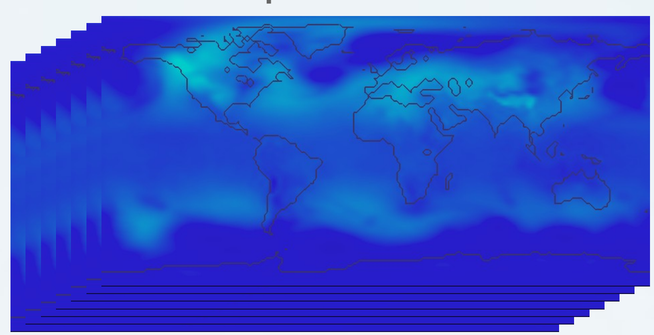

2m temperature

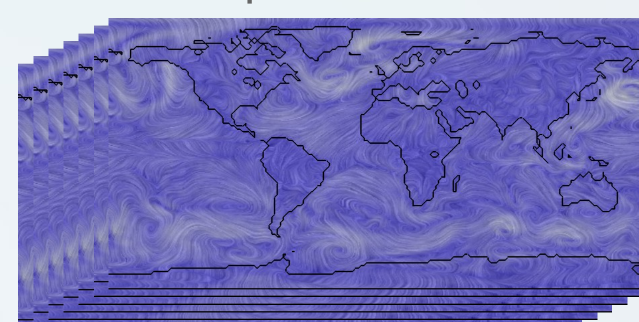

Convective precipitation


Precipitation


Evaporation

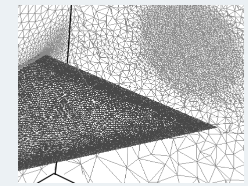

Surface pressure

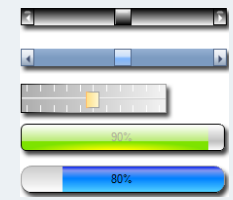

0m pressure

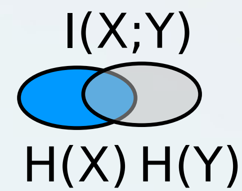

Wind

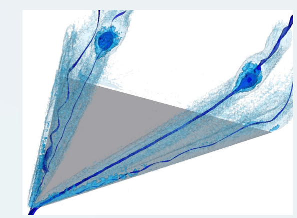
Outline

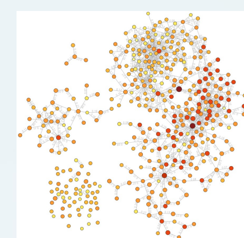
- Data representation
- Related work
- Information Theory
- Local Statistical Complexity
- Epsilon-machines
- Eulerian/ Lagrangian flow
- Conclusion/ future directions

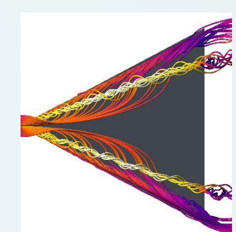


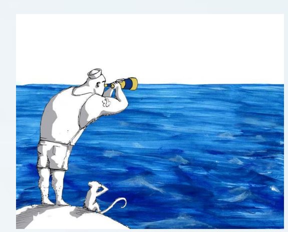












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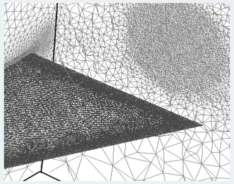
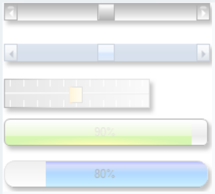
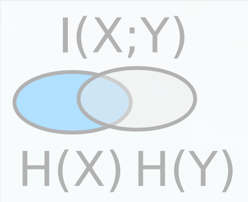
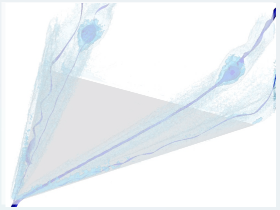
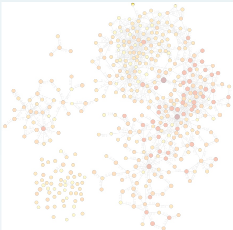
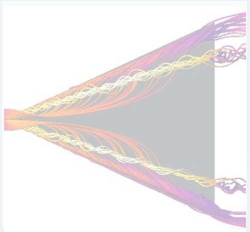


