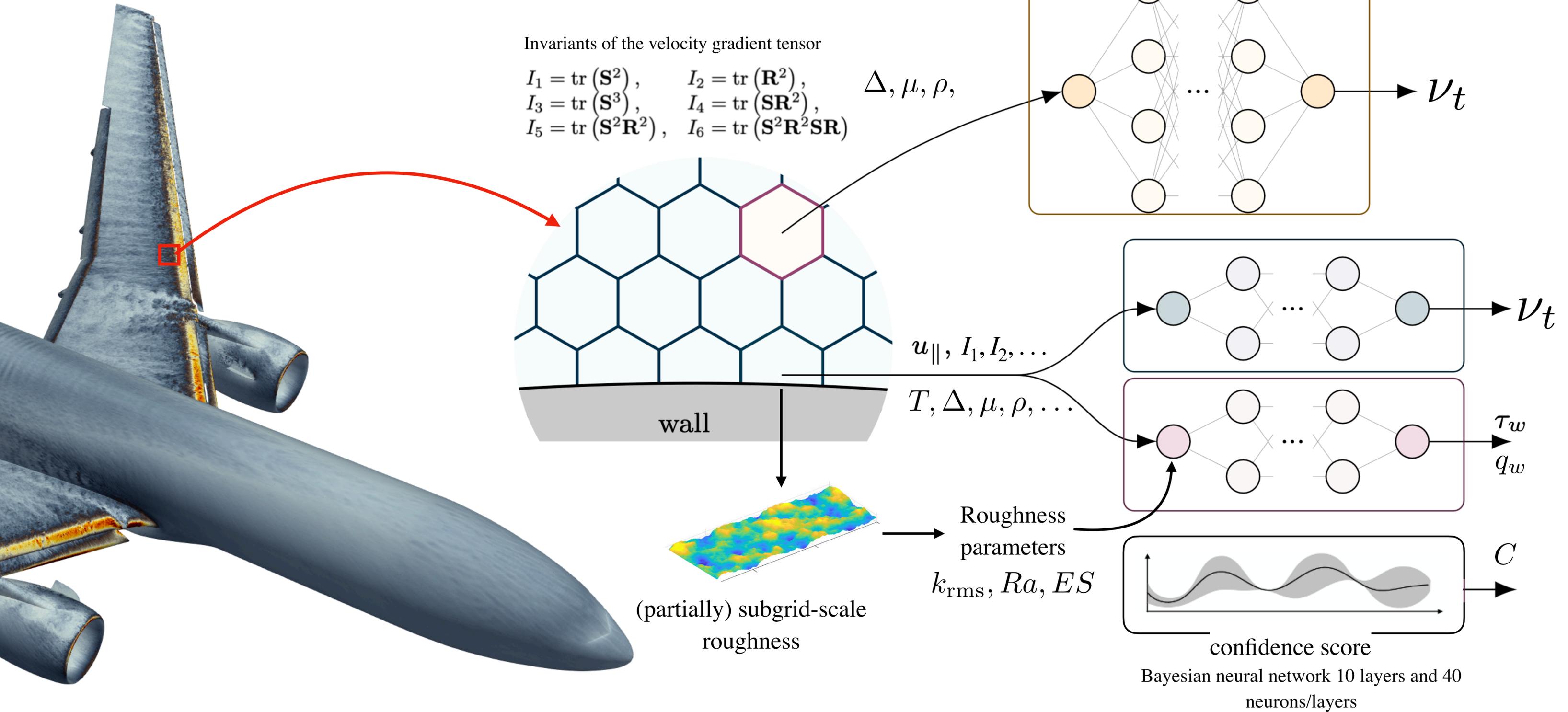


Causal inference for scientific discovery in fluid dynamics

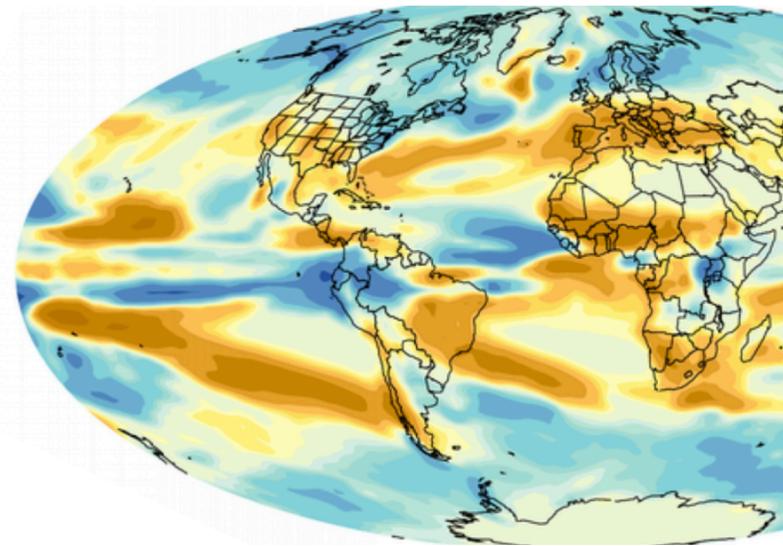
Adrian Lozano Duran
Caltech

ERCOFTAC, ML for Fluids
March 4, 2026

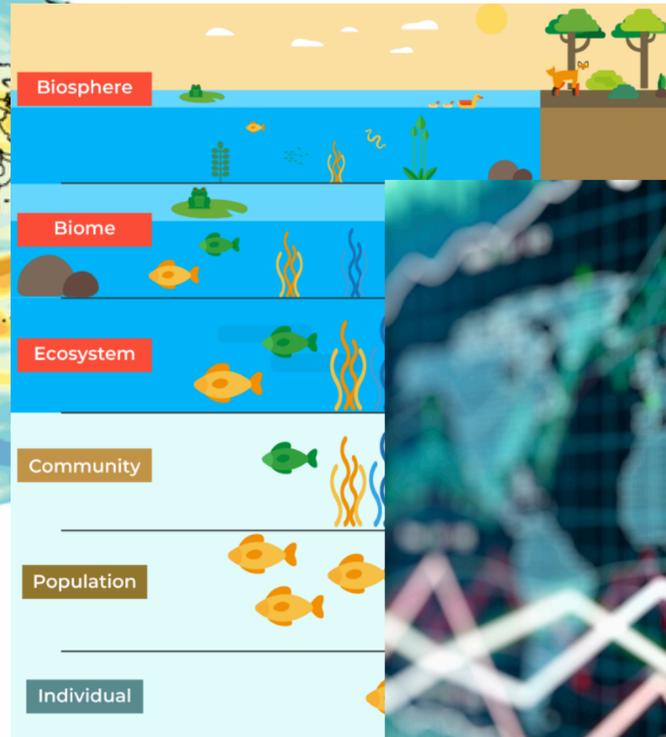
ML for turbulence closures



Causality in Science



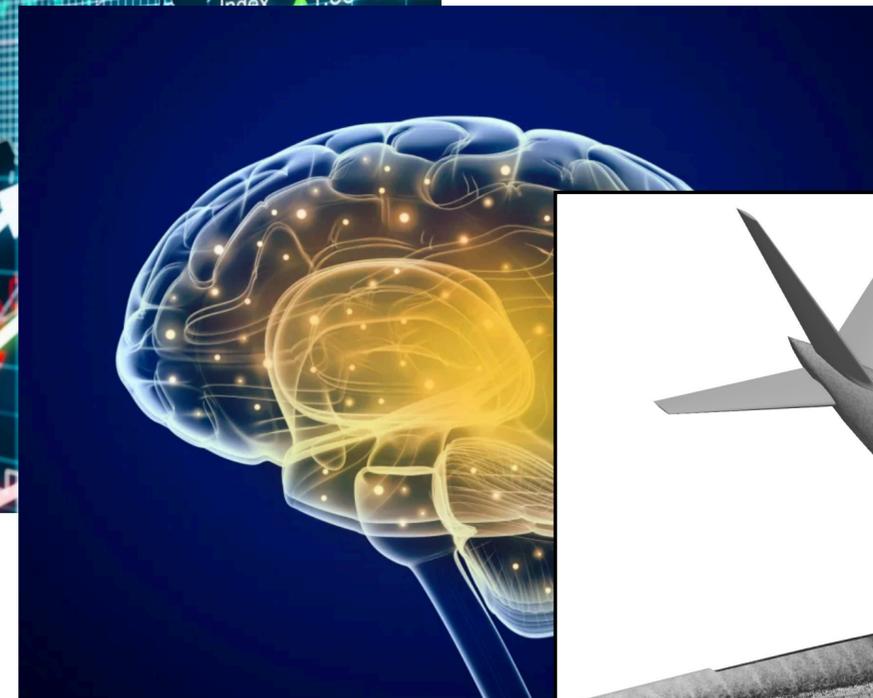
Climate



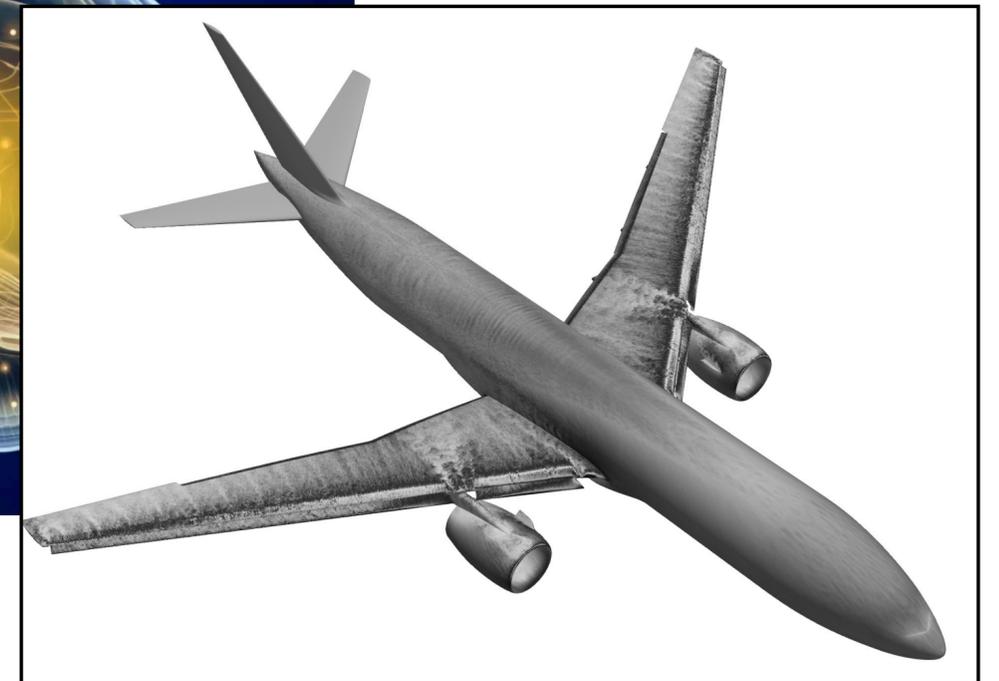
Ecology



Economics



Neuroscience



Fluid dynamics

Outline

- **What is causality?**
- **Frameworks for causal inference**
 - Interventional vs. observational
- **Three level of causality**
 - Average causality
 - State-dependent causality
 - Space-time causality
- **Limitations**

Outline

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Related publications at

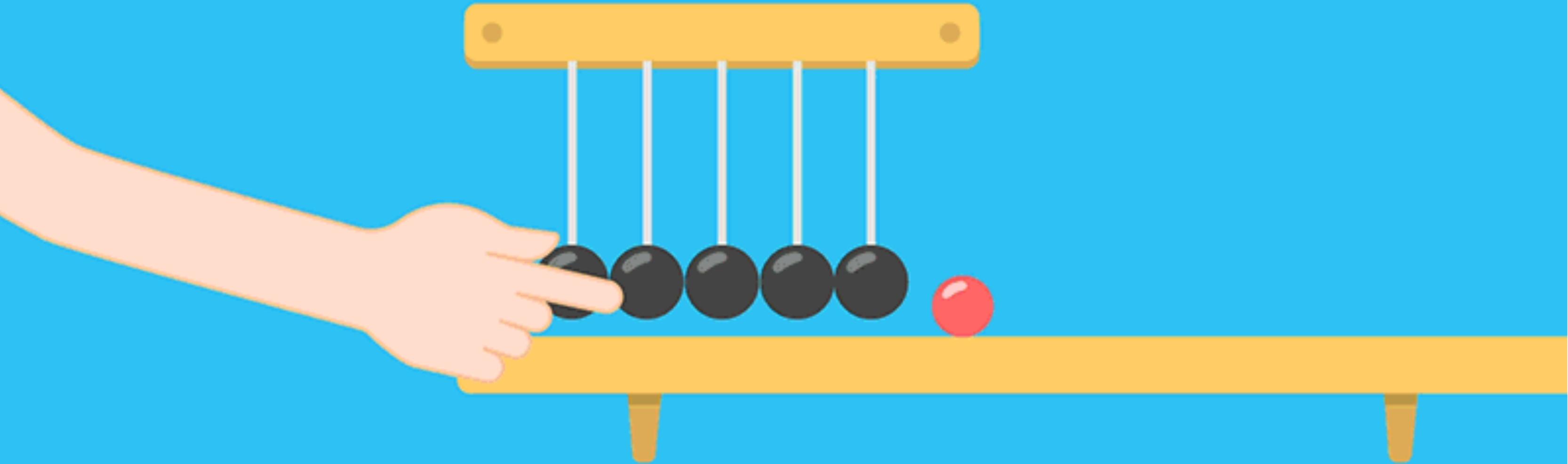
adrianld.mit.edu

Outline

- **What is causality?**
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“Causality is the mechanism by which one event contributes to the genesis of another”