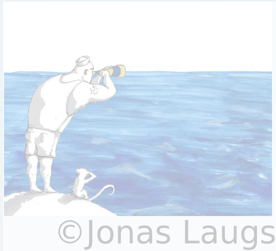






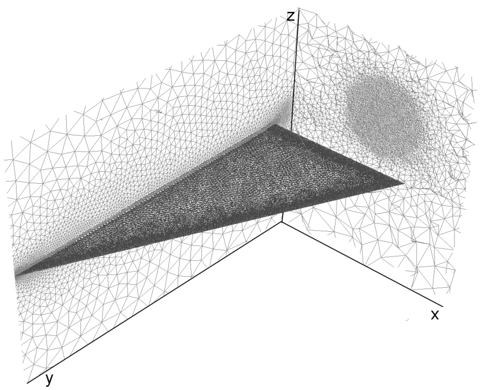


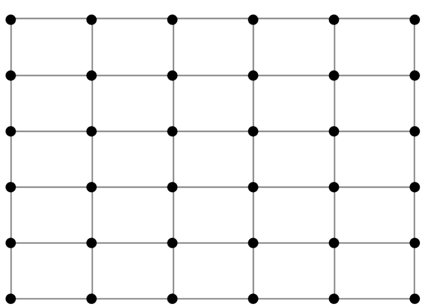




Computational Fluid Dynamics

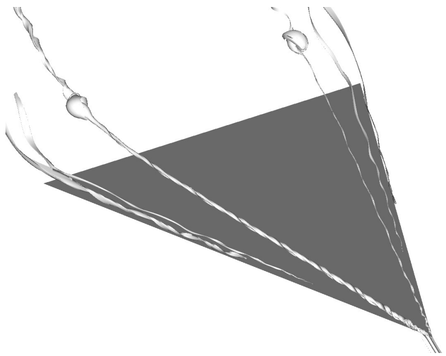
Preprocessing

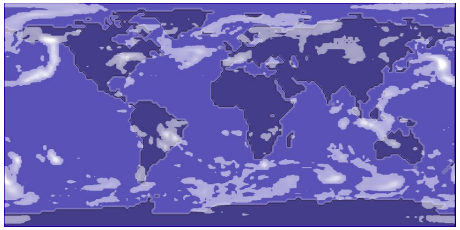




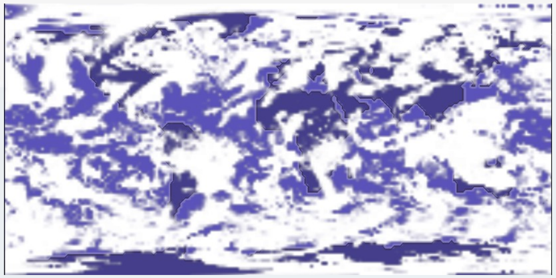
Problem solving

Postprocessing

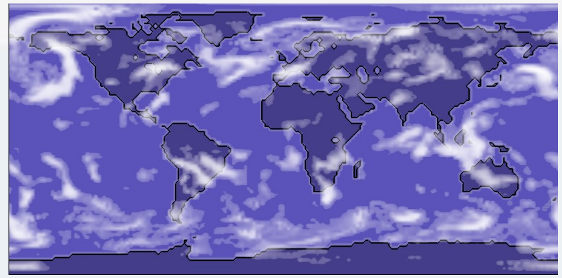




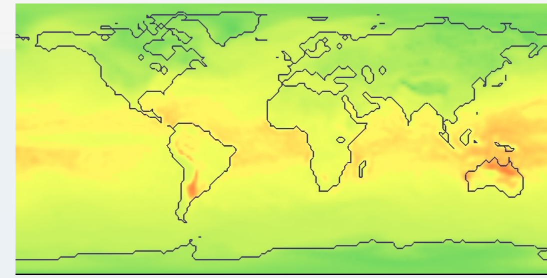
Data Sets – Weather Simulation



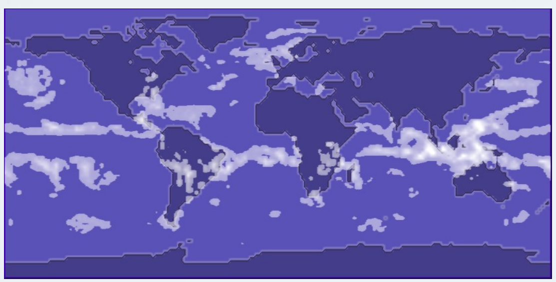
Cloud cover



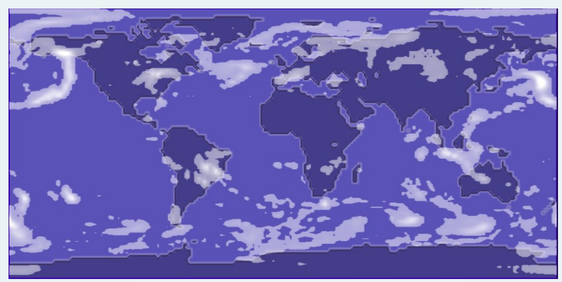
Cloud ice



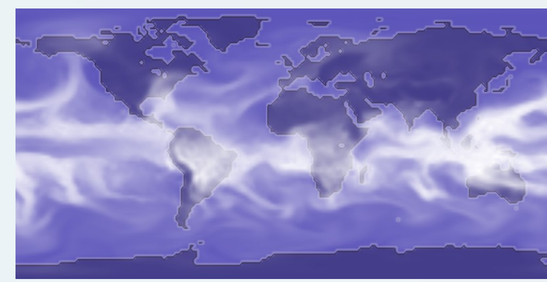
2m temperature



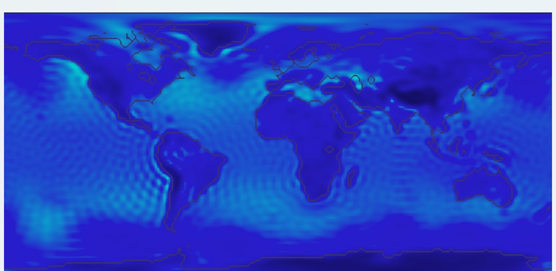
Convective precipitation



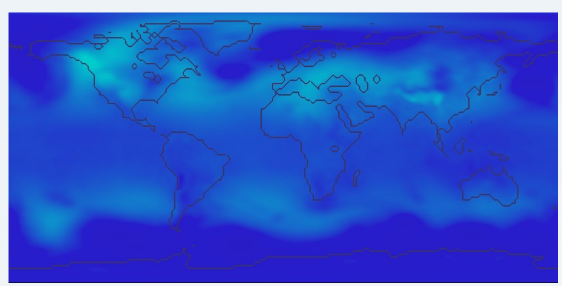
Precipitation



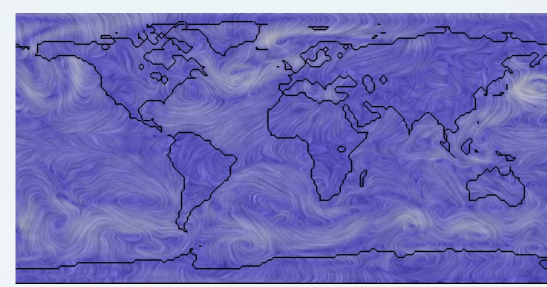
Evaporation



Surface pressure

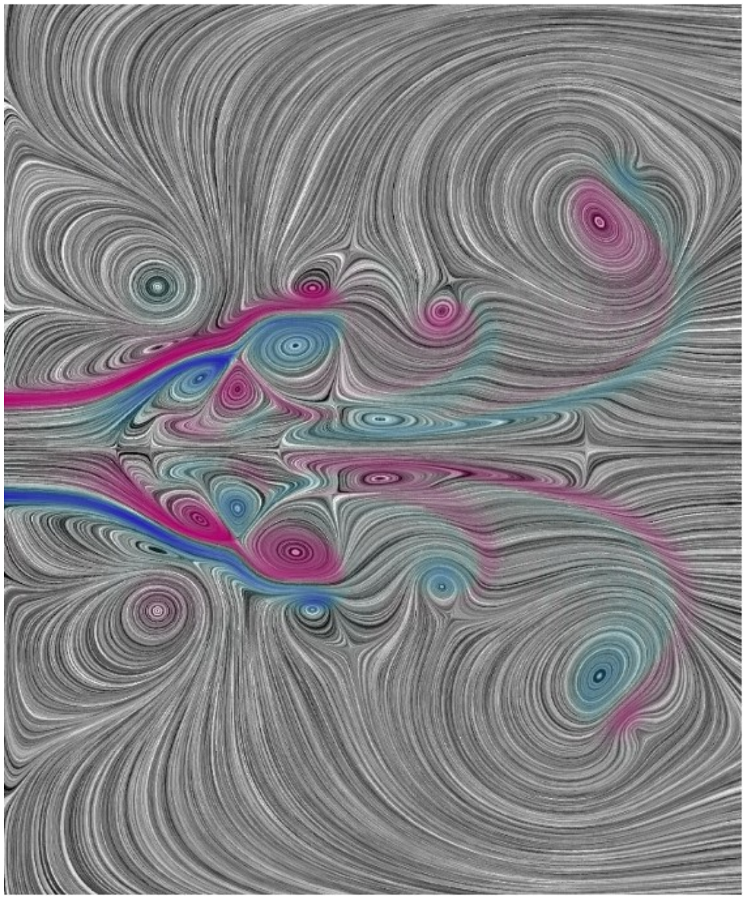


0m pressure

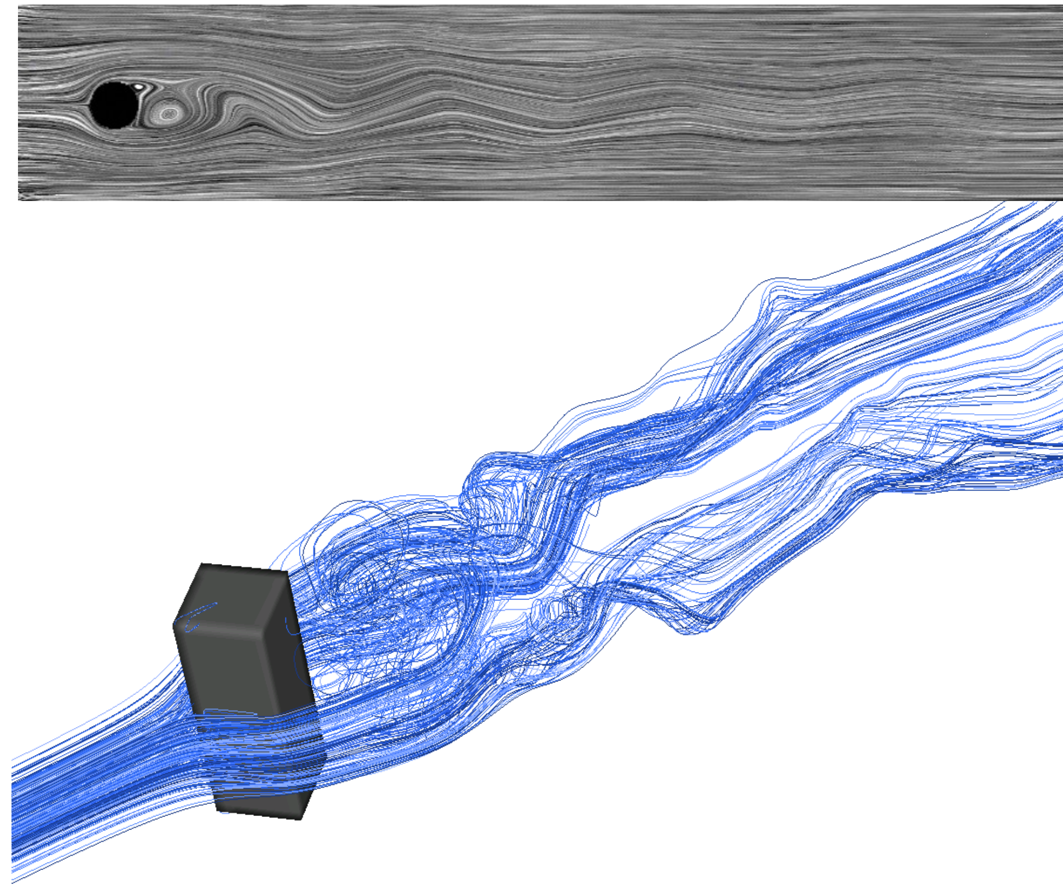


Wind

Data Sets – Flow Simulation I



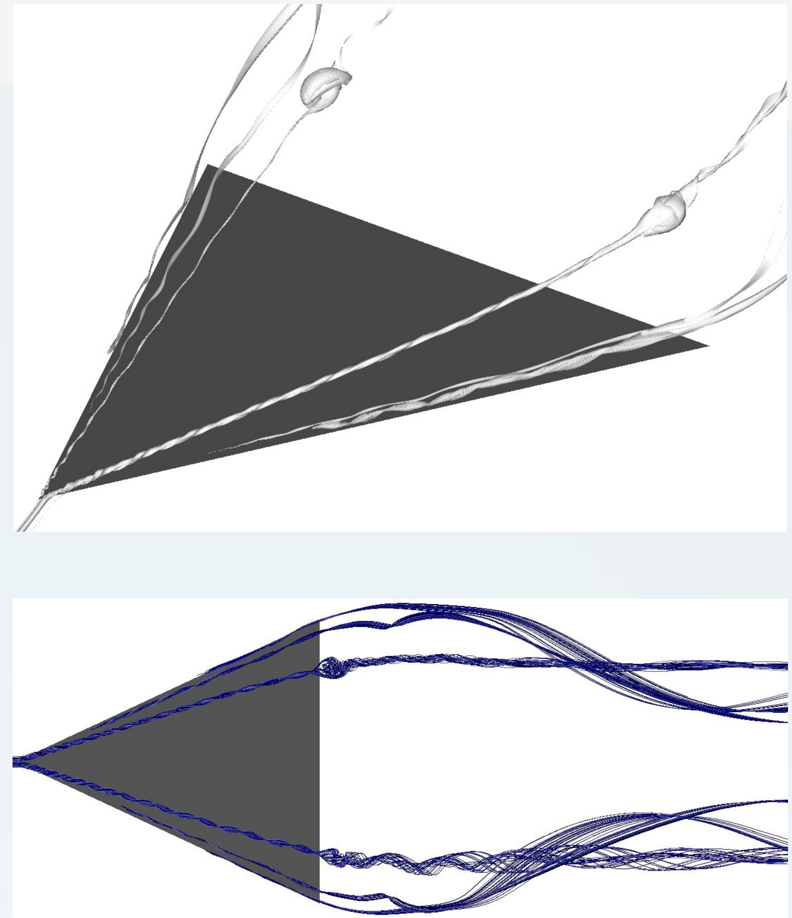
Swirling flow
[Wolfgang Kollmann, UCDavis]



Flow around an obstacle
[NaSt2D/NaSt3D, Universität Bonn]

Data Sets – Flow Simulation II

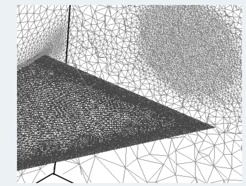
Francis draft tube
[Ronny Peikert, ETH Zürich;
VA Tech Hydro]

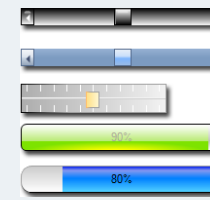


Delta wing
[Markus Rütten, DLR]

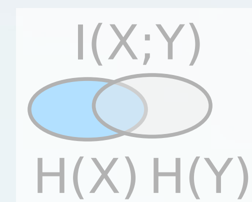
Outline

- Data representation

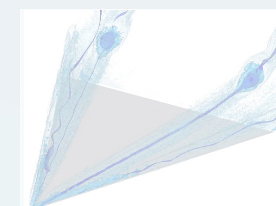




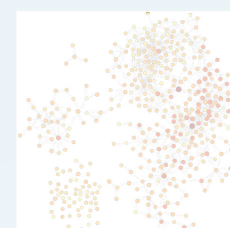
- Related work
- Information Theory



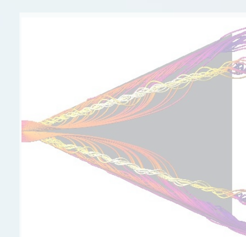
- Local Statistical Complexity



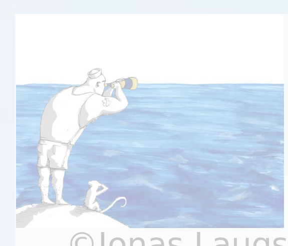
- Epsilon-machines



- Eulerian/ Lagrangian flow



- Conclusion/ future directions



VisWeek 09
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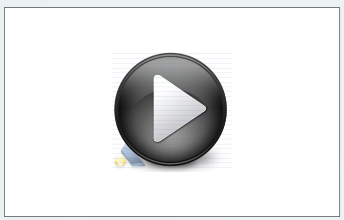
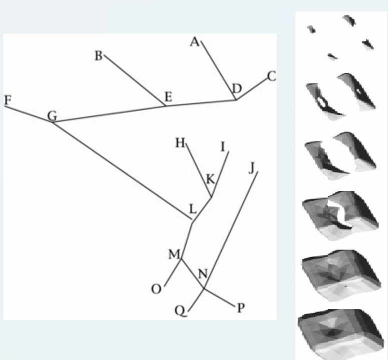
Related Work

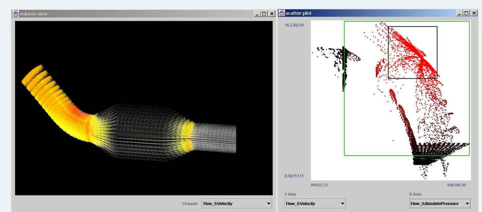
Time-dependent data | **Multivariate data** | **Feature extraction**



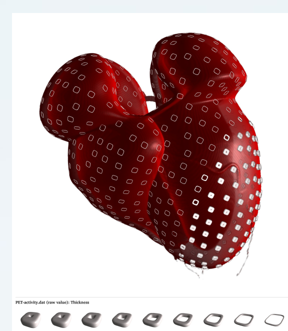
movie



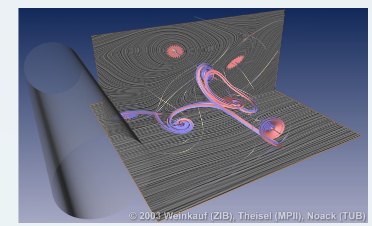
contour tree



linking and brushing



glyphs



topology

mathematical def.

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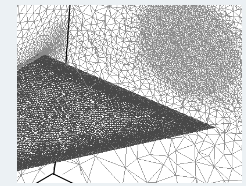
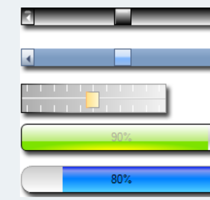
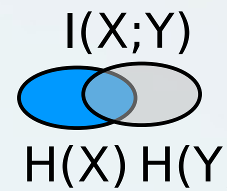
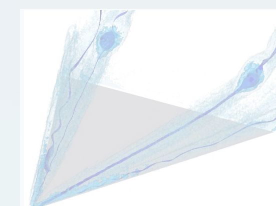
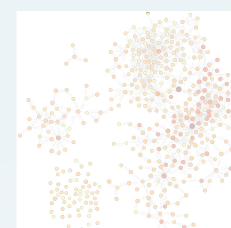
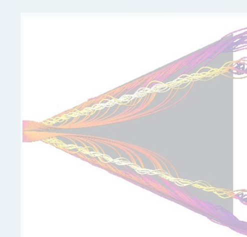


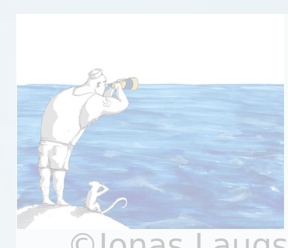




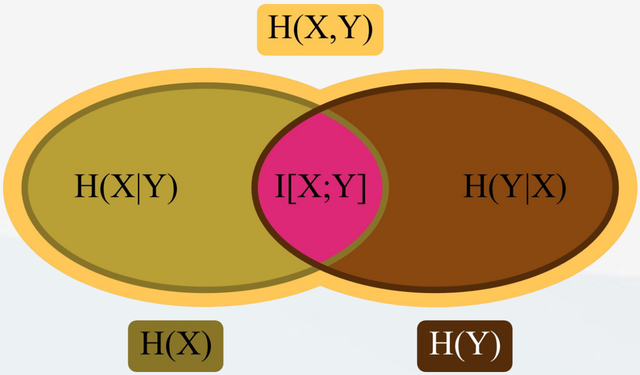








Information Theory



- **Entropy** (uncertainty in X)

$$H(X) = -\sum_{x \in X} p(x) \log_2 p(x)$$

- **Conditional entropy** (Remaining uncertainty in X when Y is known)

$$H(X|Y) = -\sum_{y \in Y} \sum_{x \in X} p(x,y) \log_2 p(y|x)$$

- **Mutual information** (Information X contains about Y and vice versa)

$$I(X;Y) = H(X) - H(X|Y)$$

$$= H(Y) - H(Y|X) = I(Y;X)$$

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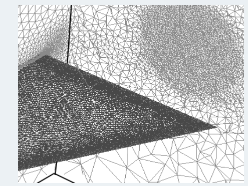
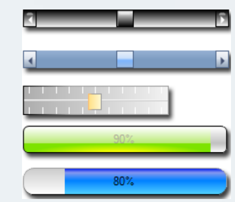
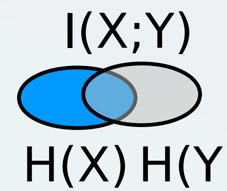
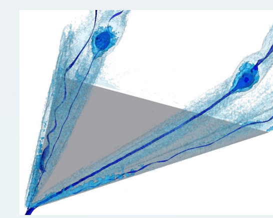
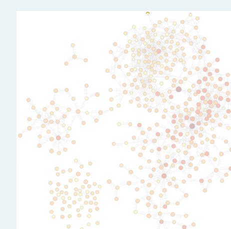
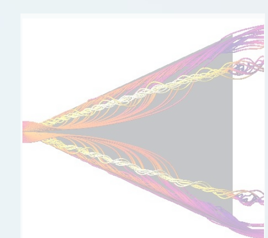


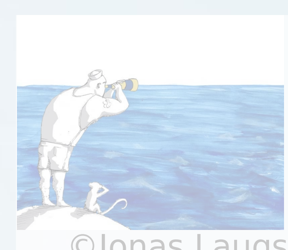






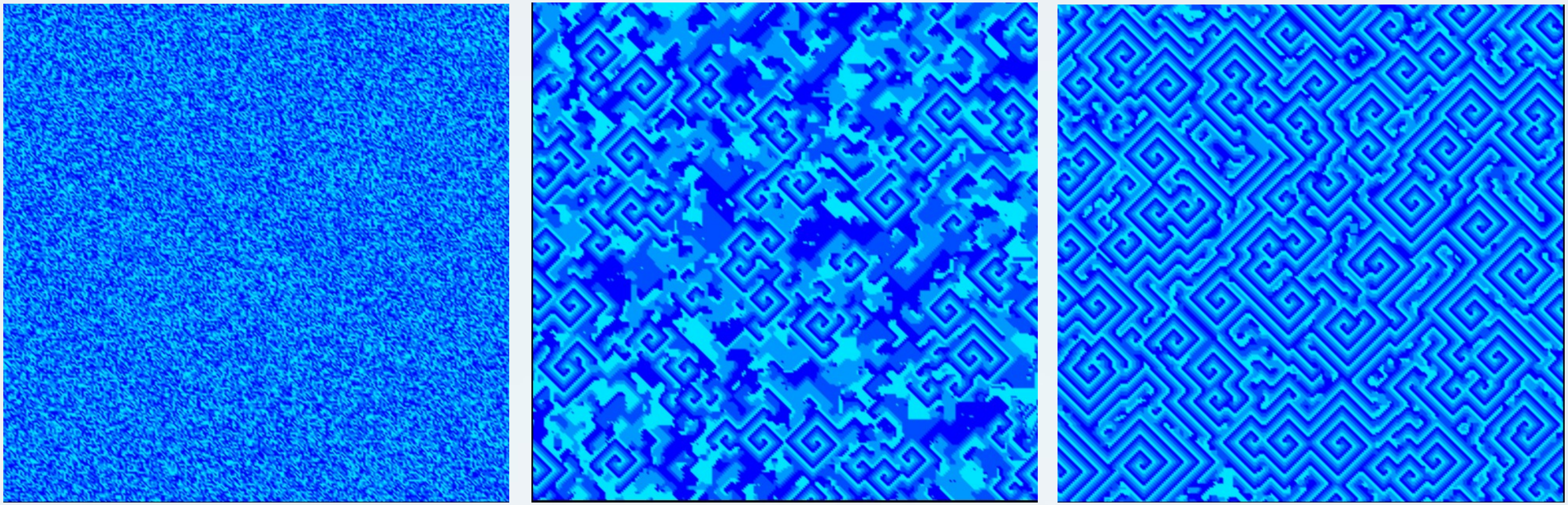






Cellular Automaton

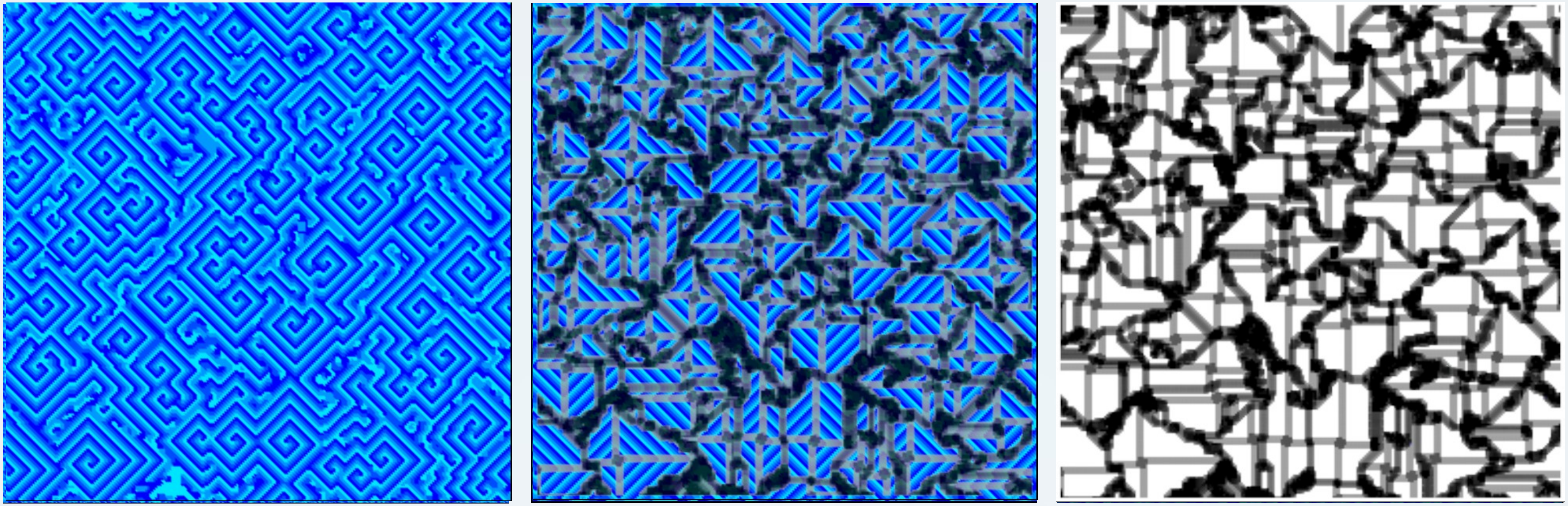
- Rule: cyclic cellular automaton (CCA) forming spirals



t = 0 t = 40 t = 99

Cellular Automaton

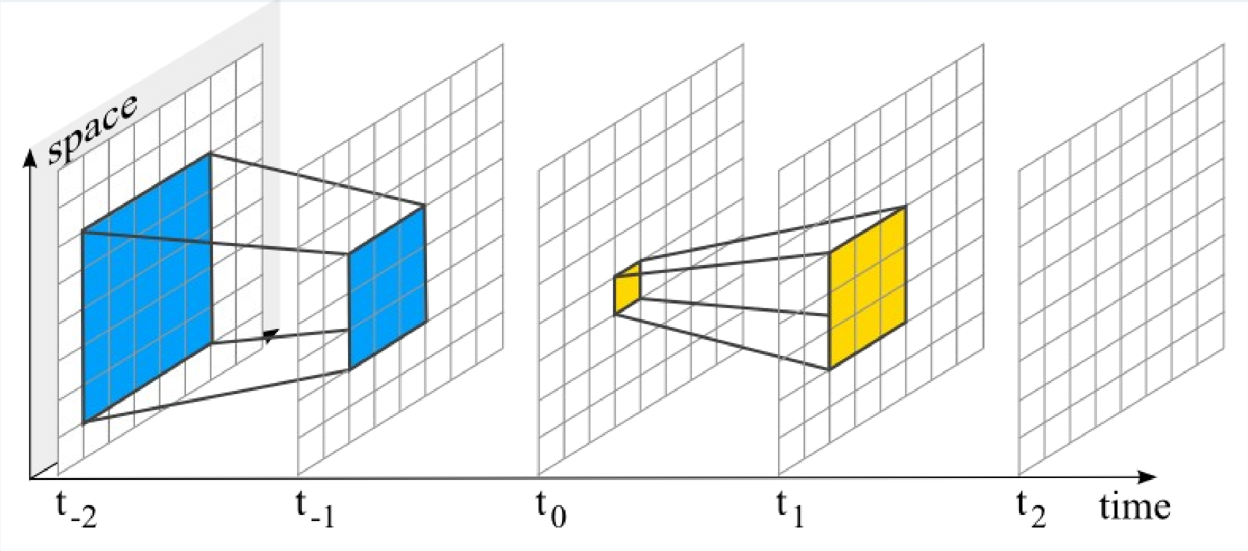
- Rule: cyclic cellular automaton (CCA) forming spirals



t = 99   t = 99 + filter   filter

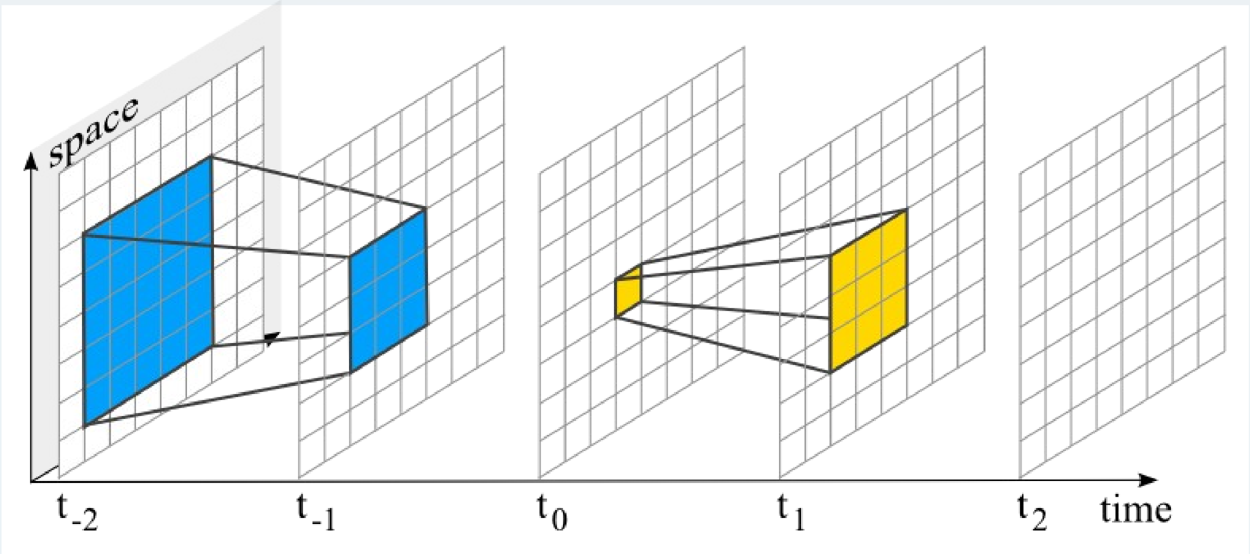
Local Statistical Complexity

- How much information from the local past do I need to predict the dynamics in the local future?



Local Statistical Complexity

- How much information from the local past do I need to predict the dynamics in the local future?

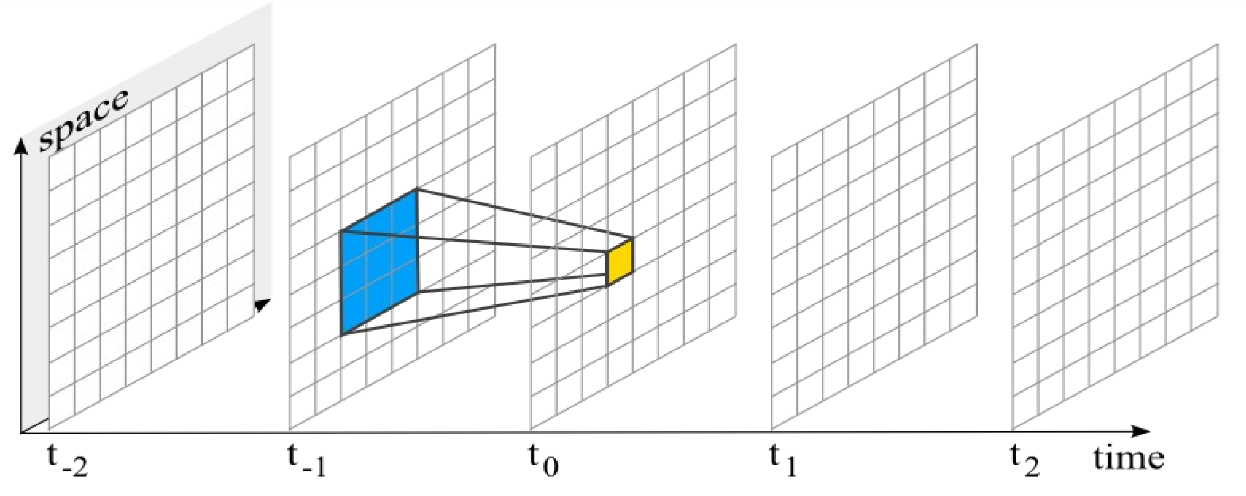


- **Mutual information**:

$$I[X;Y] = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x)\,p(y)}$$

Specification

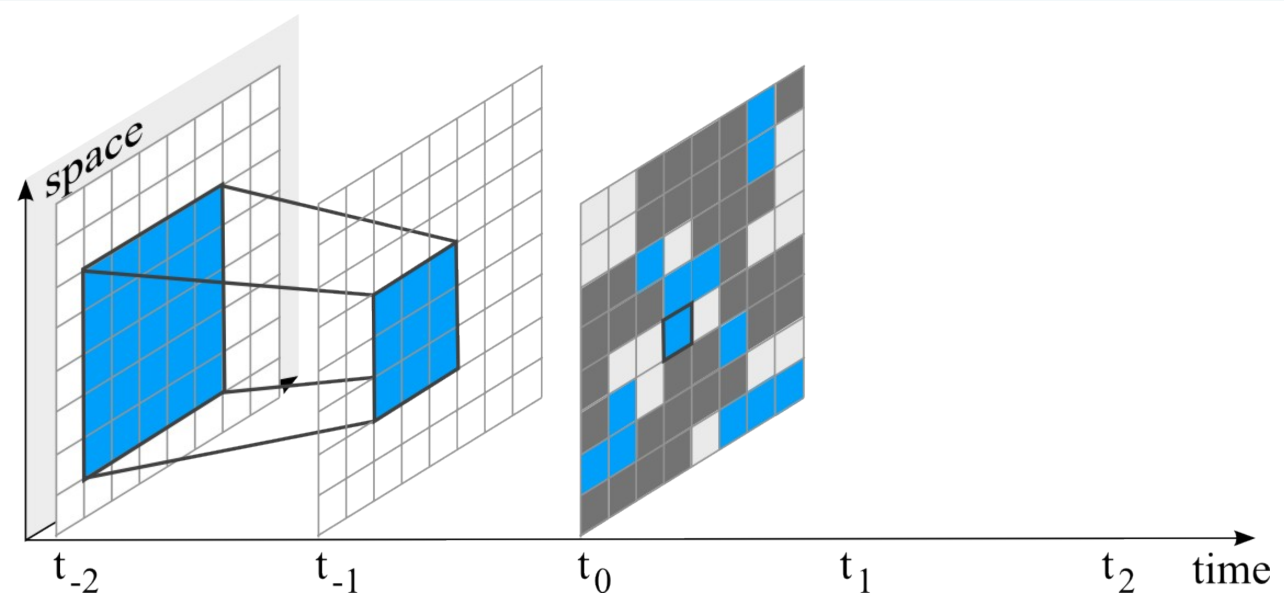
- PDE-simulation (e.g. engineering or natural sciences)
- Simulation using finite differences on a Cartesian grid
- Time-dependent data including all time steps