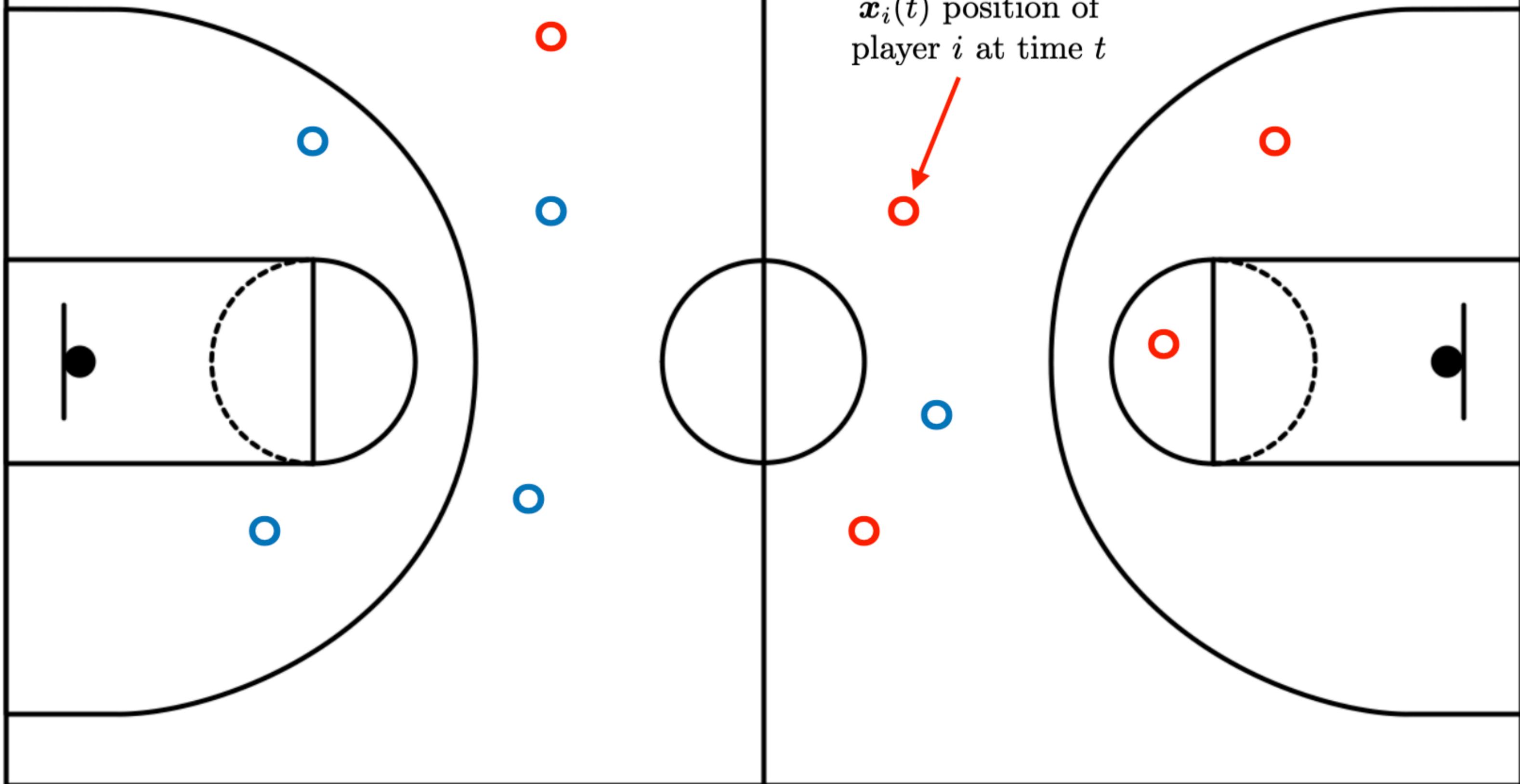
What is causality?



“Causality” in turbulence research

- Space/Temporal correlations
- One/two-point statistics
- Energy budget
- Linear stability analysis
- Modal decomposition
- ...

An analogy with Basketball

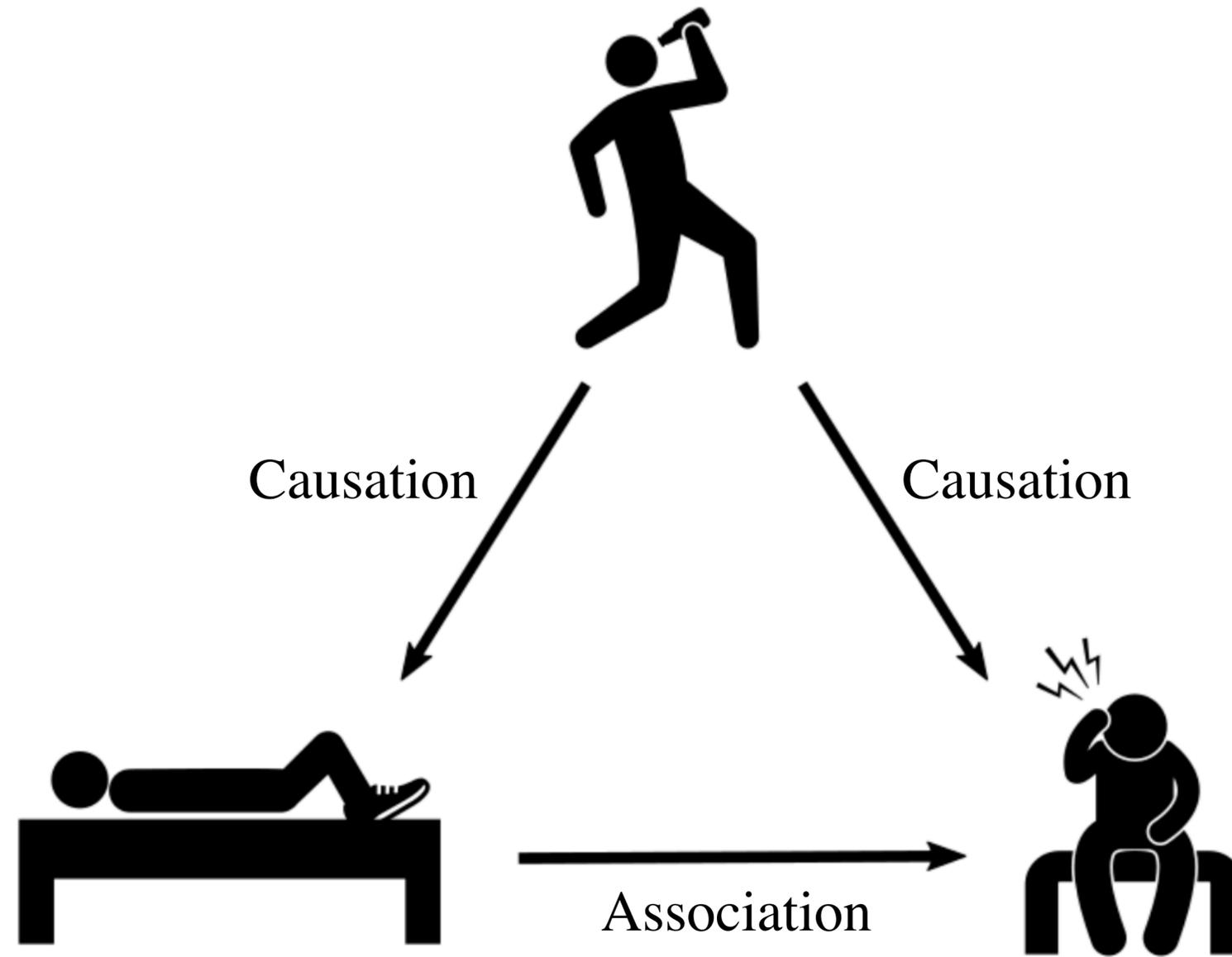


An analogy with Basketball

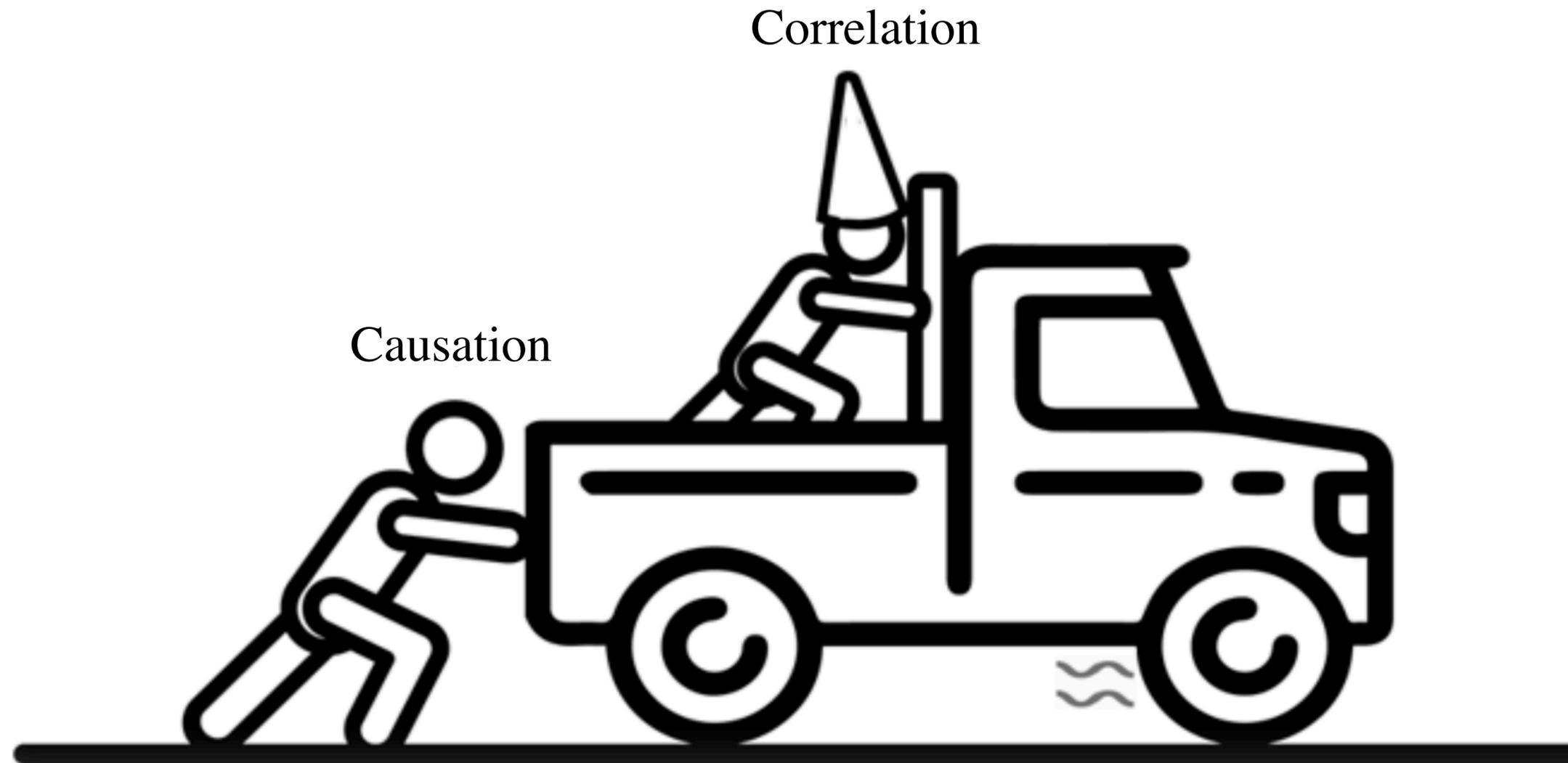
$x_i(t)$ position of player i at time t

Could we understand basketball using correlation-based quantities?