$$I[X;Y] = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)}$$

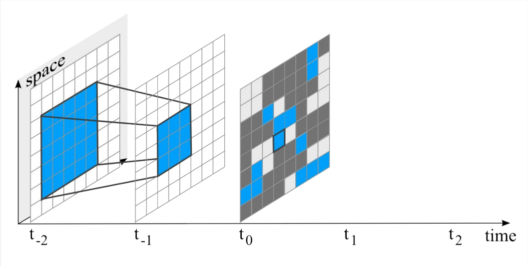
Local Statistical Complexity

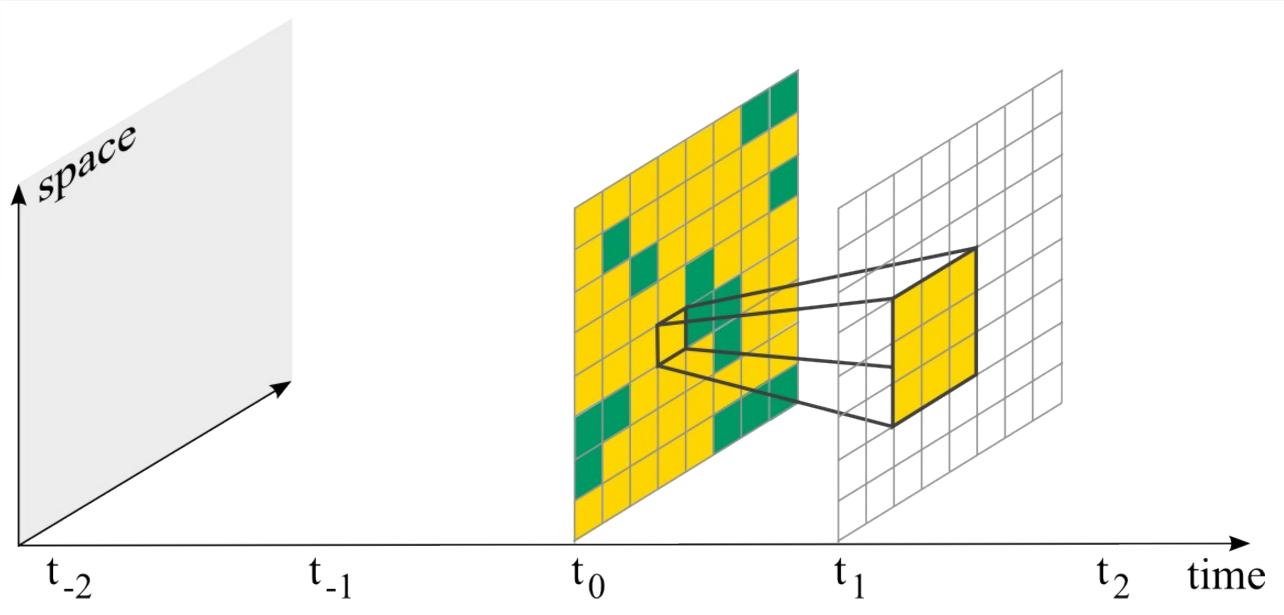
- Identify pasts



Local Statistical Complexity

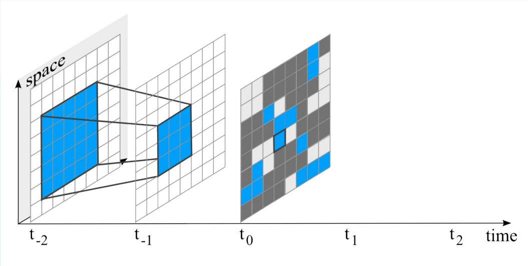
- Identify pasts
- Identify futures

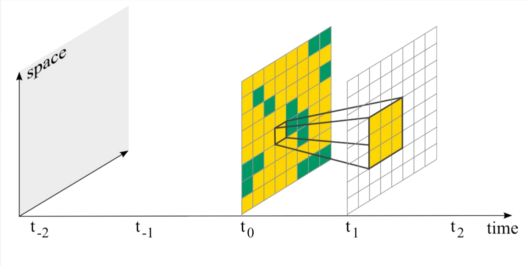


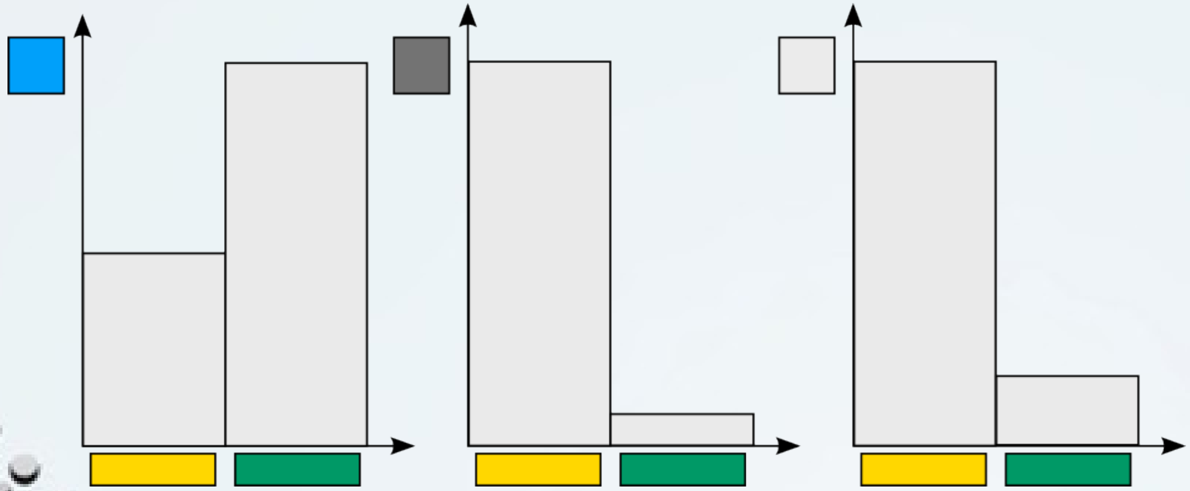


Local Statistical Complexity

- Identify pasts
- Identify futures
- Estimate distributions

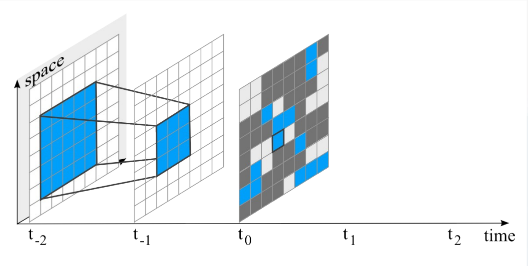


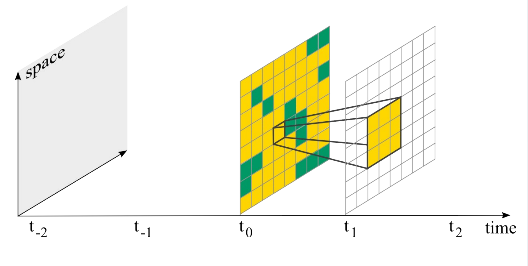


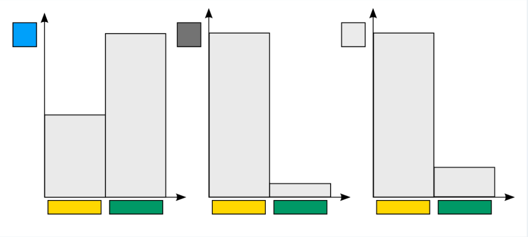


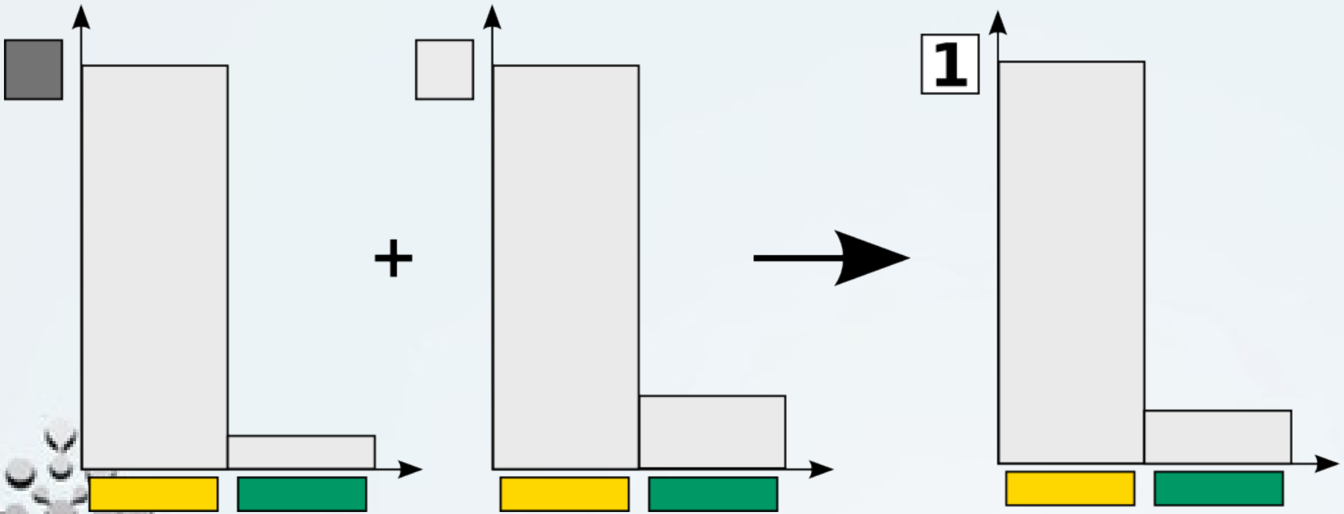
Local Statistical Complexity

- Identify pasts
- Identify futures
- Estimate distributions
- Cluster similar patterns (χ^2-Test)
  → **causal states**









Local Statistical Complexity

- Identify pasts
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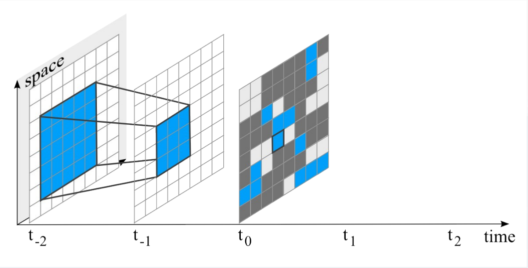
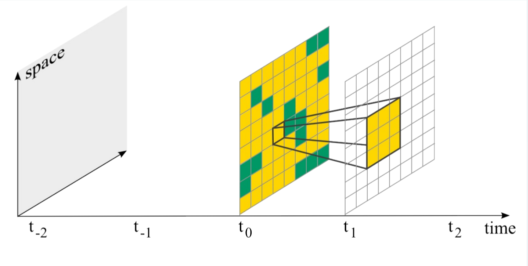
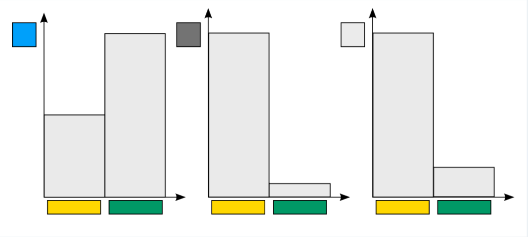
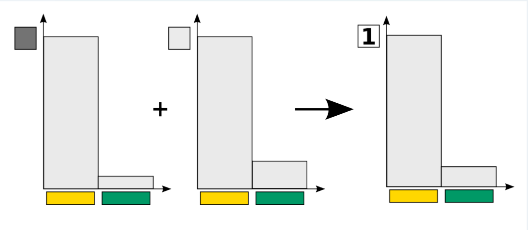






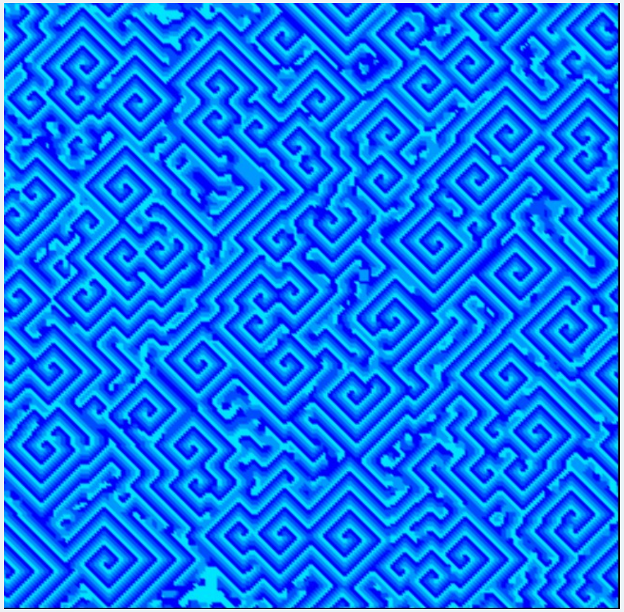


$$\textit{causal state} = \epsilon(l^-) = \{\lambda : P(l^+ | \lambda) = P(l^+ | l^-)\}$$