Causality \neq Association



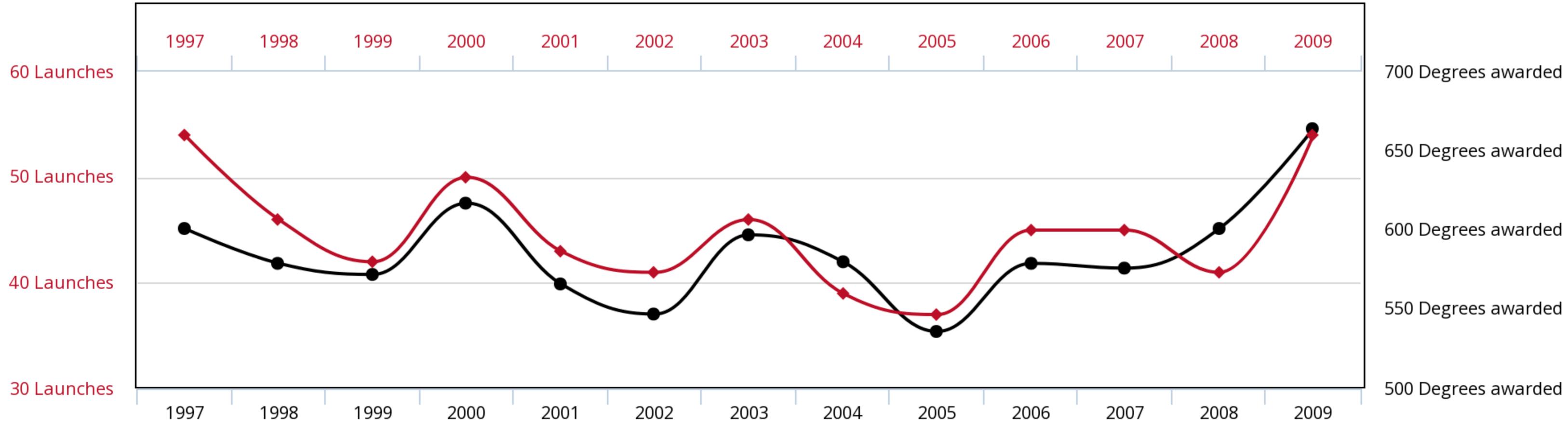
Causality \neq Correlation



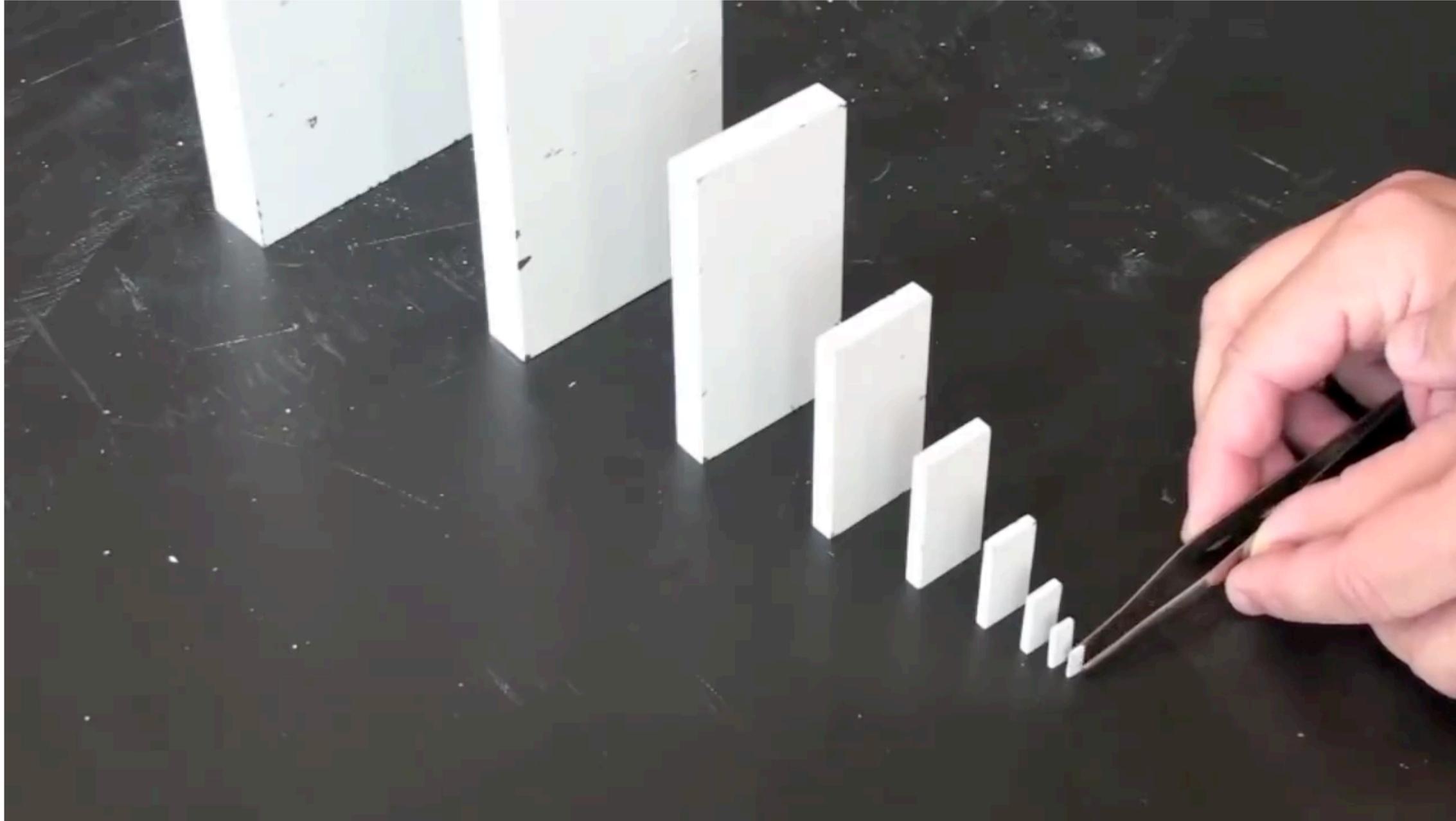
Worldwide non-commercial space launches

correlates with

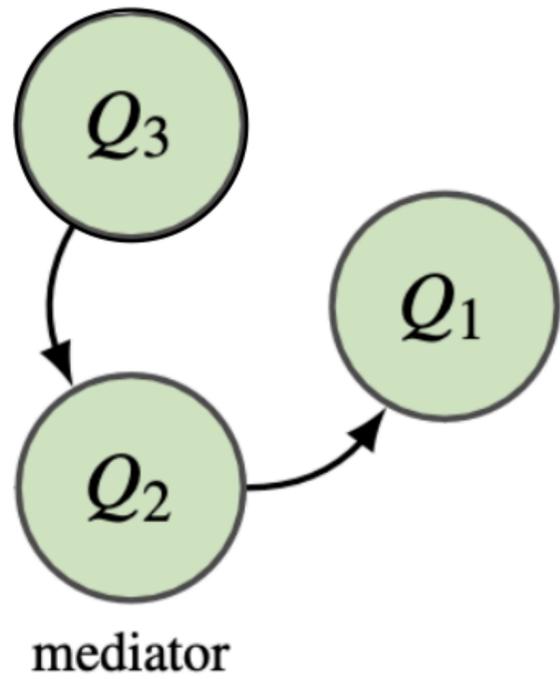
Sociology doctorates awarded (US)



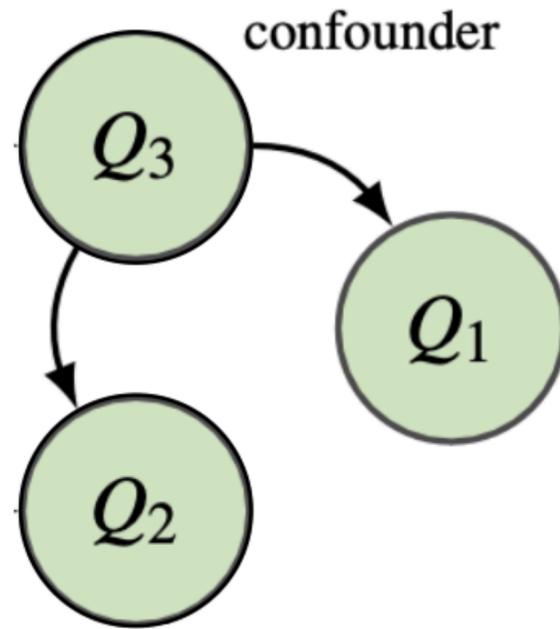
Causality \neq Strength



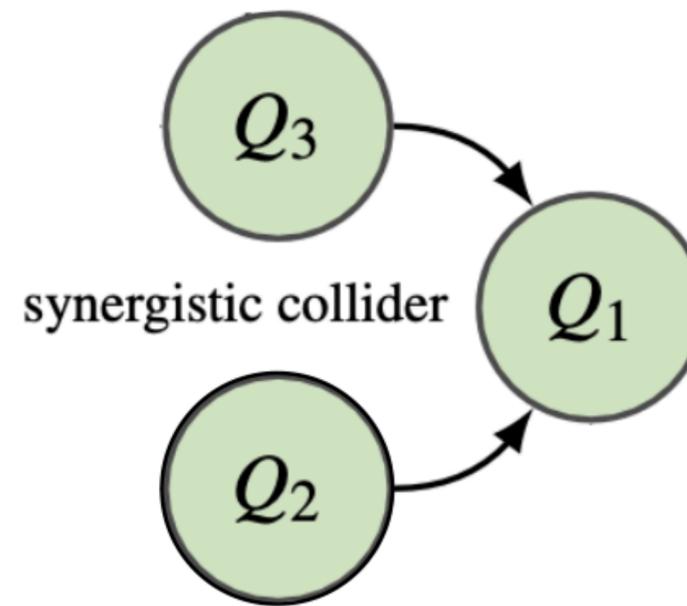
Fundamental interactions in causality



education level \rightarrow job skills \rightarrow income

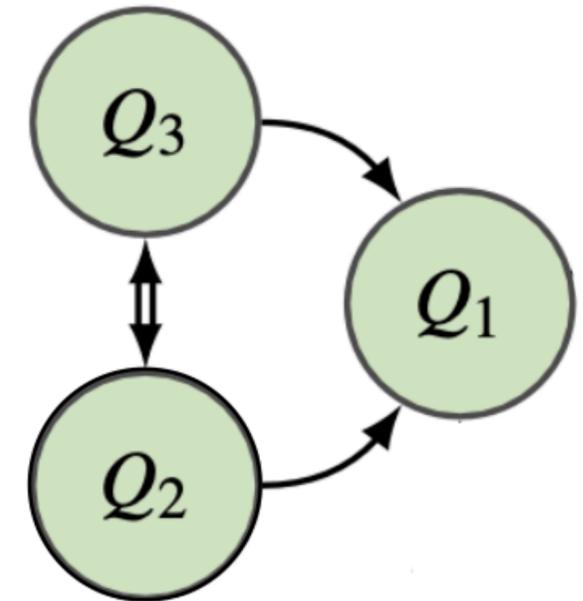


Rainy season \rightarrow umbrella sales
 Rainy season \rightarrow raincoat sales



only drug A \rightarrow not recovery
 only drug B \rightarrow not recovery
 drug A + drug B \rightarrow recovery

redundant collider



smart student
 hard-working student \rightarrow good grades

Why causal analysis in fluid dynamics?

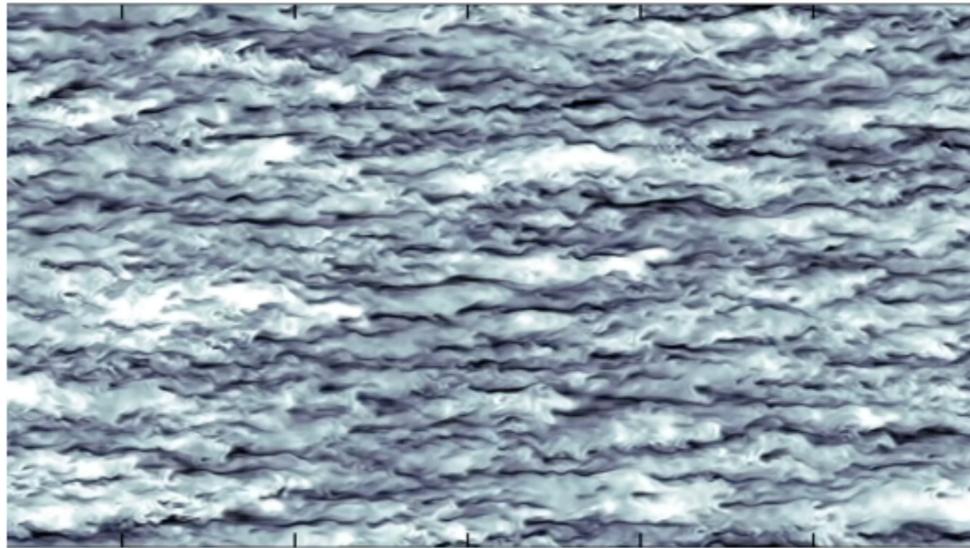
Physical insight

Causality-preserving
reduced-order models

Causality-driven control

Why causal analysis in fluid dynamics?

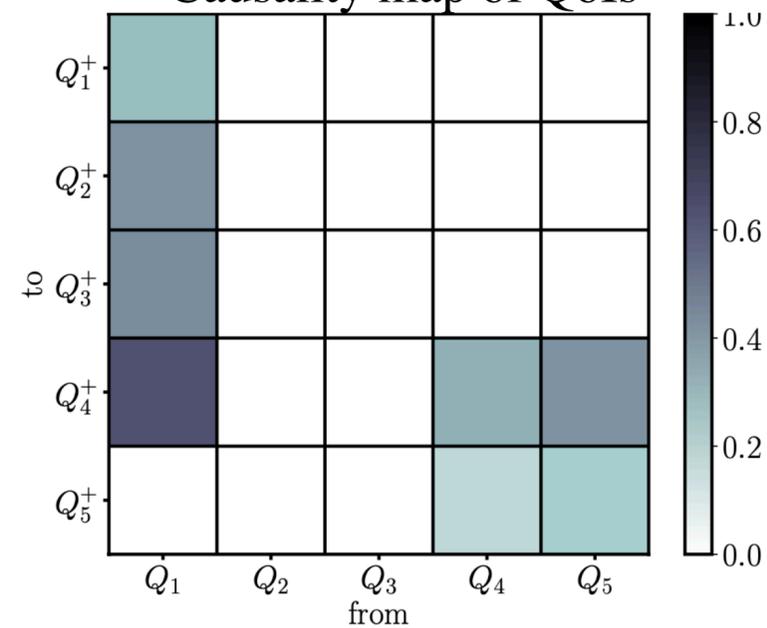
Physical insight



Causality-preserving
reduced-order models

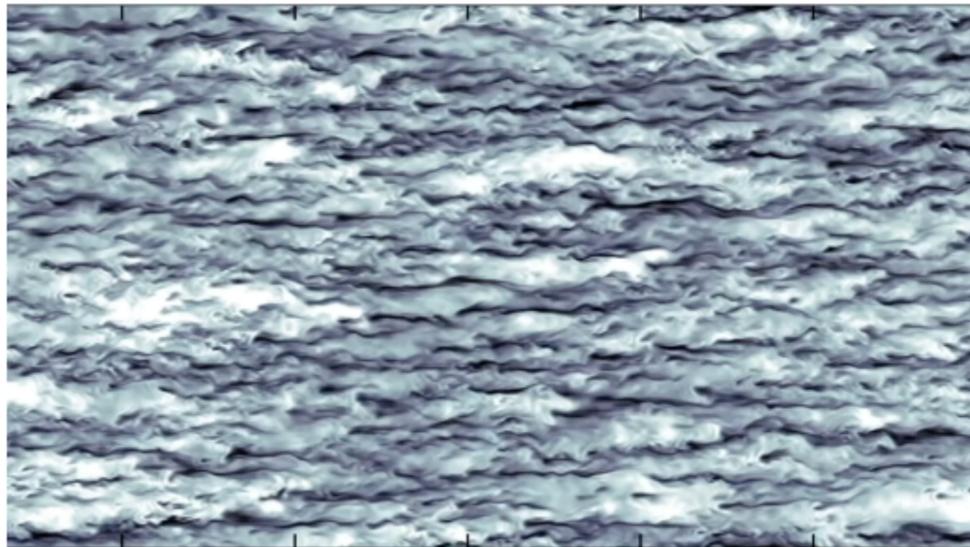
Causality-driven control

Causality map of QoIs

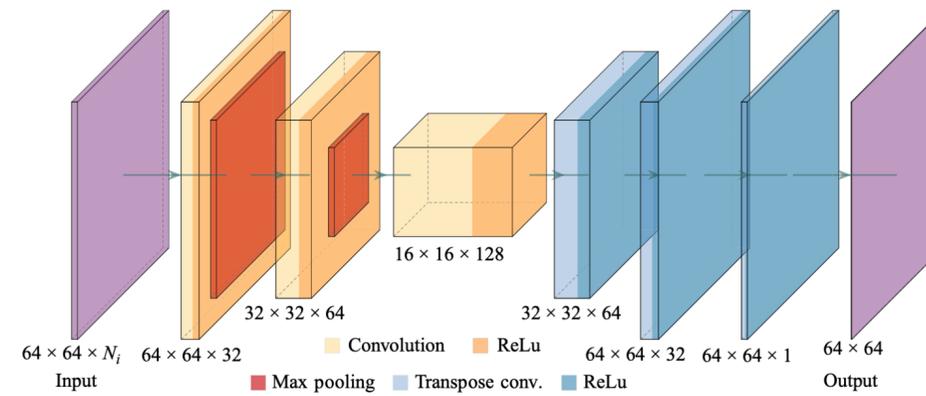


Why causal analysis in fluid dynamics?