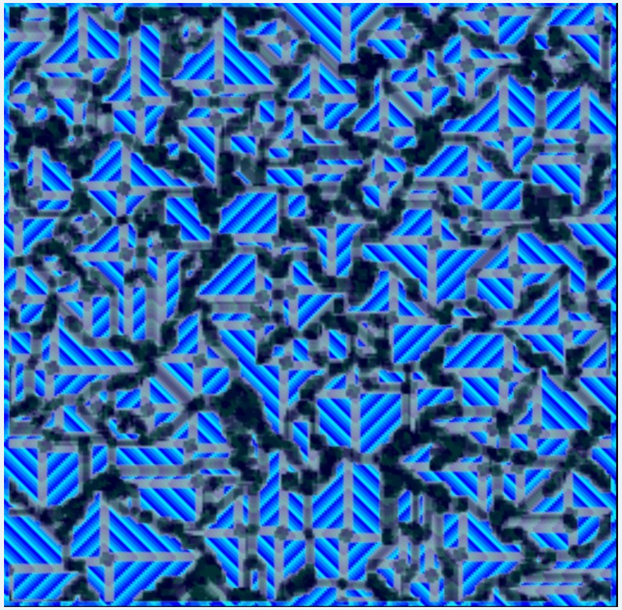
$$I[L^-(\vec{x},t); S(l^-(\vec{x},t))] = \sum_{l^-,s} P(l^-,s) \log \frac{P(l^-,s)}{P(l^-)P(s)}$$

$$= -\log P(s(l^-(\vec{x},t)))$$

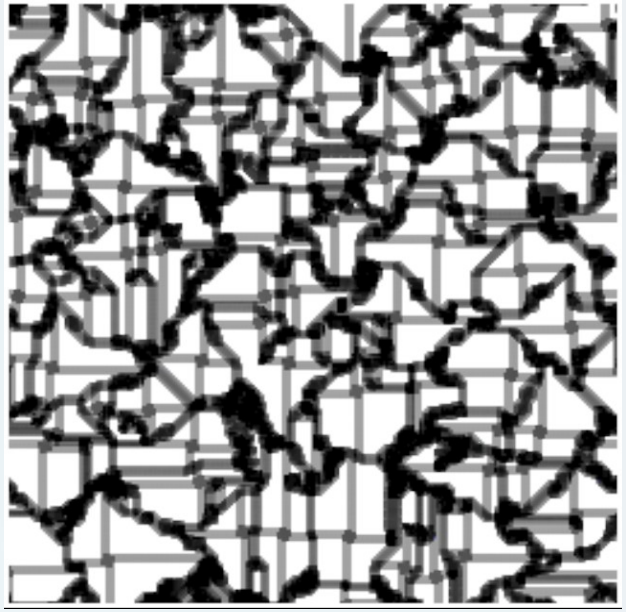
Local Statistical Complexity



t = 99

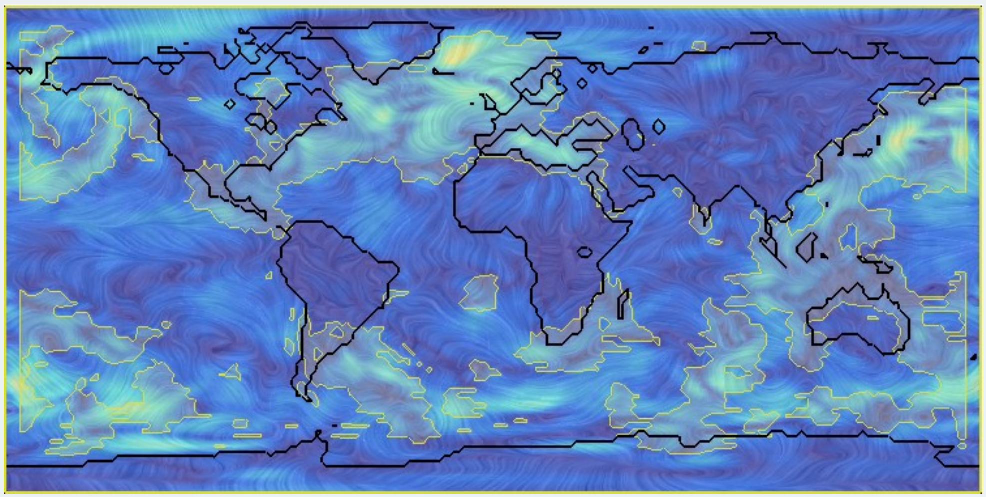


t = 99 + LSC

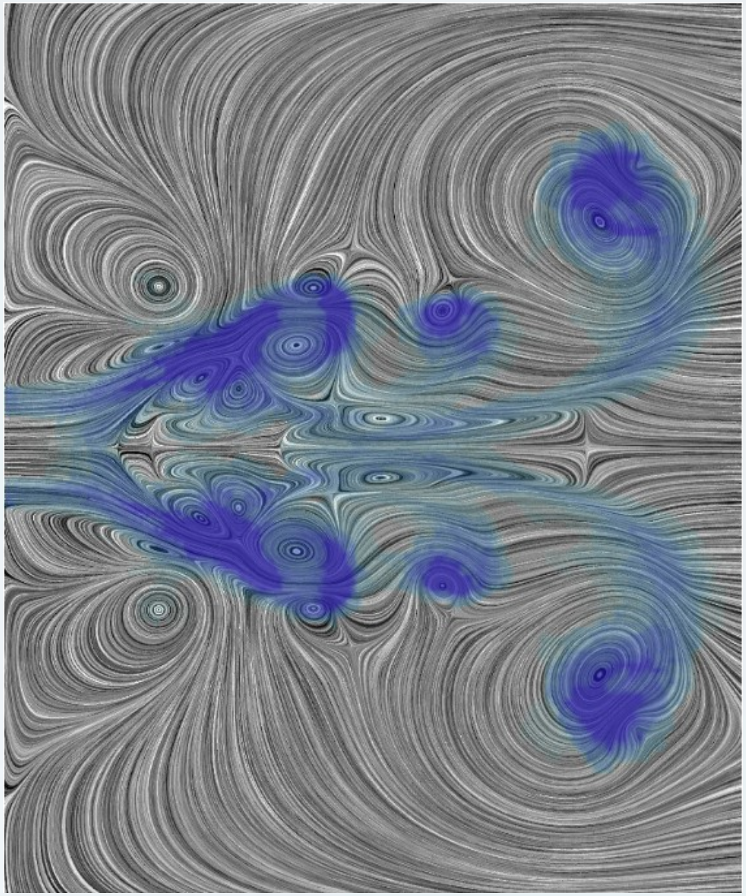


LSC

Results 2D



LSC wind and evaporation



LSC velocity and vorticity

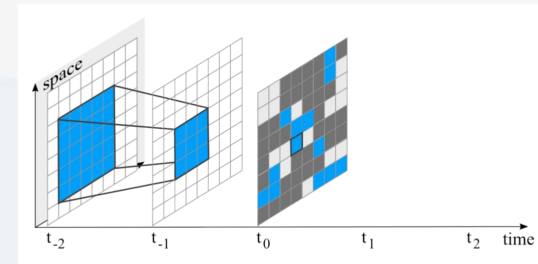
Difficult Part

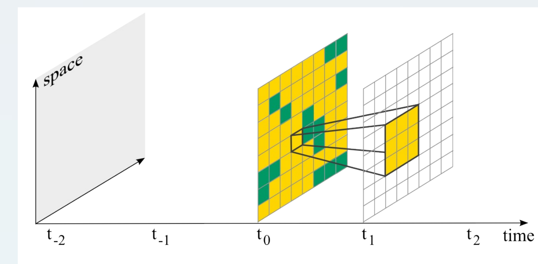
- Identify pasts
- Identify futures
- Estimate distributions
- Cluster similar patterns (χ^2-Test)
  → **causal states**

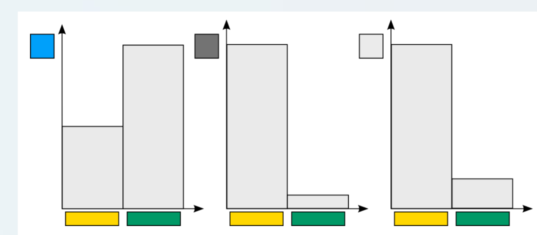
$$causal\ state = \epsilon(l^-) = \{\lambda : P(l^+|\lambda) = P(l^+|l^-)\}$$

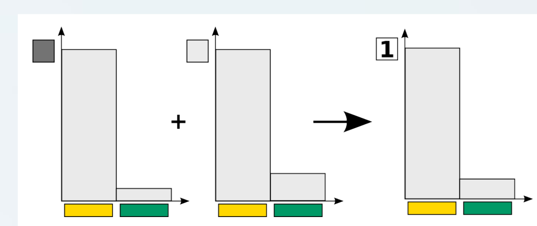
$$I[L^-(\vec{x},t); S(l^-(\vec{x},t))] = \sum_{l^-,s} P(l^-,s) \log \frac{P(l^-,s)}{P(l^-)P(s)}$$