Physical insight

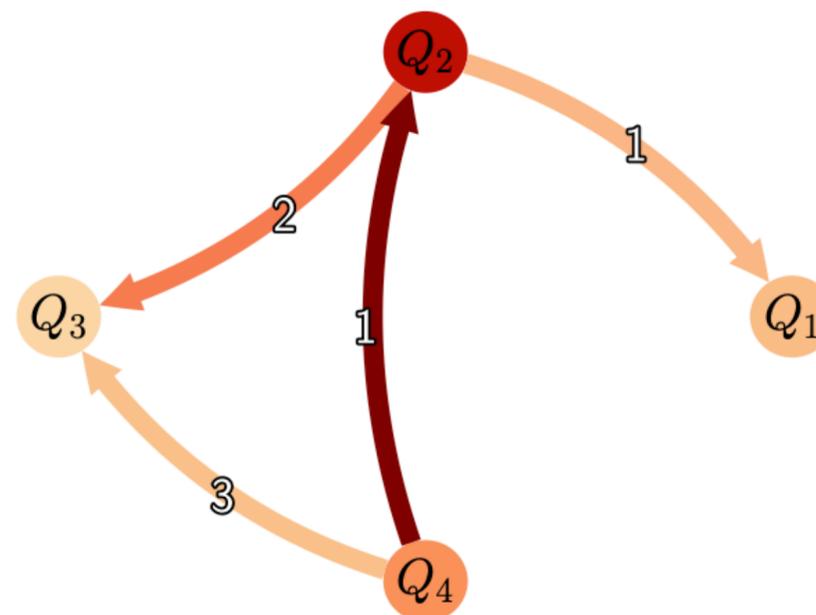
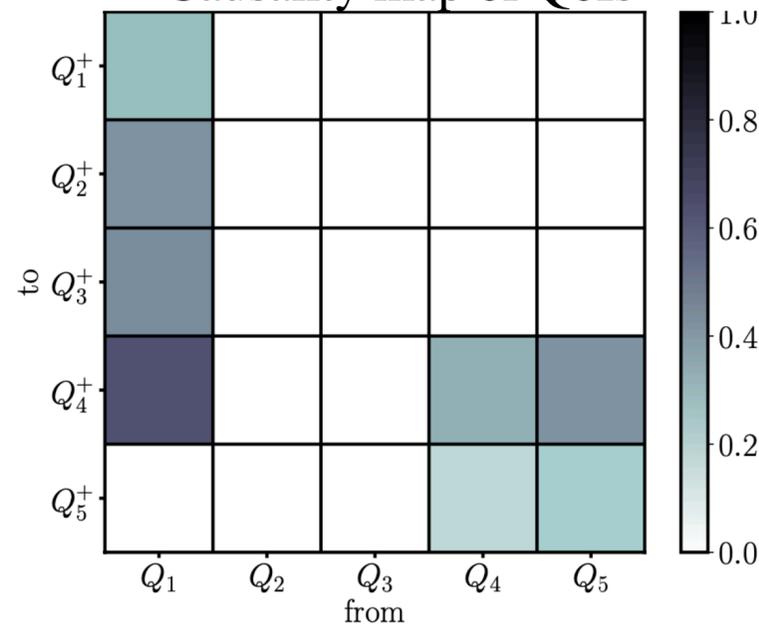


Causality-preserving reduced-order models



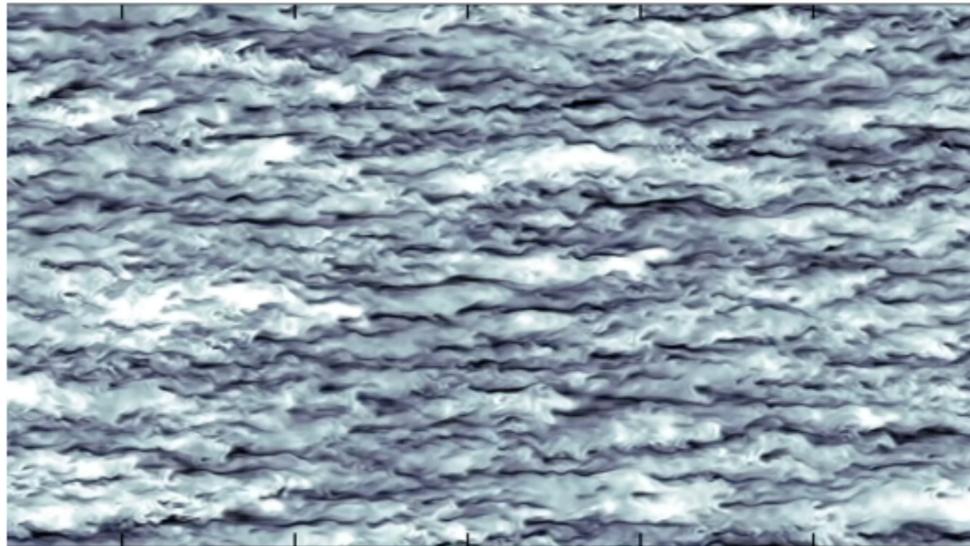
Causality-driven control

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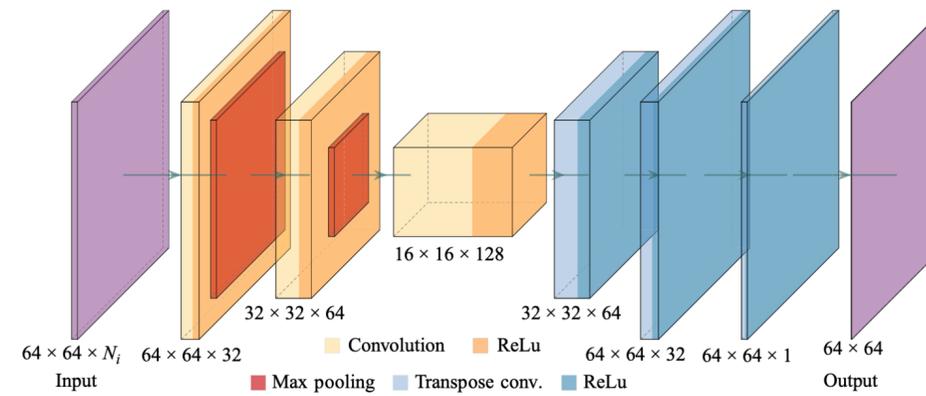


Why causal analysis in fluid dynamics?

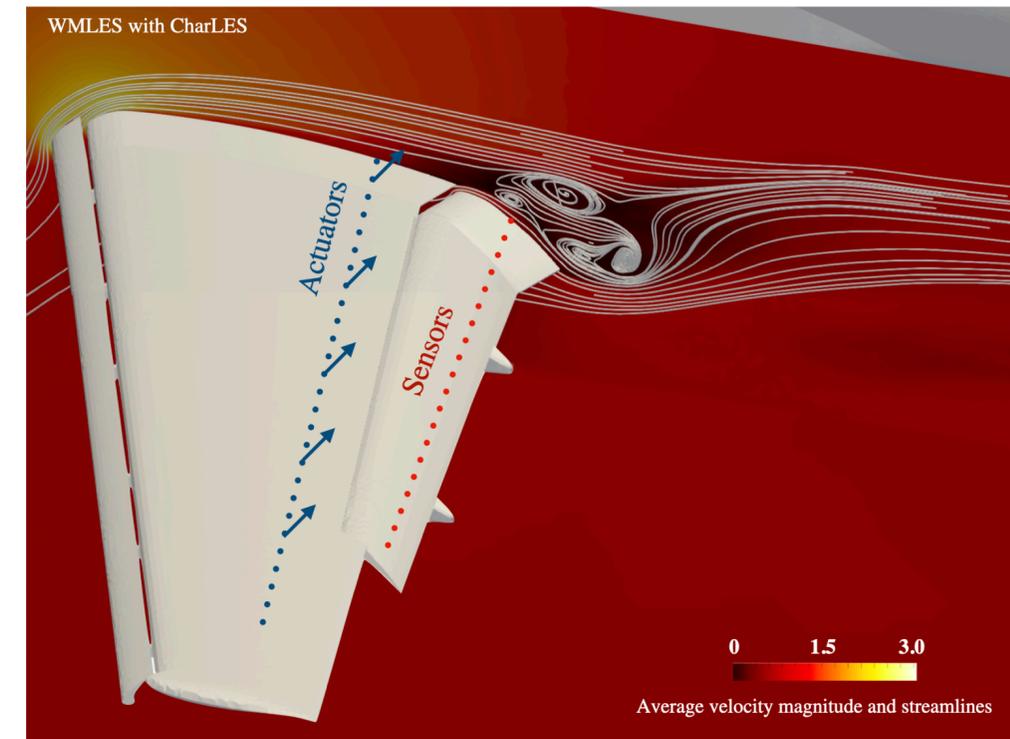
Physical insight



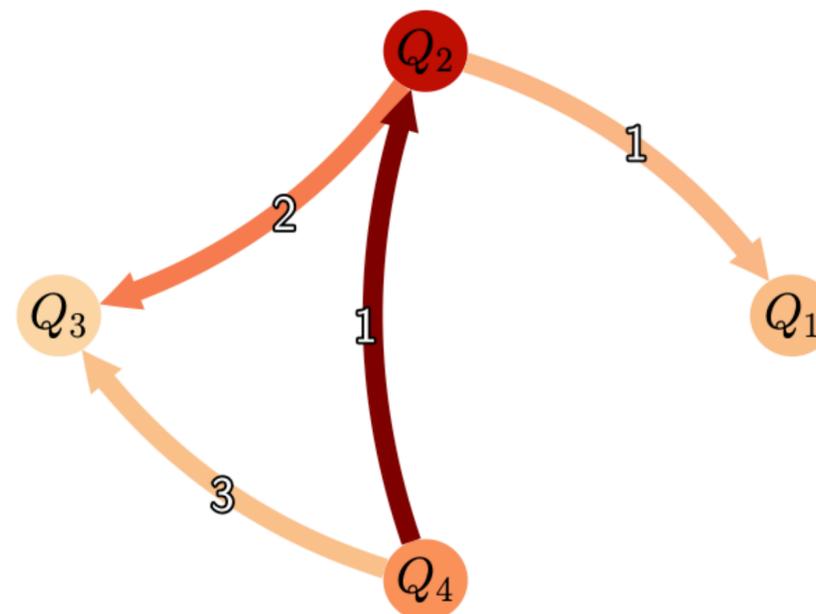
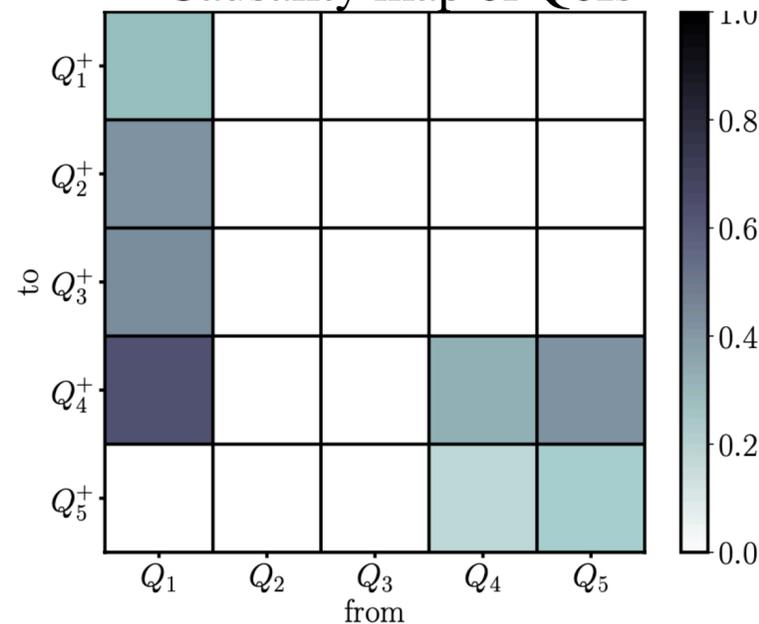
Causality-preserving reduced-order models



Causality-driven control



Causality map of QoIs



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Causality with **Interventions**

Modify the system and observe the consequences

Causality with **Interventions**

Modify the system and observe the consequences

Challenges:

- Impossible: interventions to assess the causality in the stock market in 2008 not possible
- Ethical problems: manipulating living organisms or altering natural environmental conditions
- Taking the system out of its natural attractor
- What interventions to perform?
- Even if interventions are possible, quantity of interest might not be straight forward to intervene

Causality with Interventions



Alexander the Great

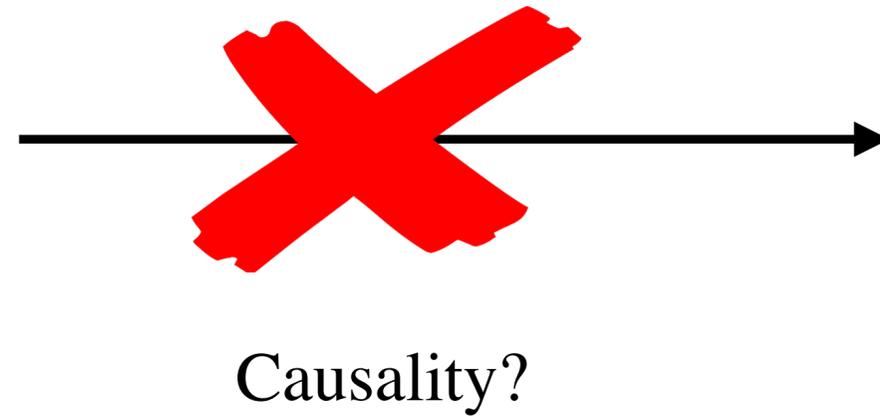


Alexander the Great, victorious over Darius at the Battle of Gaugamela by [Jacques Courtois](#)

Causality with Interventions



Alexander the Great



Alexander the Great, victorious over Darius at the Battle of Gaugamela by Jacques Courtois

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Observational methods for causal inference

Causality with Observations

Infer causal relationship by observing the system in its ‘natural’ state without disturbances

- **Model forecasting methods:**
 - Granger causality (Granger, 1969)
 - Conditional GC (Barrett, 2010)
 - ...
- **Statistical independence relations in data:**
 - Structural causal model (Pearl, 1995)
 - PC (Peter and Clark,)
 - tsPC (Spirtes, 2004)
 - PCMCI (Runge, 2019)
 - ...
- **Randomized experiments:**
 - Potential outcomes (Rubin, 2007)
 - ...
- **Information-theoretic methods:**
 - Transfer entropy (Schreiber, 2000)
 - Liang’s information flow (Liang, 2008)
 - Information flux (Lozano-Duran, 2022)
 - SURD (Martinez-Sanchez, 2024)
 - ...
- **Attractor reconstruction:**
 - Convergent cross-mapping (Sugihara, 2012)
 - Partial convergent cross-mapping (Long, 2020)
 - ...

Two Nobel Prizes in Economic Sciences

Granger Causality, 2003



Sir Clive Granger
U. Nottingham and UCSD

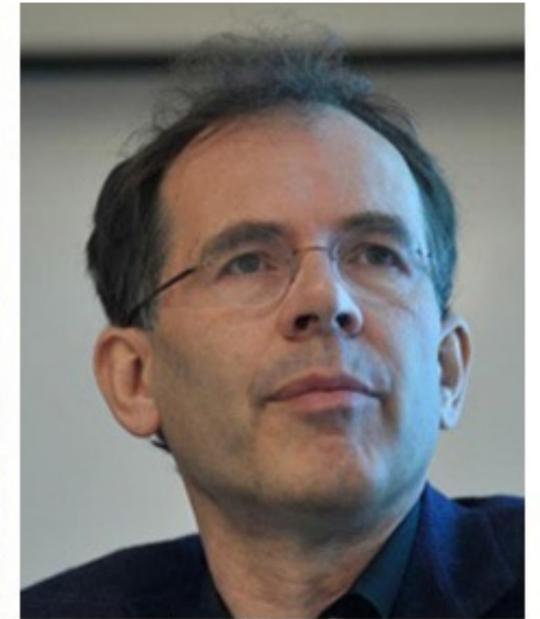
Natural Experiments, 2021



Joshua Angrist



David Card



Guido Imbens

MIT, UC Berkeley and Stanford

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Three levels of causality

Average Causality

State-dependent Causality

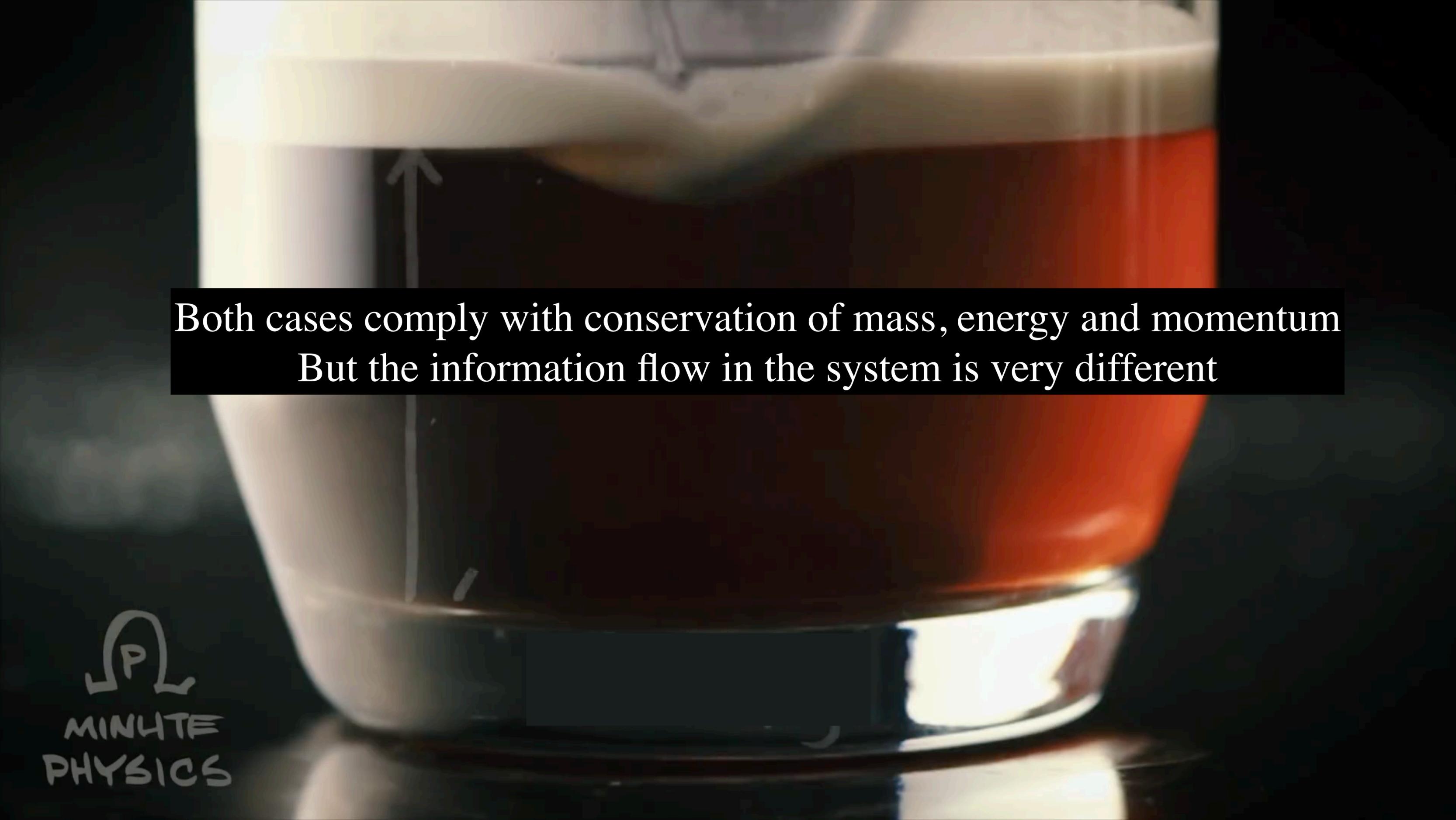
Space-time Causality

Mixing



Mixing





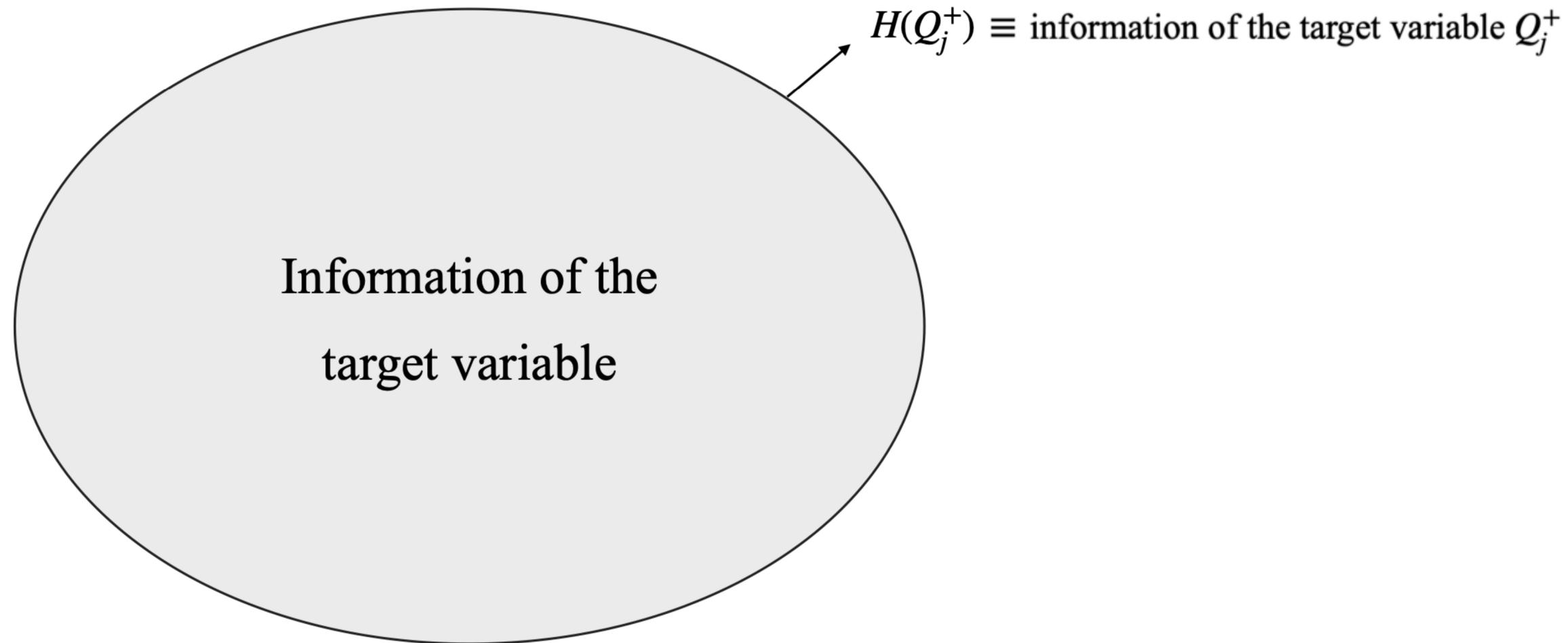
Both cases comply with conservation of mass, energy and momentum
But the information flow in the system is very different

Average causality: Method

“Causality is the mechanism by which one event contributes to the genesis of another” (Pearl 2008)

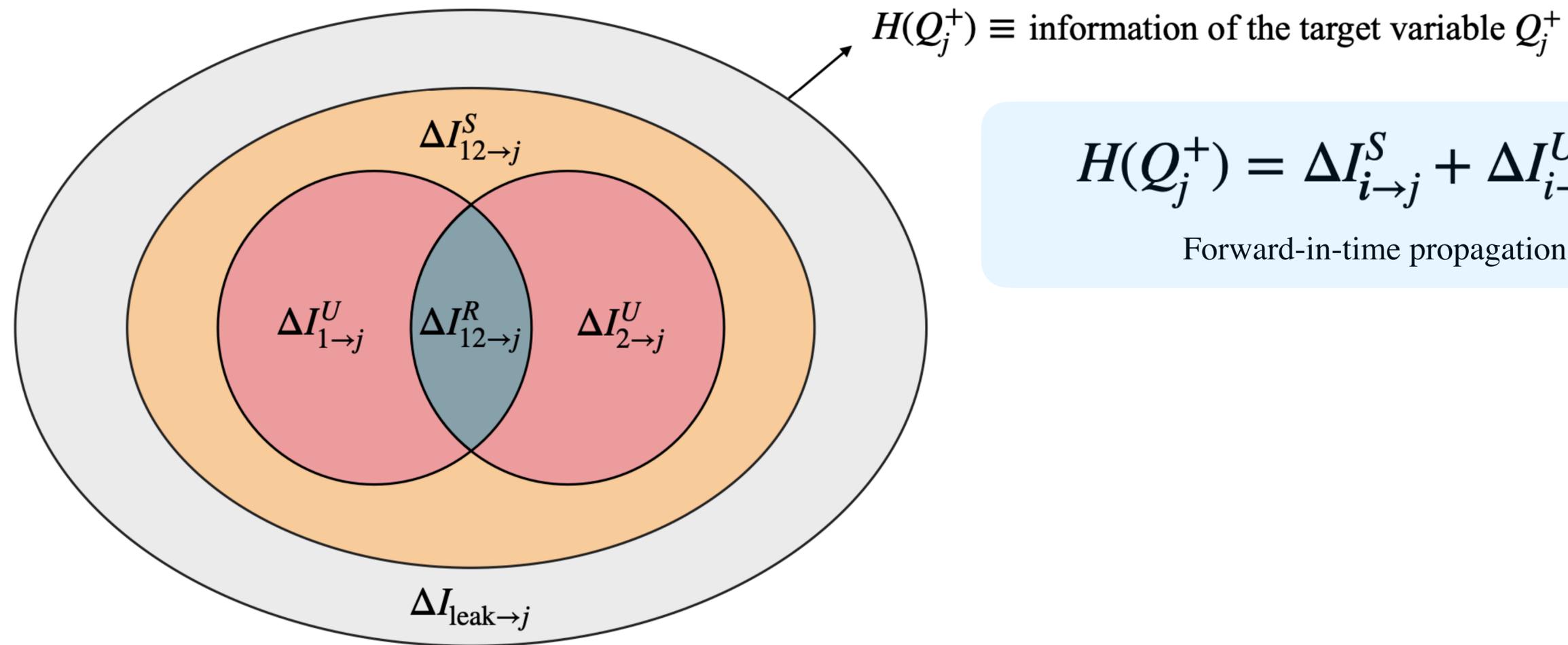
Average causality: Method

Quantify the causality from observed variables $\mathbf{Q} = [Q_1, Q_2]$ to target variable $Q_j^+ = Q_j(t + \Delta T)$



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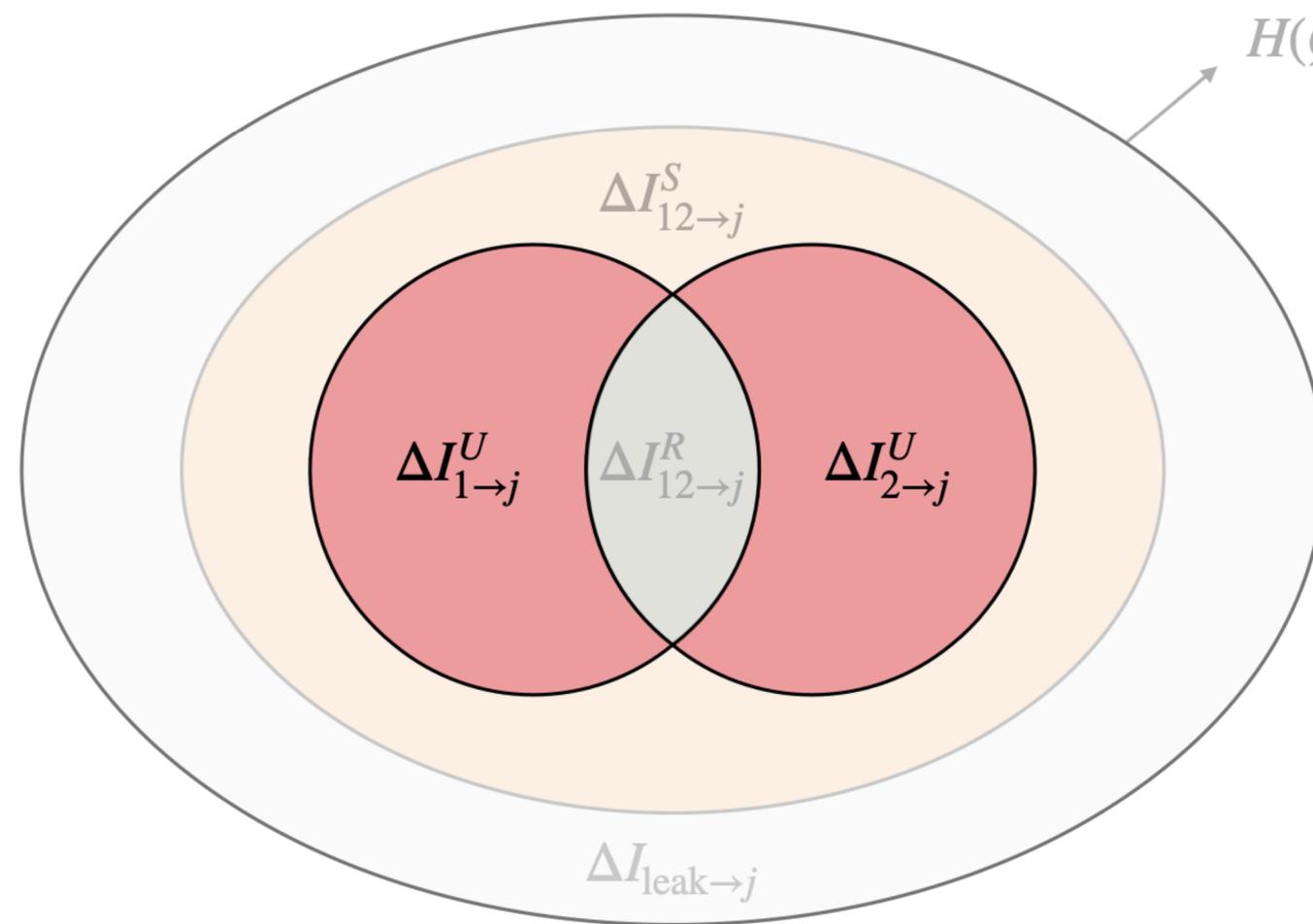


$$H(Q_j^+) = \Delta I_{i \rightarrow j}^S + \Delta I_{i \rightarrow j}^U + \Delta I_{i \rightarrow j}^R + \Delta I_{\text{leak} \rightarrow j}$$

Forward-in-time propagation of information equation

Average causality: Method

Quantify the causality from observed variables $\mathbf{Q} = [Q_1, Q_2]$ to target variable $Q_j^+ = Q_j(t + \Delta T)$



$H(Q_j^+) \equiv$ information of the target variable Q_j^+

$$H(Q_j^+) = \Delta I_{i \rightarrow j}^S + \Delta I_{i \rightarrow j}^U + \Delta I_{i \rightarrow j}^R + \Delta I_{\text{leak} \rightarrow j}$$