$$= -\log P(s(l^-(\vec{x},t)))$$

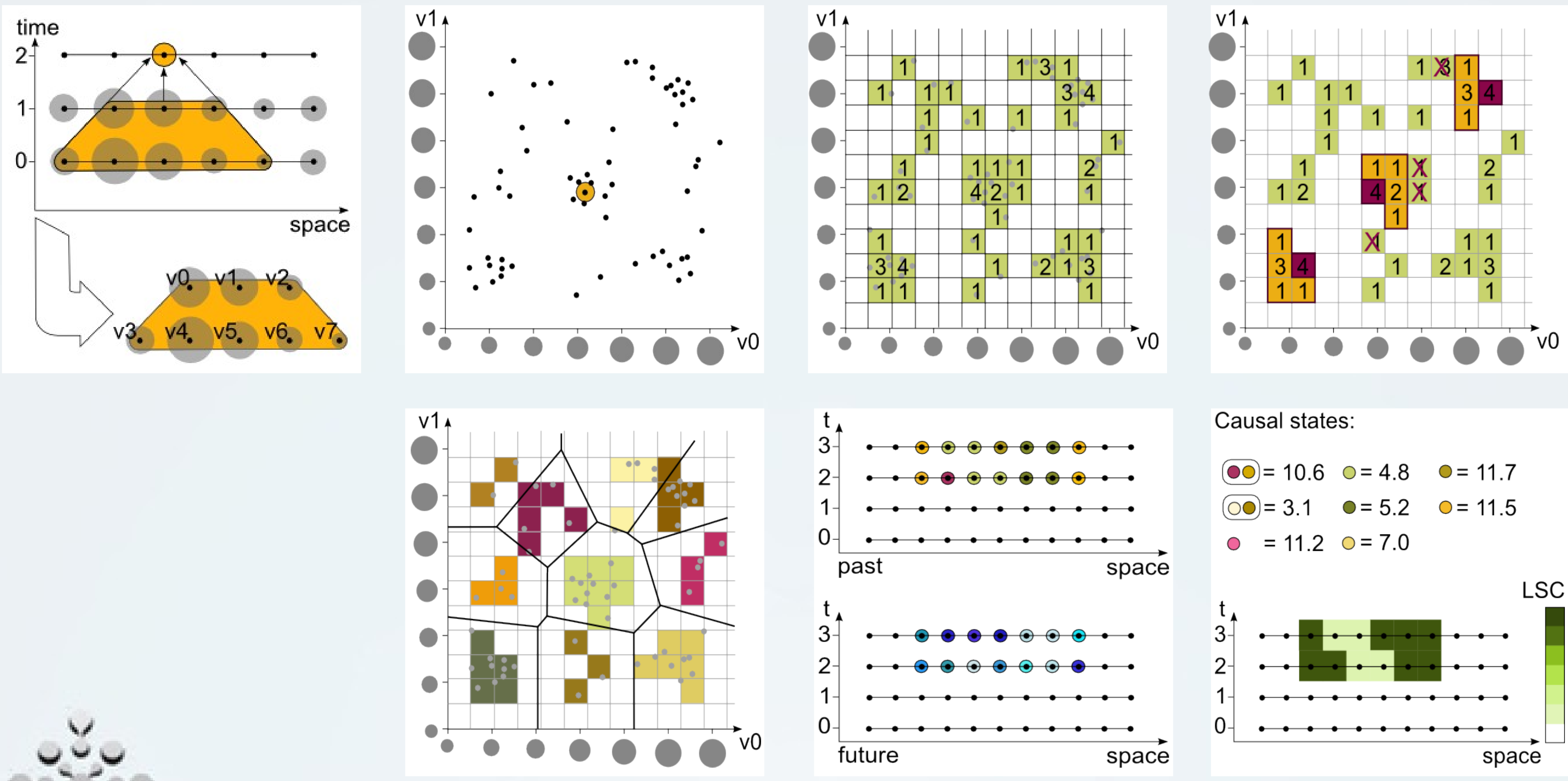




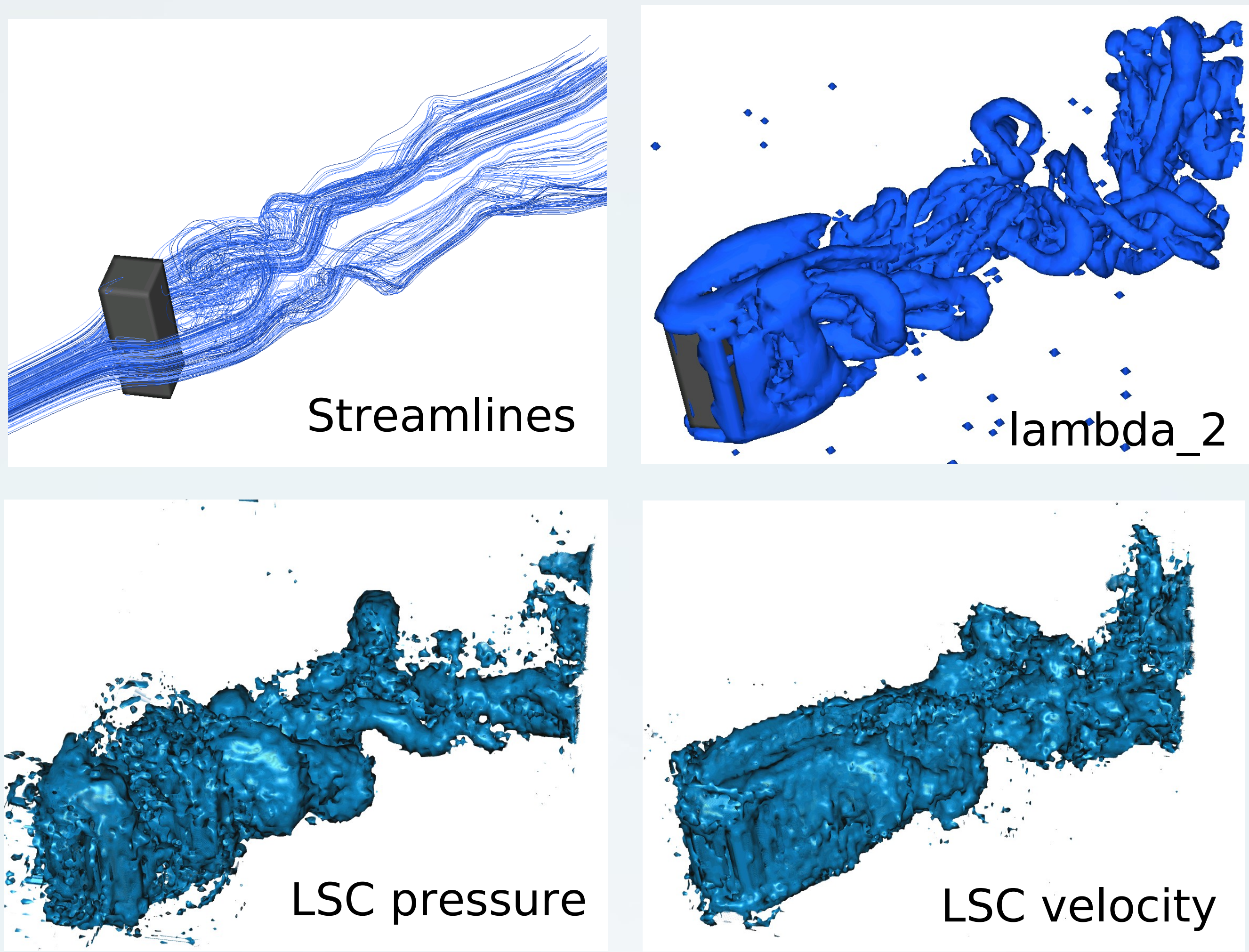




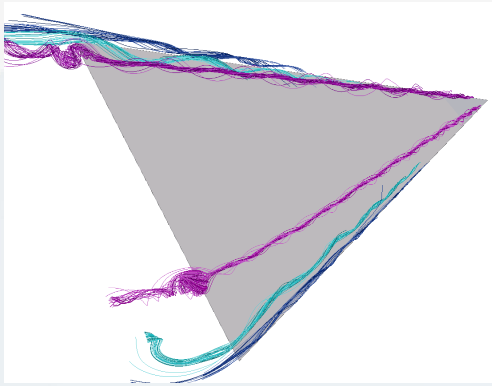
Density-driven Voronoi Tessellation



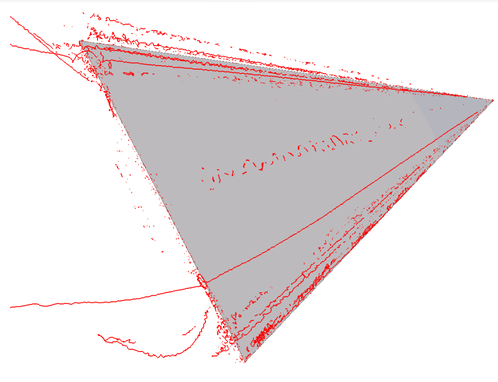
Flow Around an Obstacle



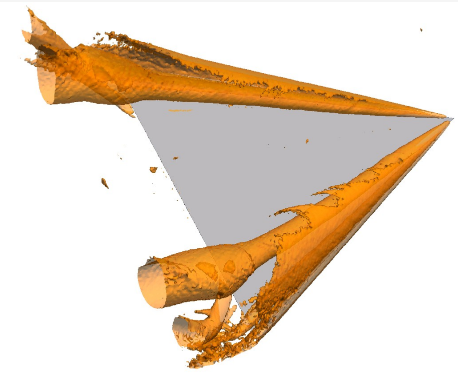
Delta Wing



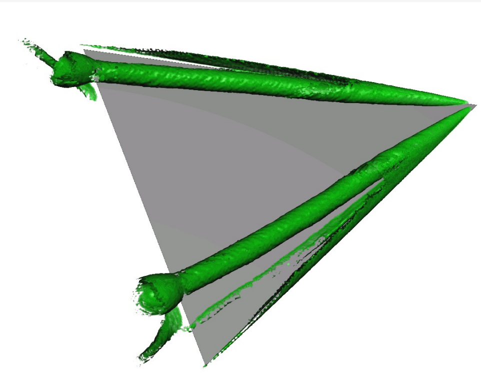
Streamlines



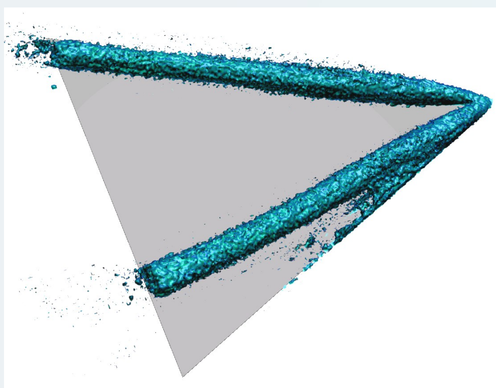
Sujudi-Haimes



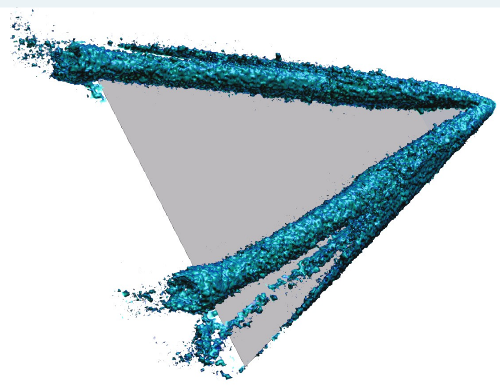
lambda_2



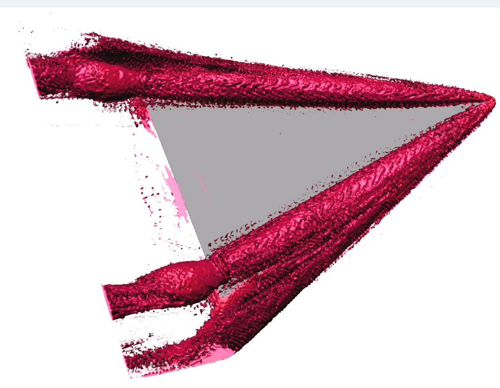
|vorticity|



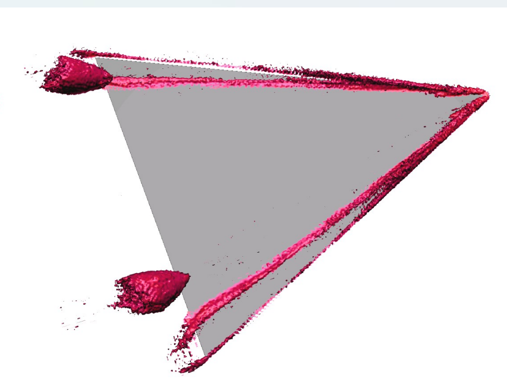
LSC pressure



LSC density



LSC |velocity| > 10



LSC |velocity| > 14

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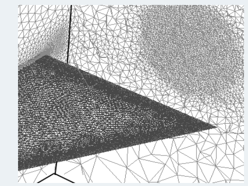
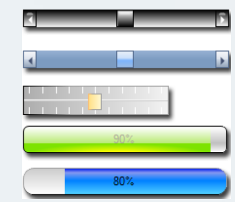
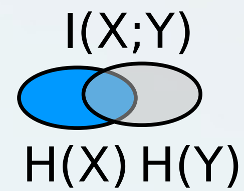
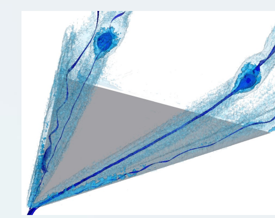
Outline

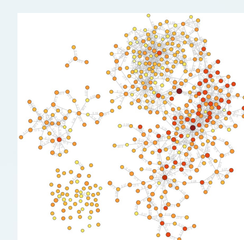
- Data representation
- Related work
- Information Theory
- Local Statistical Complexity
- Epsilon-machines
- Eulerian/ Lagrangian flow
- Conclusion/ future directions

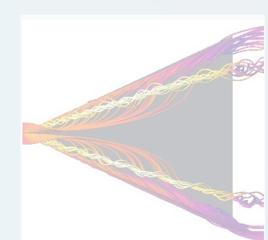




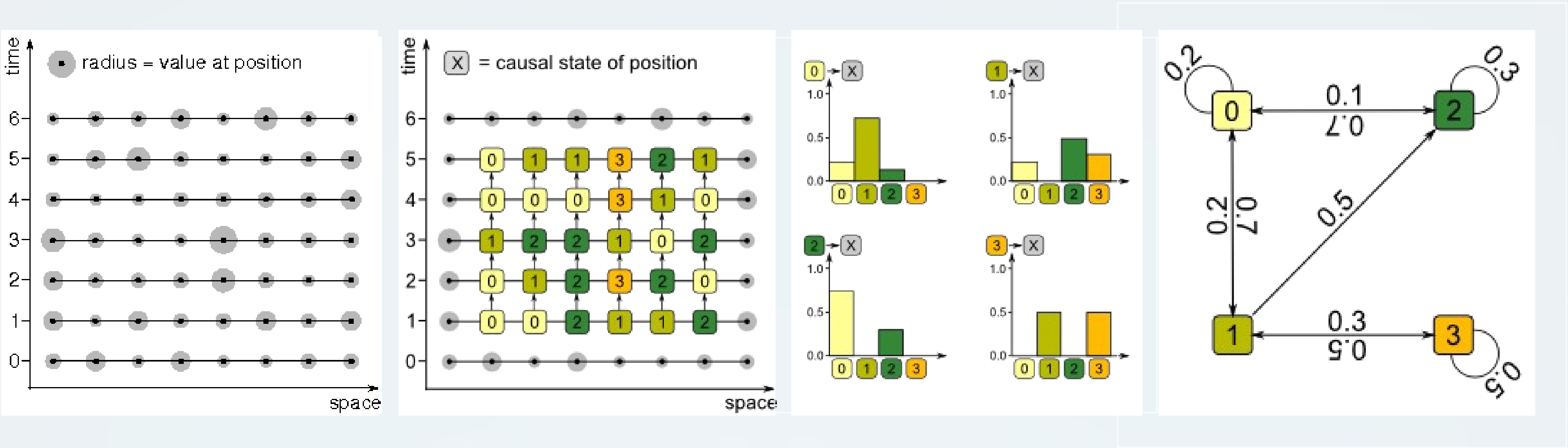




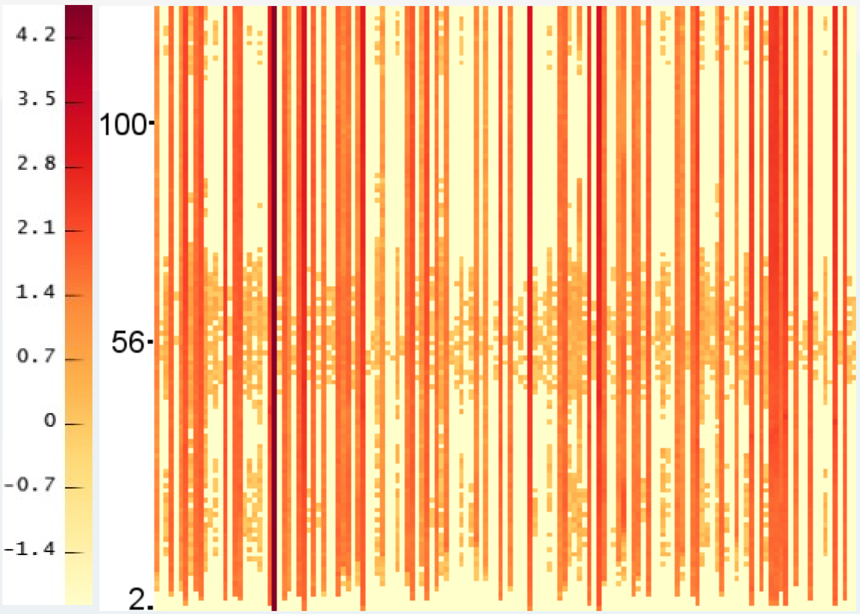


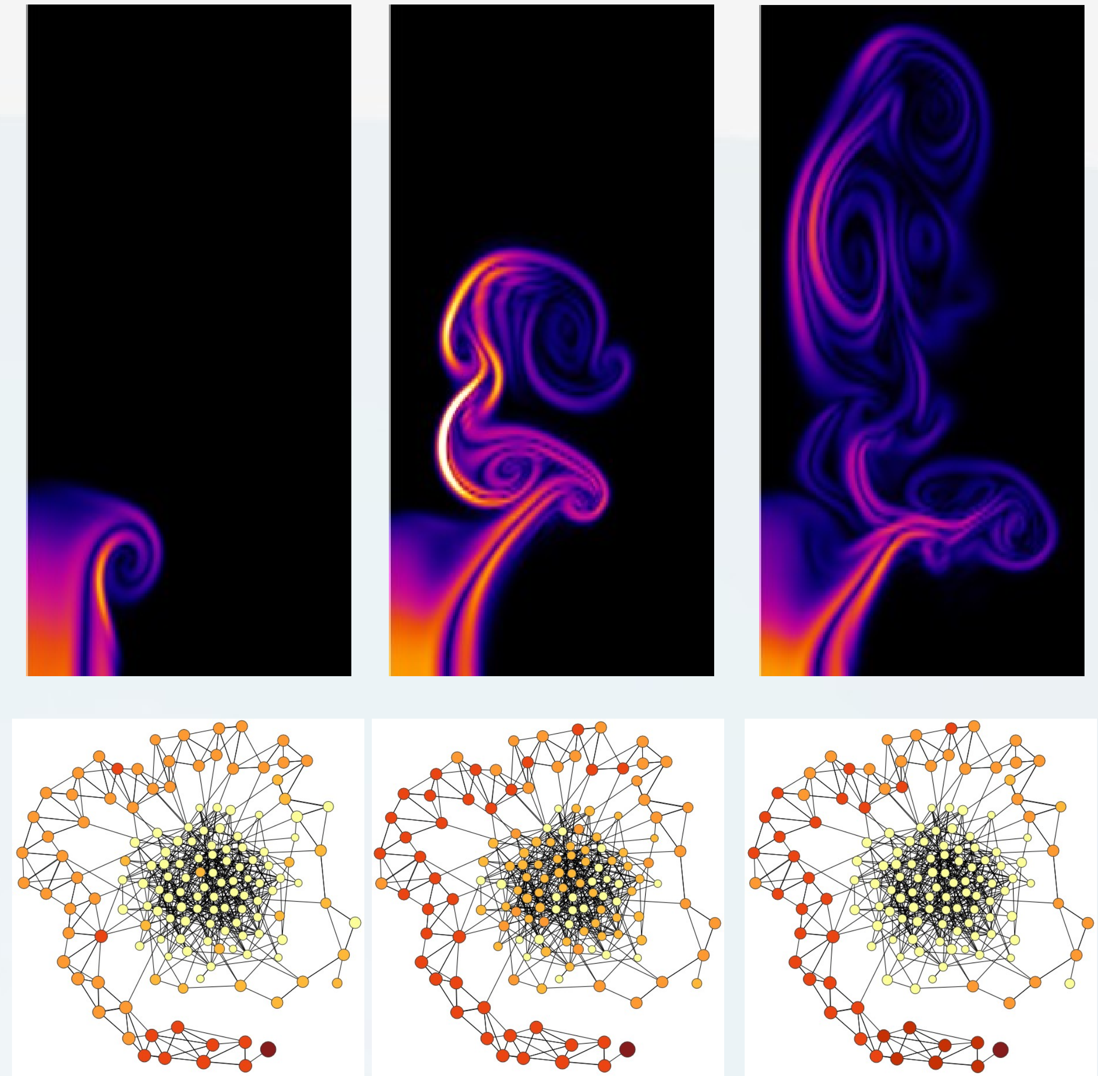


ε-Machine


time
radius = value at position
space
time
X = causal state of position
space

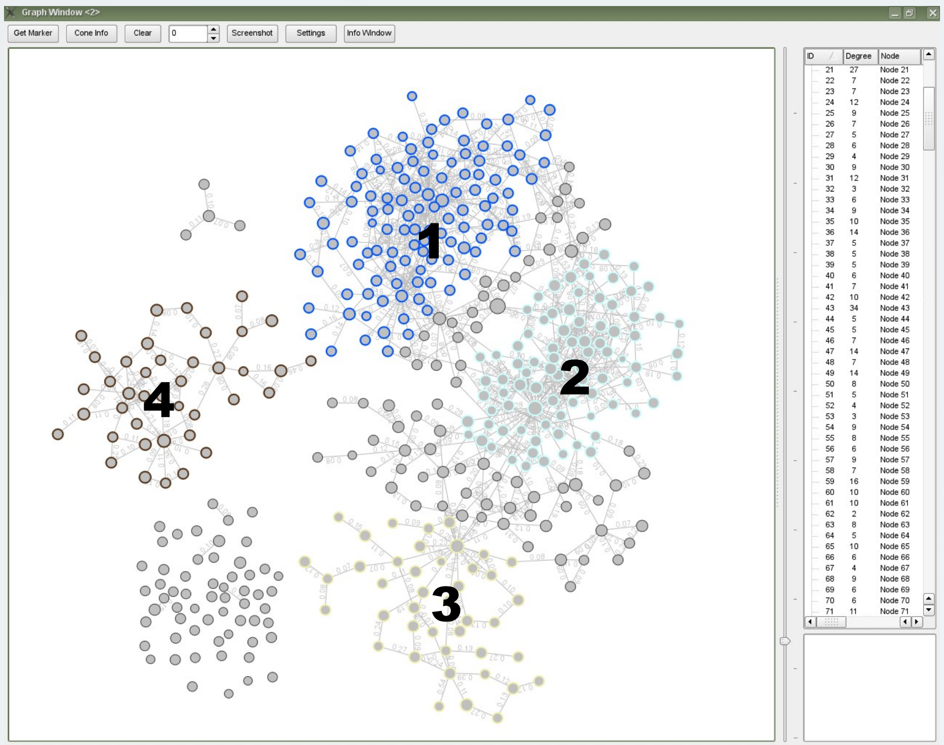
Swirling Flow

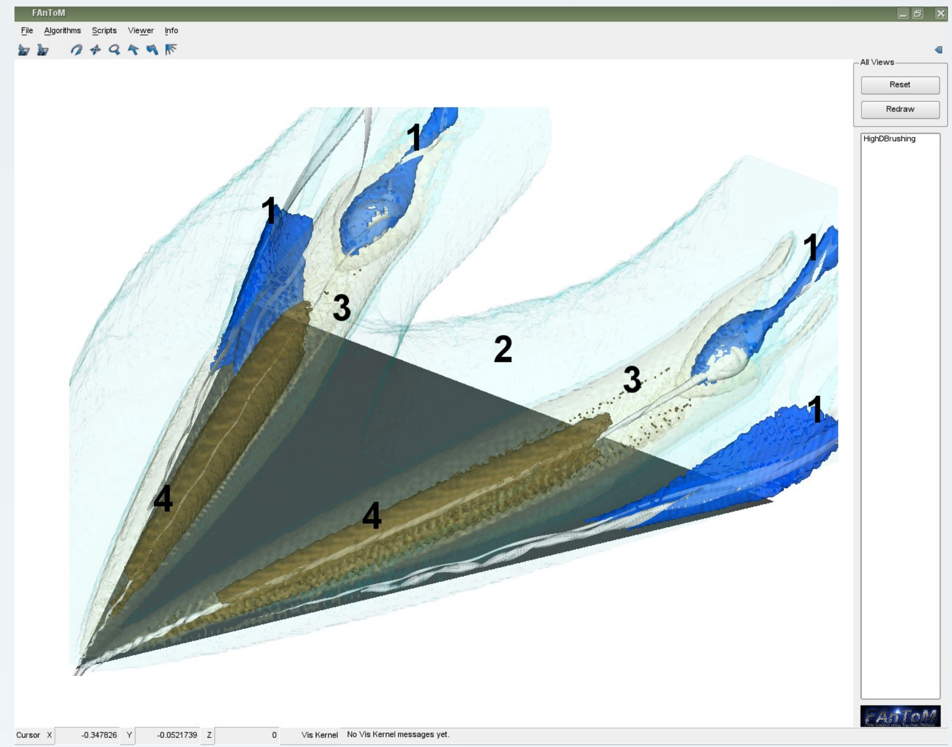




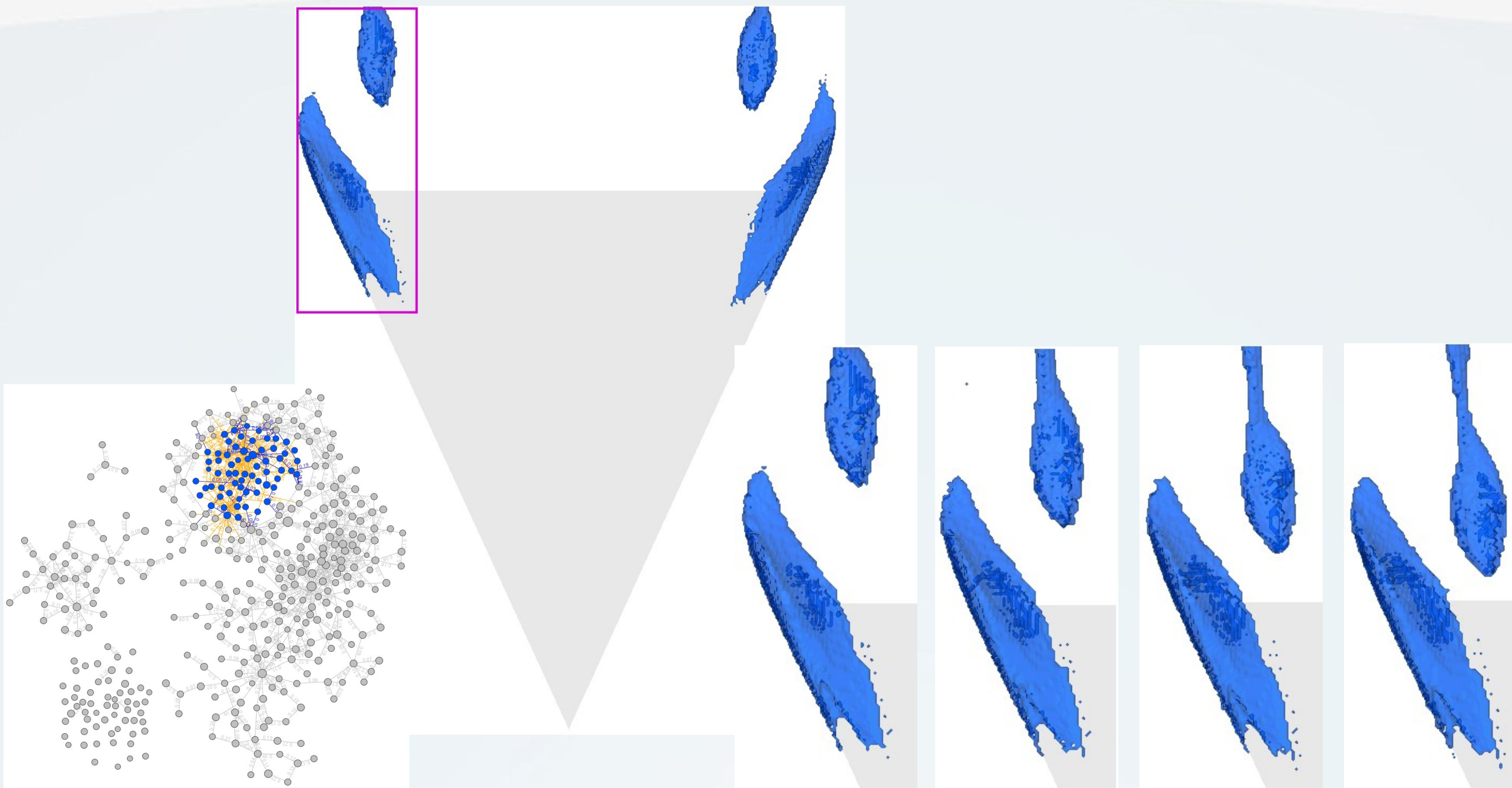
t = 8 t = 56 t = 100

ε-Machine of the Delta Wing





Delta Wing



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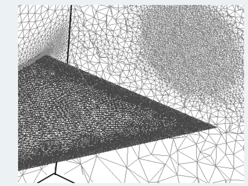
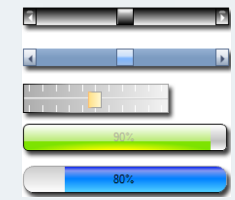
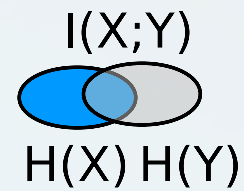
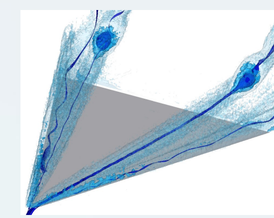
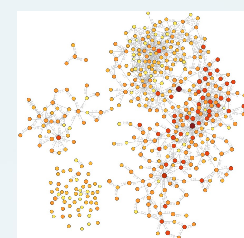
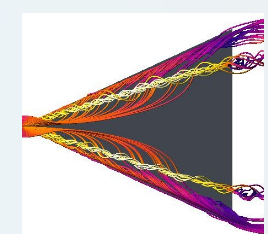