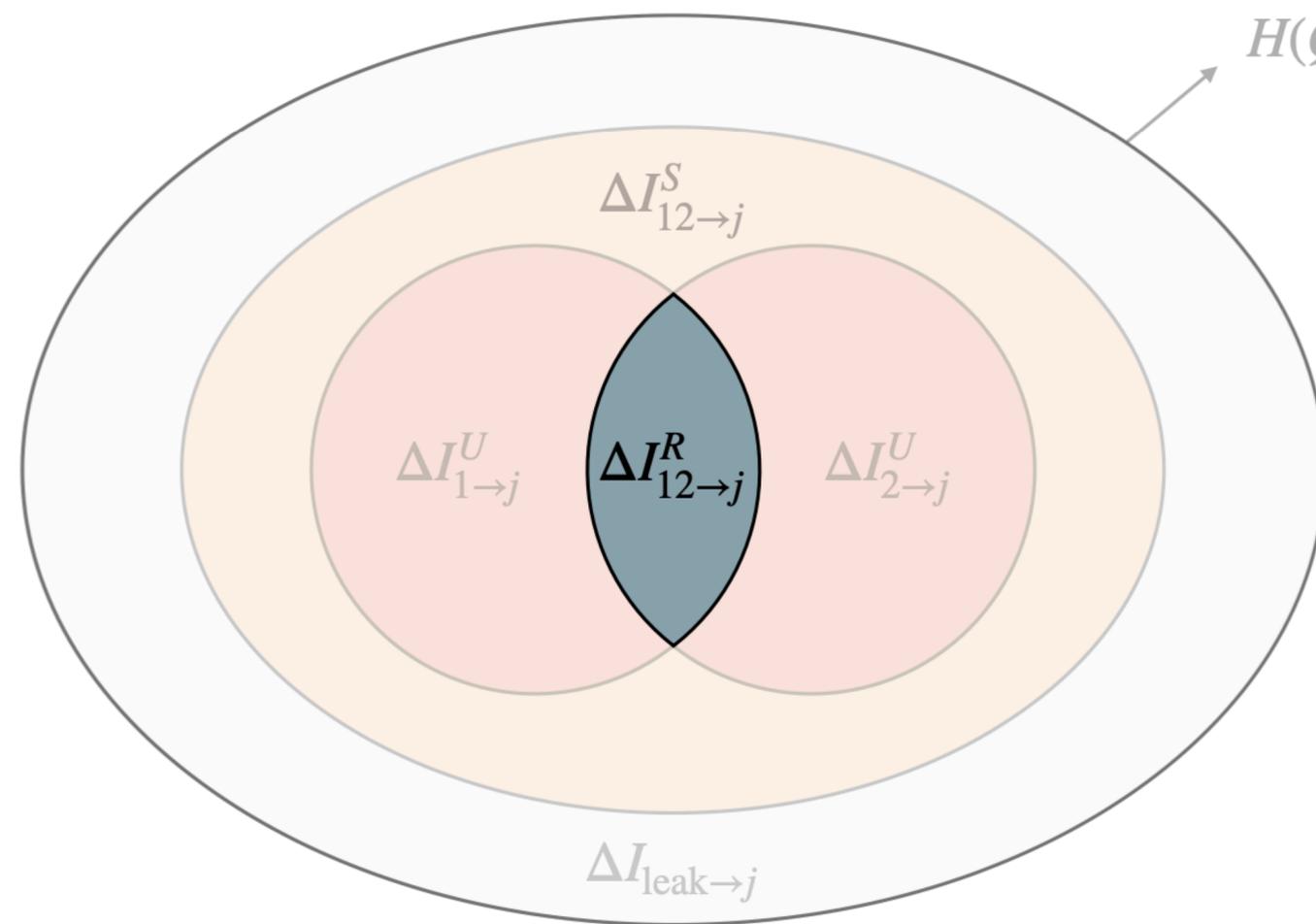
Unique causality

Q_i contains unique information about Q_j^+

Rainy season \rightarrow umbrella sales

Average causality: Method

Quantify the causality from observed variables $\mathbf{Q} = [Q_1, Q_2]$ to target variable $Q_j^+ = Q_j(t + \Delta T)$



$$H(Q_j^+) = \Delta I_{i \rightarrow j}^S + \Delta I_{i \rightarrow j}^U + \Delta I_{i \rightarrow j}^R + \Delta I_{\text{leak} \rightarrow j}$$

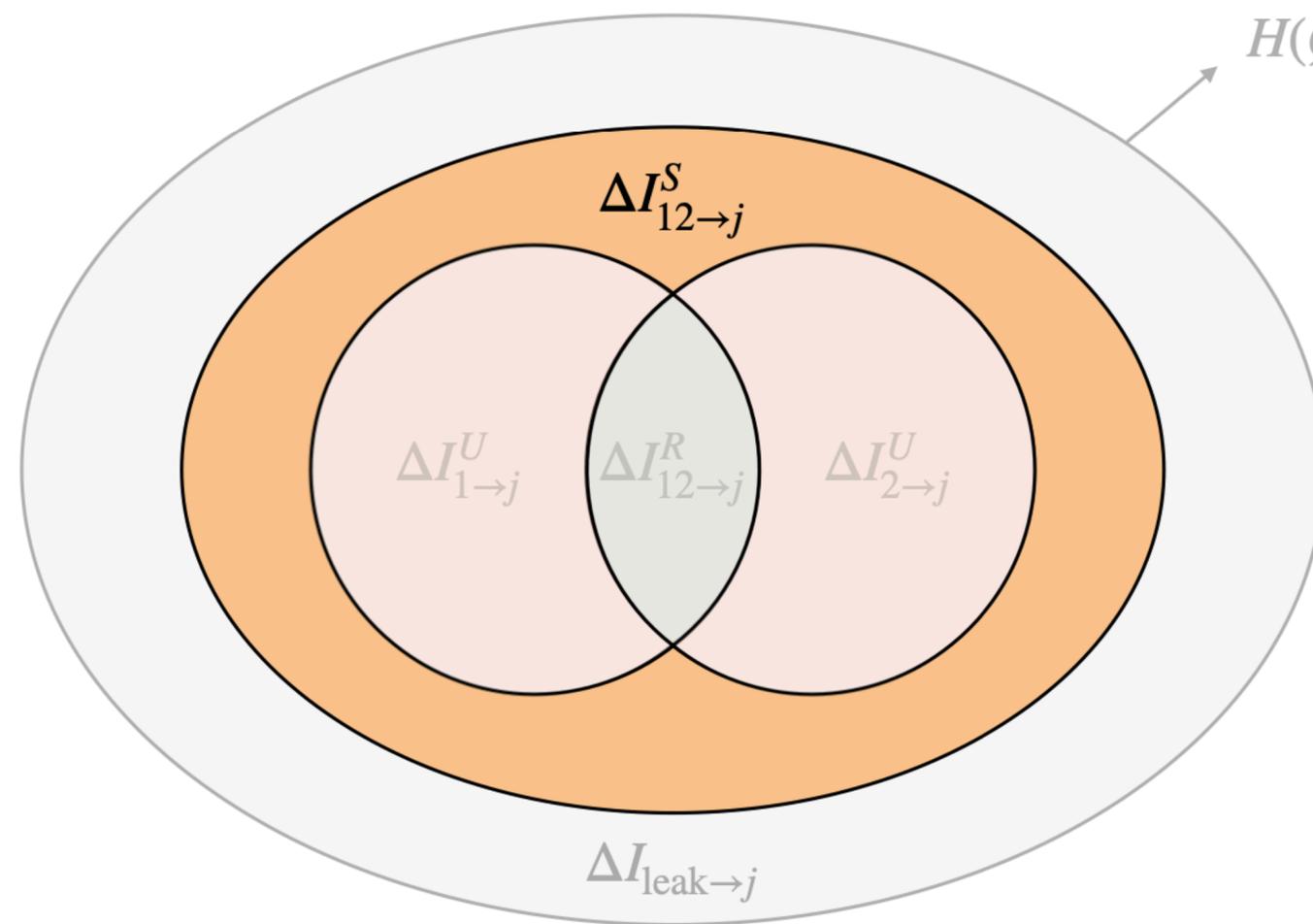
Redundant causality

Q_1 and Q_2 contain the same information about Q_j^+

smart student
hard-working student \rightarrow good grades

Average causality: Method

Quantify the causality from observed variables $Q = [Q_1, Q_2]$ to target variable $Q_j^+ = Q_j(t + \Delta T)$



$H(Q_j^+) \equiv$ information of the target variable Q_j^+

$$H(Q_j^+) = \Delta I_{i \rightarrow j}^S + \Delta I_{i \rightarrow j}^U + \Delta I_{i \rightarrow j}^R + \Delta I_{\text{leak} \rightarrow j}$$

Synergistic causality

Q_1 and Q_2 together yield more information about Q_j^+

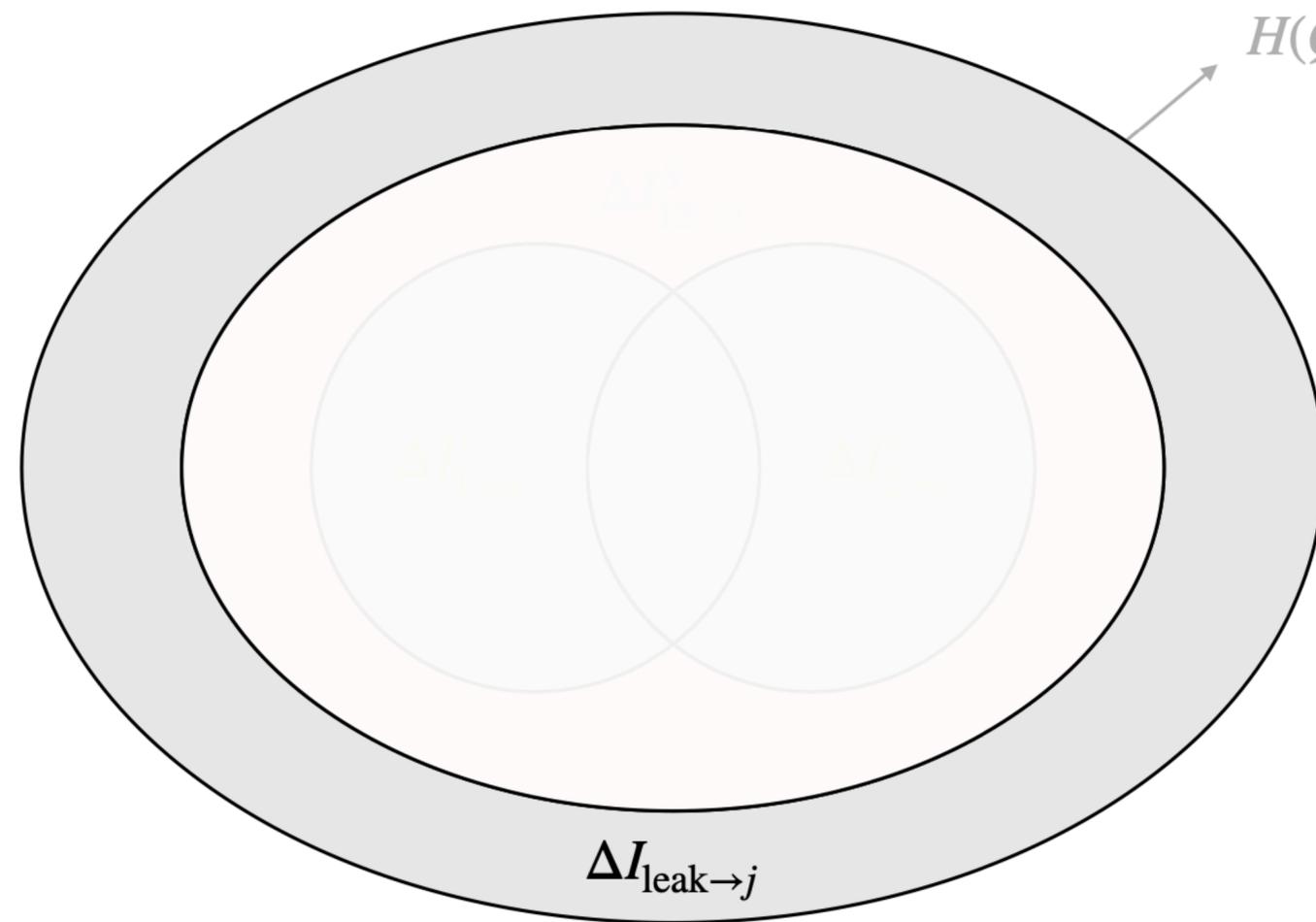
only drug A \rightarrow not recovery

only drug B \rightarrow not recovery

drug A + drug B \rightarrow recovery

Average causality: Method

Quantify the causality from observed variables $\mathbf{Q} = [Q_1, Q_2]$ to target variable $Q_j^+ = Q_j(t + \Delta T)$



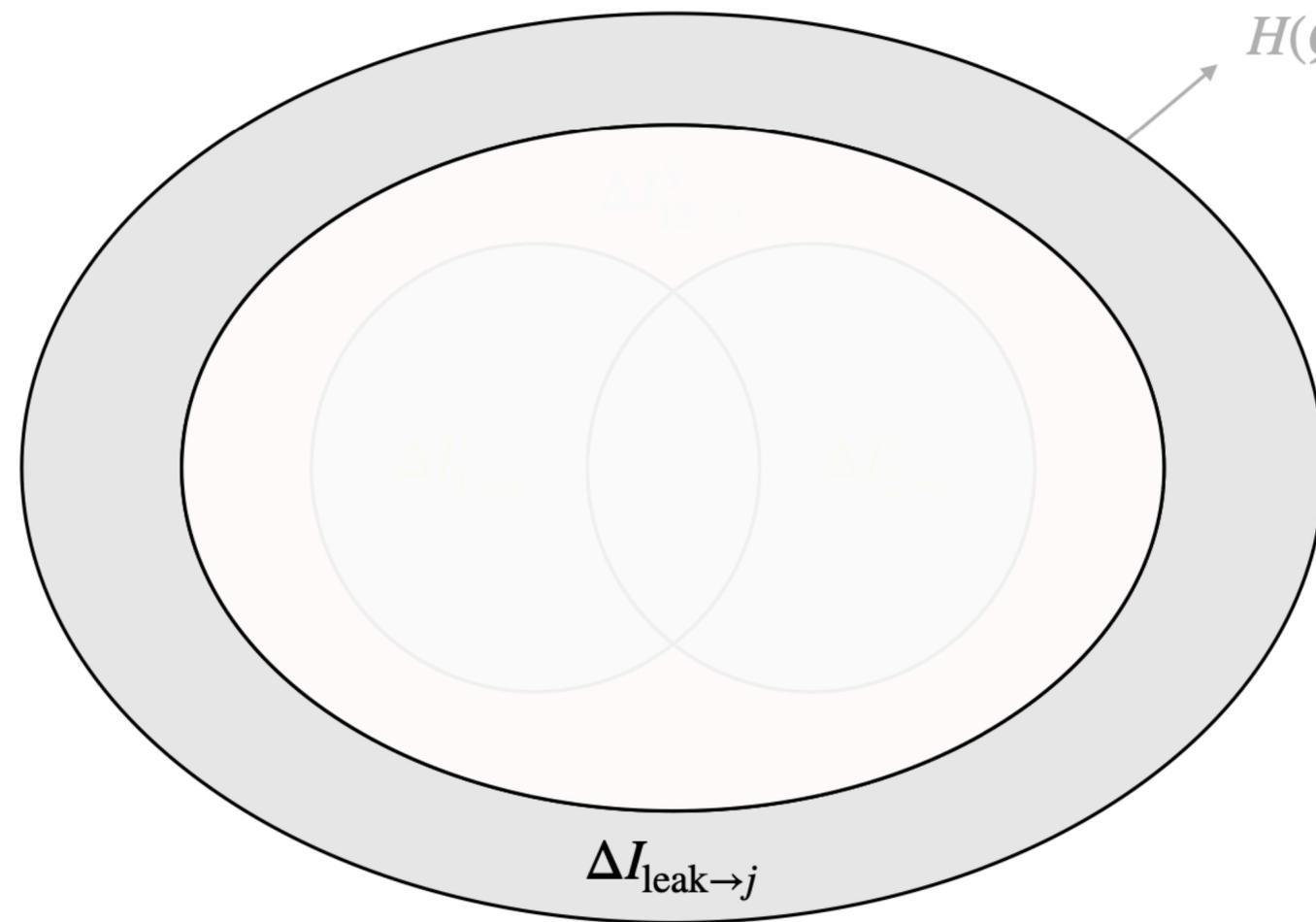
$$H(Q_j^+) = \Delta I_{i \rightarrow j}^S + \Delta I_{i \rightarrow j}^U + \Delta I_{i \rightarrow j}^R + \Delta I_{\text{leak} \rightarrow j}$$