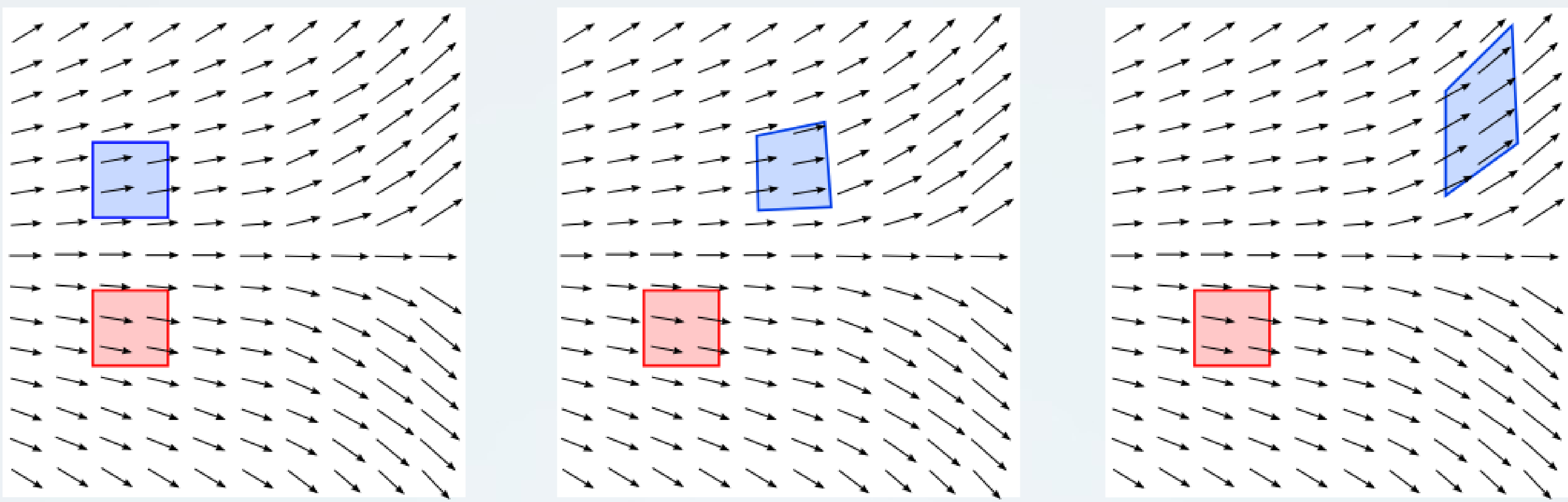






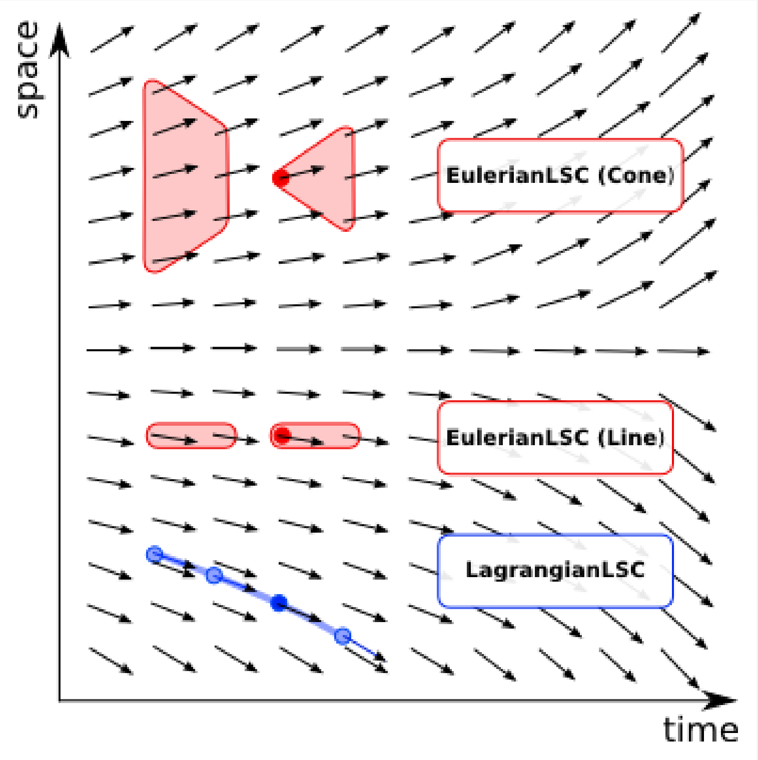
Flow Description

Lagrangian flow description

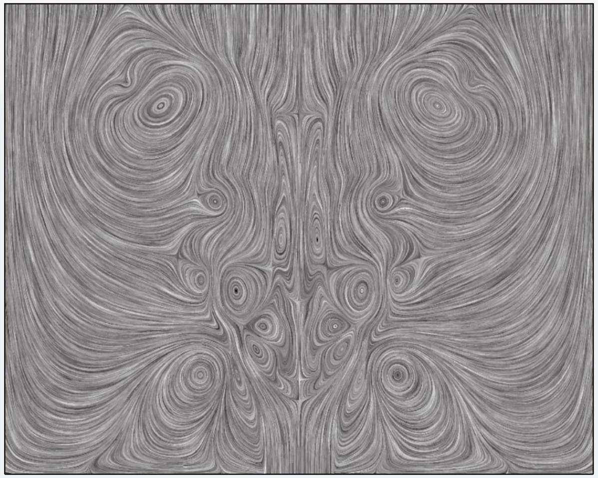


Eulerian flow description

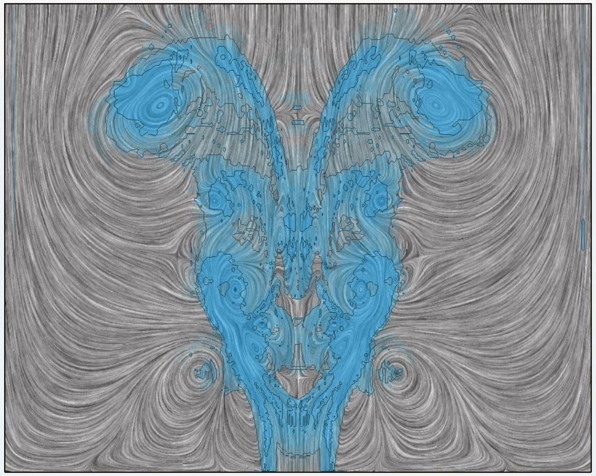
Causal States in Different Flow Descriptions



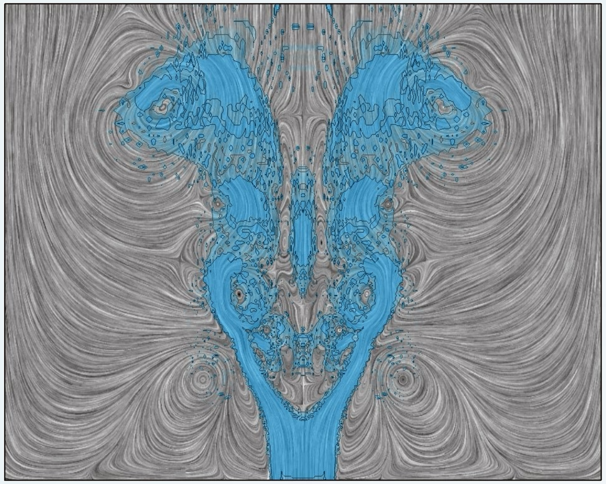
Swirling Flow



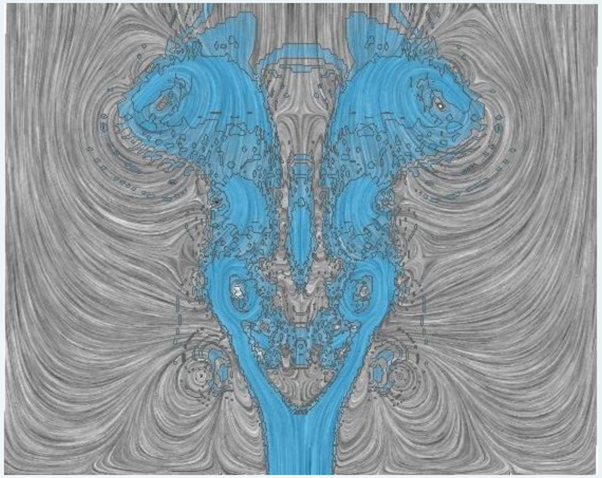
Line Integral Convolution



LIC + EulerianLSC (Cone)



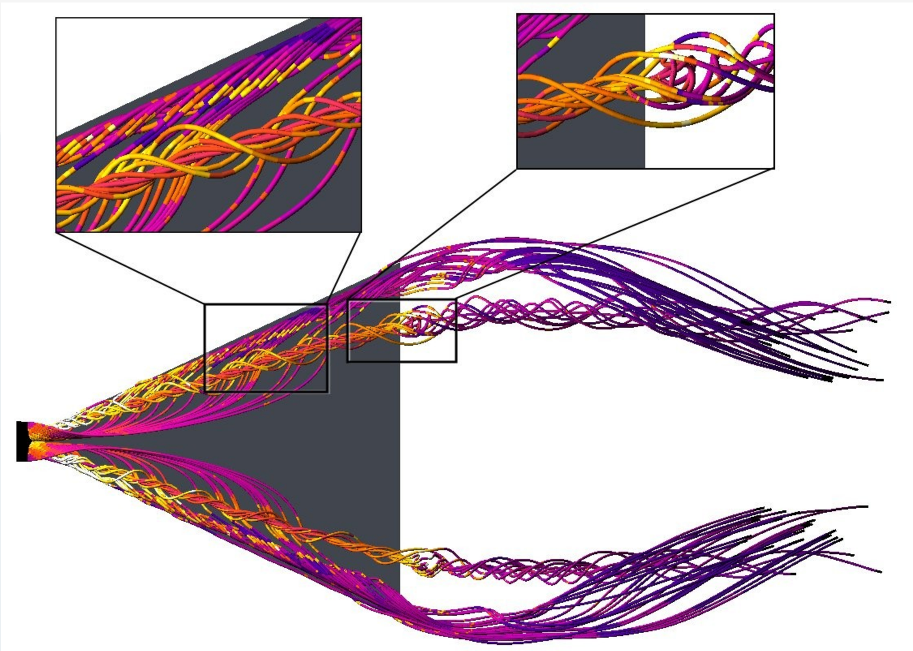
LIC + EulerianLSC (Line)



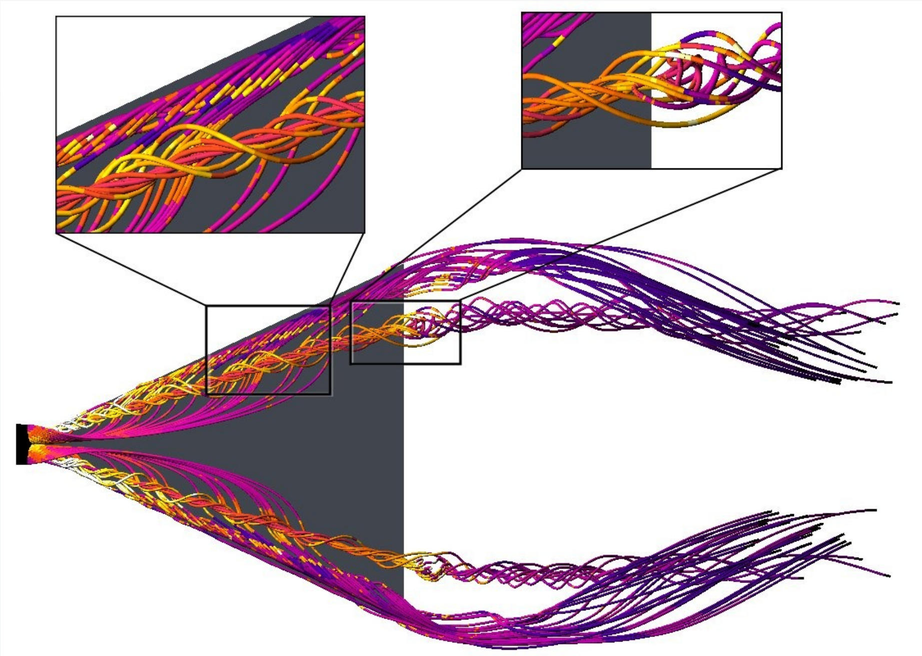
LIC + LagrangianLSC

VisWeek 09
VIS • INFOVIS • VAST

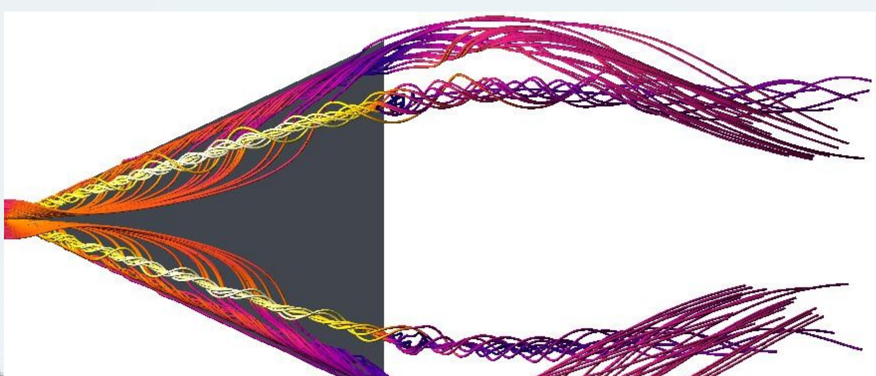
Particle-based complexity



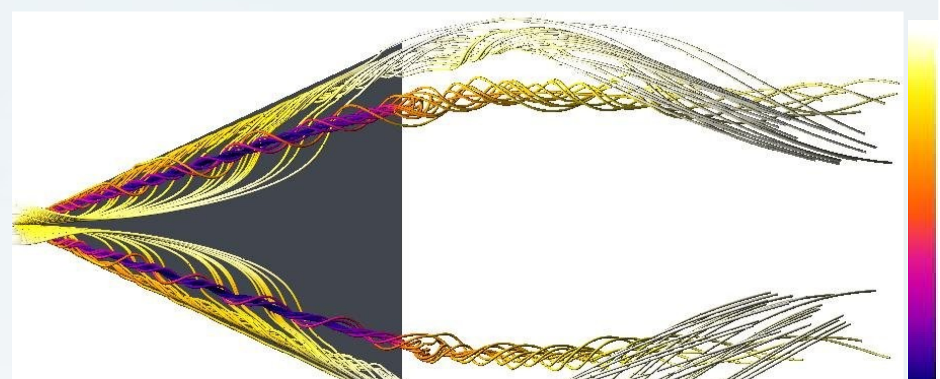
LagrangianLSC for norm of velocity



LagrangianLSC for pressure



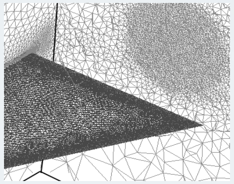
|velocity|

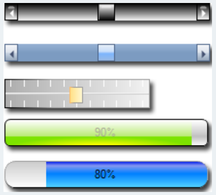


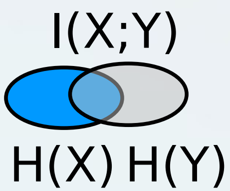
pressure

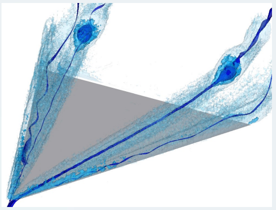
Outline

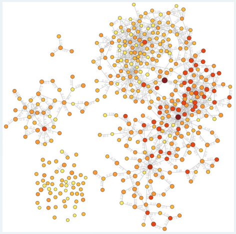
- Data representation
- Related work
- Information Theory
- Local Statistical Complexity
- Epsilon-machines
- Eulerian/ Lagrangian flow
- Conclusion/ future directions

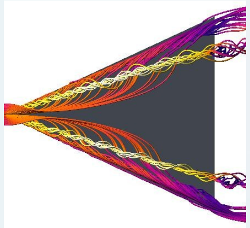


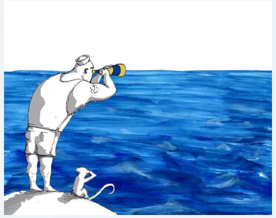












Conclusion/ Future Work

- **Conclusion**
  - Challenges in visualization
    - Multivariate data
    - Time-dependent data
    - (Automatic) feature detection
  - Automatic detection of relevant structures based on information theory
  - Steady visualization of unsteady data
  - Application to real world data sets

- **Future work**
  - Detecting structures in multivariate data
  - Better analysis of temporal changes

Thank you for your attention!

Questions?

Related publications

H. Jänicke, A. Wiebel, G. Scheuermann, W. Kollmann. Multifield Visualization Using Local Statistical Complexity. IEEE TVCG 2007.

H. Jänicke und G. Scheuermann. Principals of Information Theory Applied to Visualization. Workshop at IEEE Visualization 2007.

T. Salzbrunn, **H. Jänicke**, Th. Wischgoll und G. Scheuermann. The State of the Art in Flow Visualization: Partition-based Techniques. SCS Publishing House 2008.

H. Jänicke, M. Böttinger, X. Tricoche und G. Scheuermann. Automatic Detection and Visuali-zation of Distinctive Structures in 3D Unsteady Multi-Fields. Computer Graphics Forum 2008.

H. Jänicke, M. Böttinger und G. Scheuermann. Brushing of Attribute Clouds for the Visualization of Multivariate Data. IEEE TVCG 2008.

H. Jänicke und G. Scheuermann. Towards Automatic Feature Based Visualization. To appear in Proc. Dagstuhl Seminar – Scientific Visualization 2007.

H. Jänicke und G. Scheuermann. Steady Visualization of the Dynamics in Fluids Using ε-Machines. Accepted for publication in Computers and Graphics (Special issue on knowledge-assisted visualization) 2009.

H. Jänicke. Information Theoretic Methods for the Visual Analysis of Climate and Flow Data. PhD thesis, University of Leipzig, 2009.