Causality leak

Effect from unobserved variables that influence Q_j^+

Average causality: Method

Quantify the causality from observed variables $\mathbf{Q} = [Q_1, Q_2]$ to target variable $Q_j^+ = Q_j(t + \Delta T)$



$H(Q_j^+) \equiv$ information of the target variable Q_j^+

$$H(Q_j^+) = \Delta I_{i \rightarrow j}^S + \Delta I_{i \rightarrow j}^U + \Delta I_{i \rightarrow j}^R + \Delta I_{\text{leak} \rightarrow j}$$

Causality & predictability

For any model: $Q_j^{+\text{model}} = f(\mathbf{Q})$

$$\|Q_j^+ - Q_j^{+\text{model}}\| \geq c \exp[-\Delta I_{i \rightarrow j}^S - \Delta I_{i \rightarrow j}^U - \Delta I_{i \rightarrow j}^R]$$

Computation of Information in high-dimensional spaces

We quantify causality as increments of mutual information between different combinations of \mathbf{Q} and Q_O

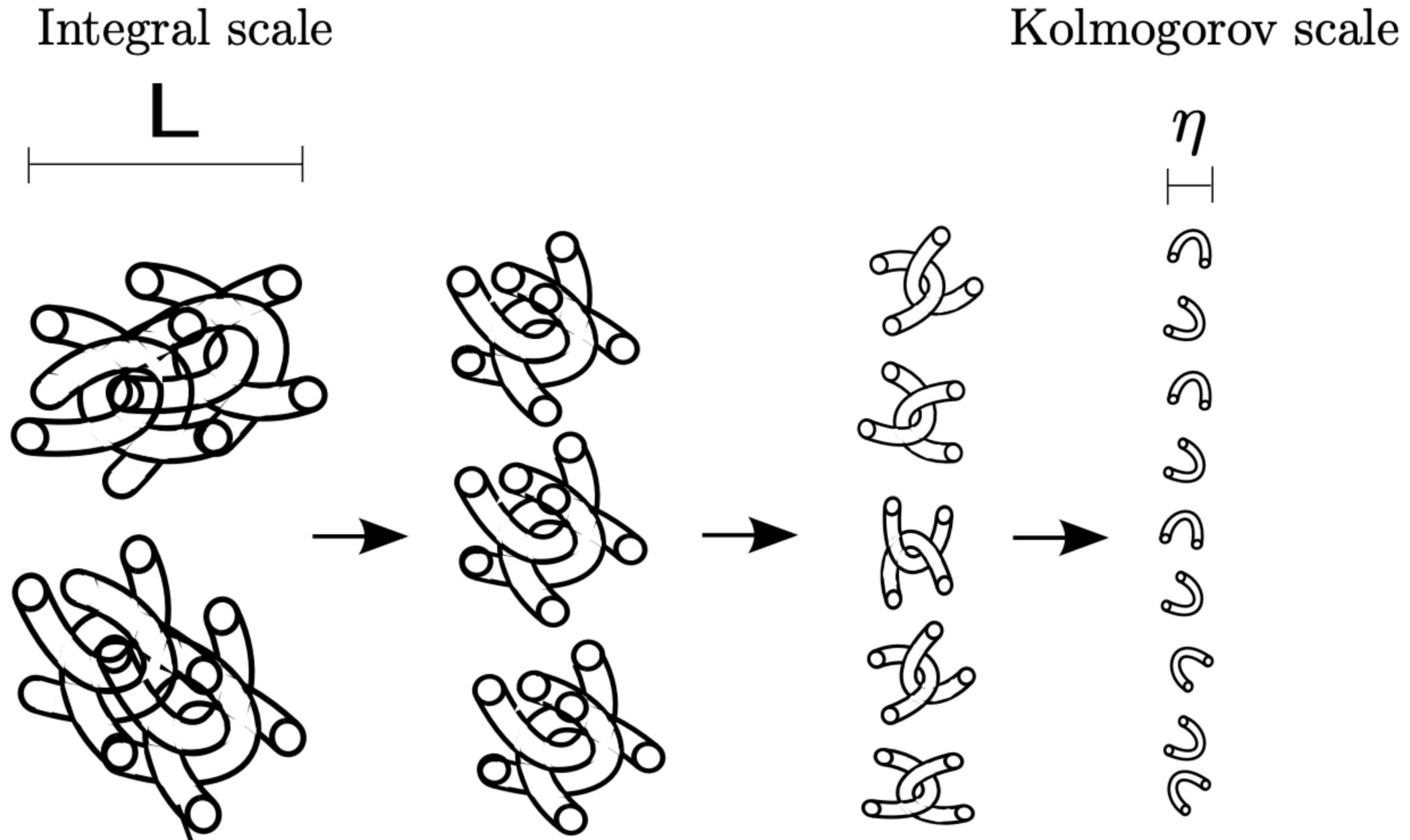
$$I(Q_O; \mathbf{Q}) = \mathbb{E}_{p(q_O, \mathbf{q})} \log \frac{p(q_O, \mathbf{q})}{p(q_O)p(\mathbf{q})} = D_{\text{KL}} (p(q_O, \mathbf{q}) \| p(q_O)p(\mathbf{q}))$$

MINE: Mutual Information Neural Estimator (Donsker-Varadhan (DV) representation)

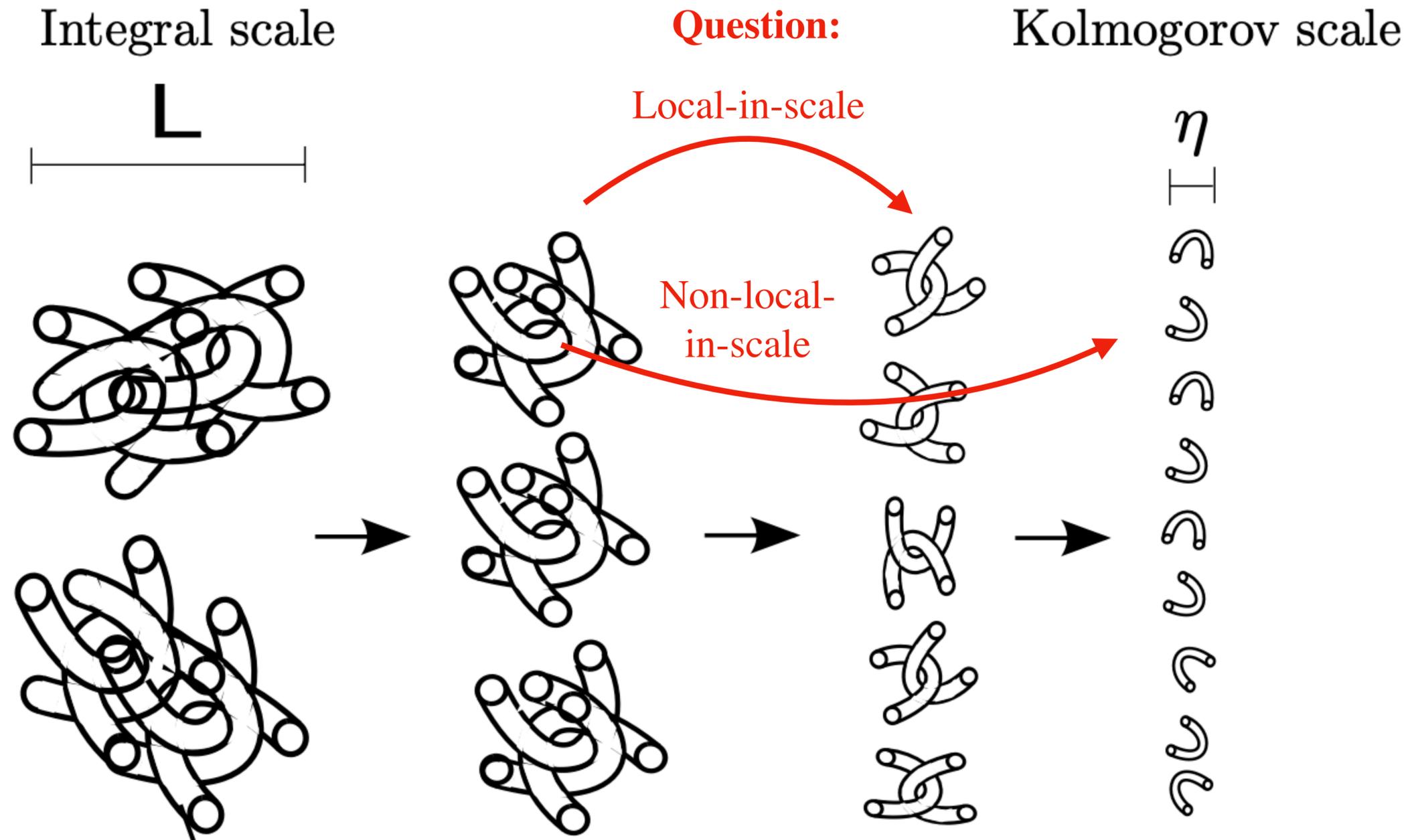
$$\hat{I}_\theta(Q_O; \mathbf{Q}) \leftarrow \frac{1}{m} \sum_{k=1}^m F_\theta(q_{O,k}, \mathbf{q}_k) - \log \left(\frac{1}{m} \sum_{k=1}^m e^{F_\theta(\tilde{q}_{O,k}, \mathbf{q}_k)} \right)$$

$m \equiv$ number of samples
 $\tilde{q}_O \equiv$ randomly shuffled q_O

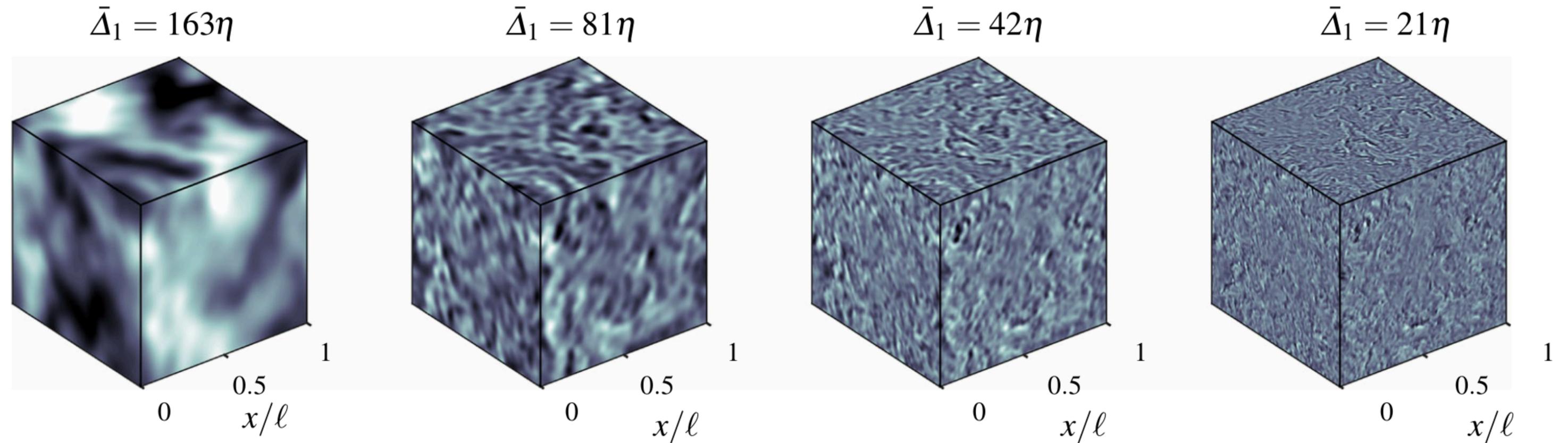
Average causality: Application



Average causality: Application



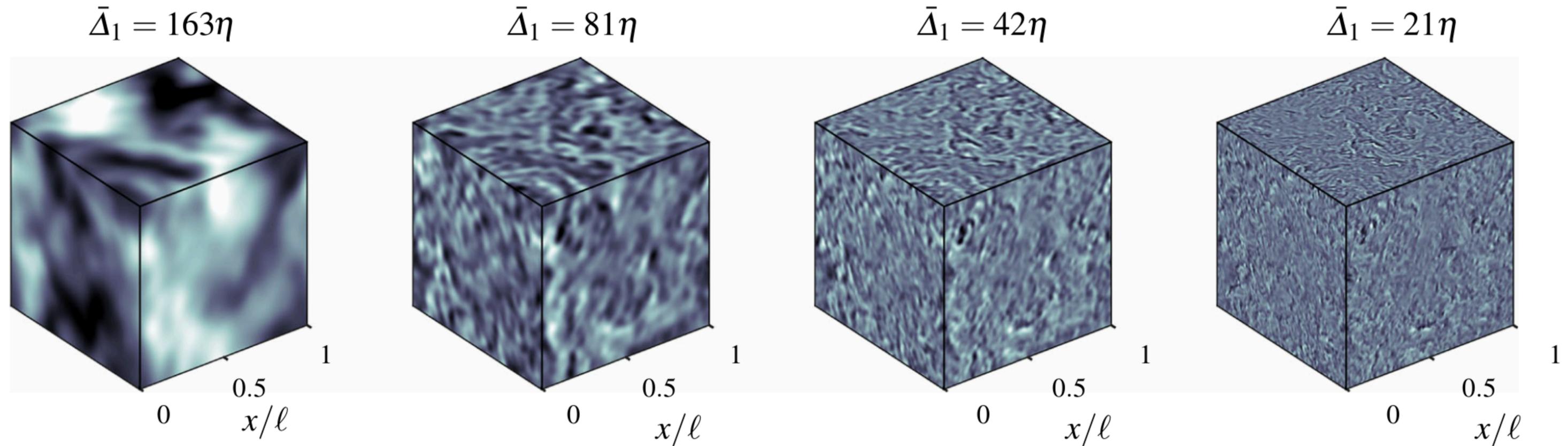
Average causality: Application



DNS of isotropic turbulence at $Re_\lambda \approx 400$

Filtered velocity field:
$$\bar{u}_i(\mathbf{x}, t) = \int_V \frac{\sqrt{\pi}}{\bar{\Delta}} \exp \left[-\pi^2 (\mathbf{x} - \mathbf{x}')^2 / \bar{\Delta}^2 \right] u_i(\mathbf{x}') d\mathbf{x}'$$

Average causality: Application

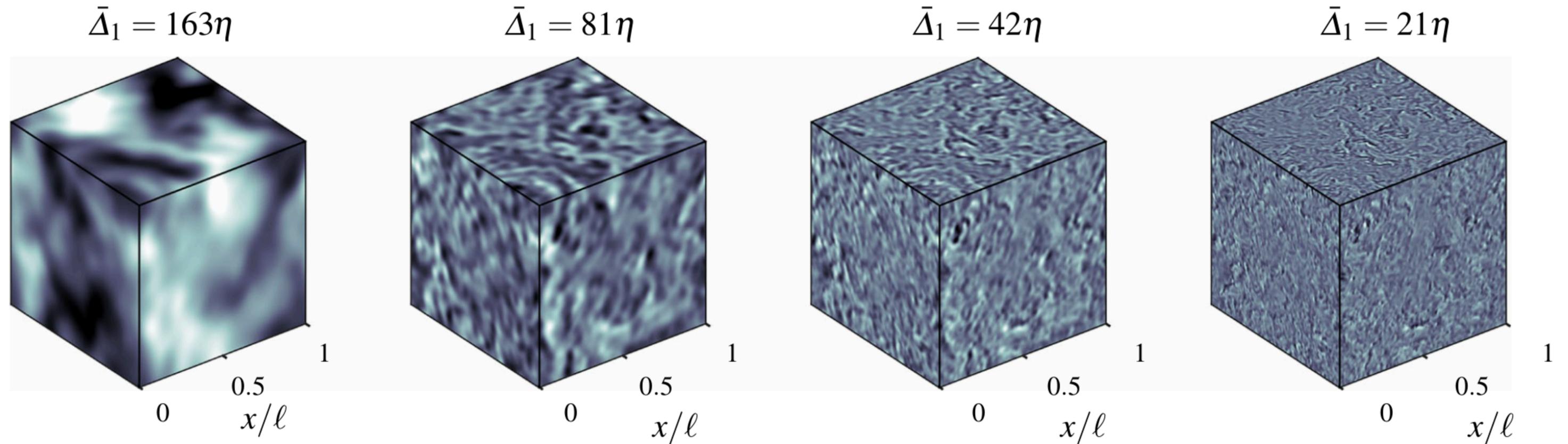


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Inter-scale energy transfer:
$$\Sigma = (\overline{u_i u_j} - \bar{u}_i \bar{u}_j) \bar{S}_{ij}$$

Average causality: Application



DNS of isotropic turbulence at $Re_\lambda \approx 400$

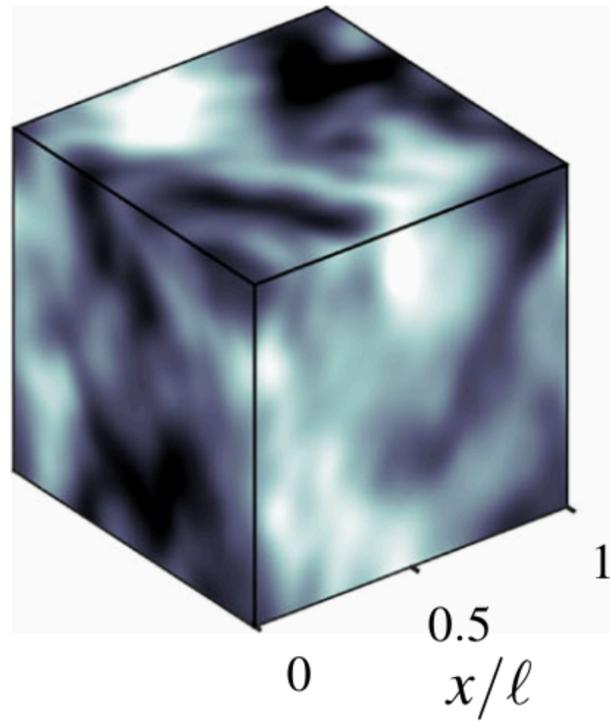
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Inter-scale energy transfer:
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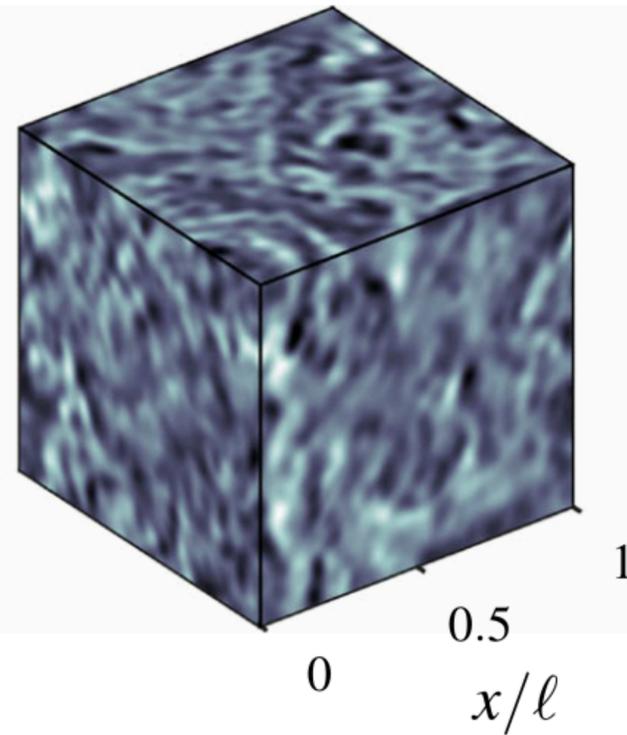
Energy transfer extracted for 4 filter widths and averaged in space: $\langle \Sigma_1 \rangle, \langle \Sigma_2 \rangle, \langle \Sigma_3 \rangle, \langle \Sigma_4 \rangle$

Average causality: Application

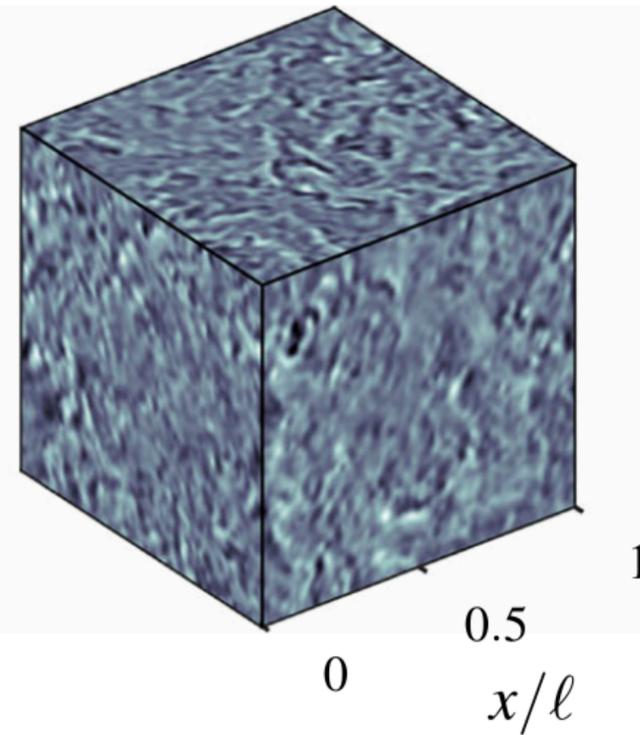
$$\bar{\Delta}_1 = 163\eta$$



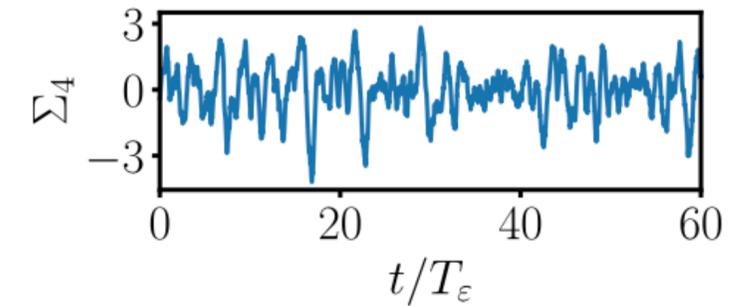
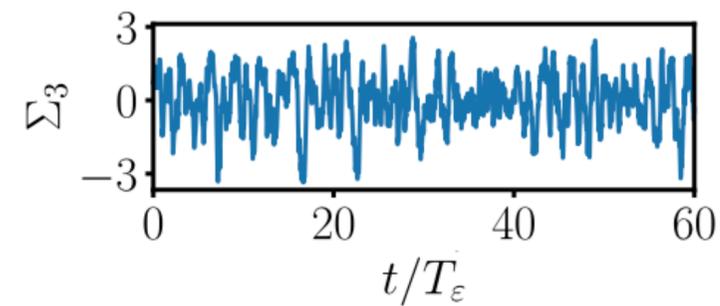
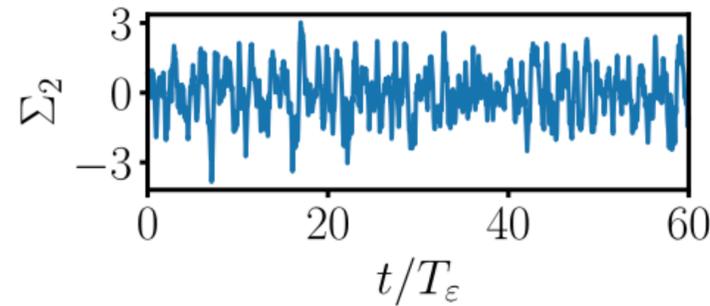
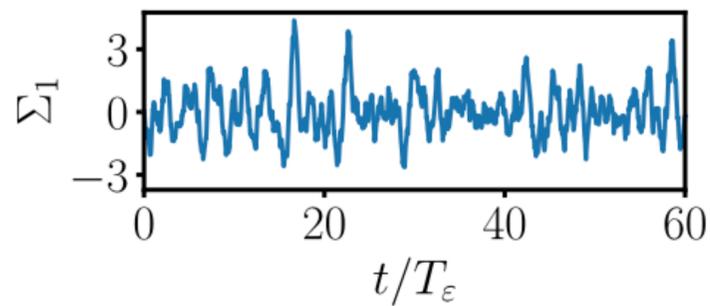
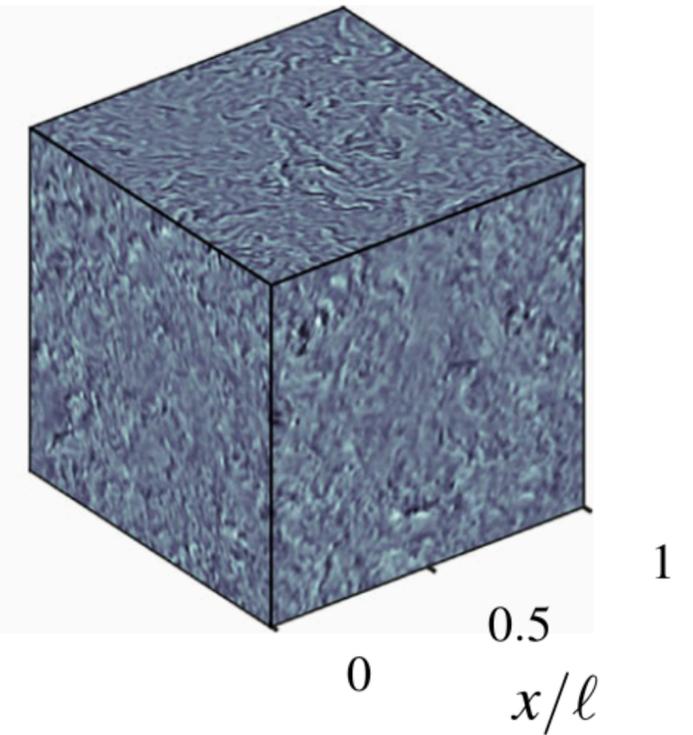
$$\bar{\Delta}_1 = 81\eta$$



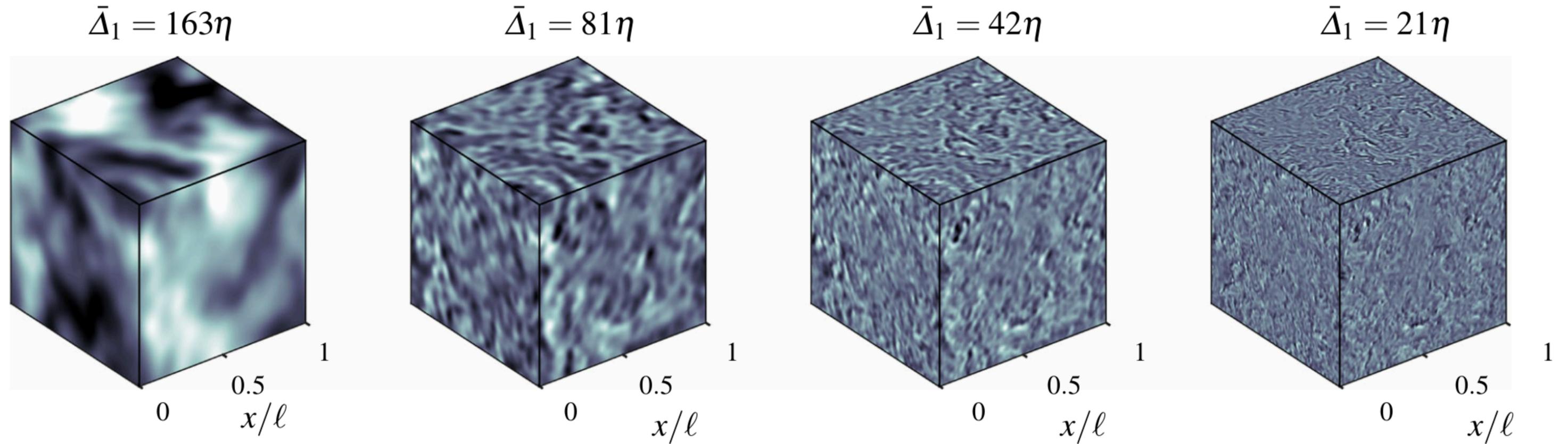
$$\bar{\Delta}_1 = 42\eta$$



$$\bar{\Delta}_1 = 21\eta$$

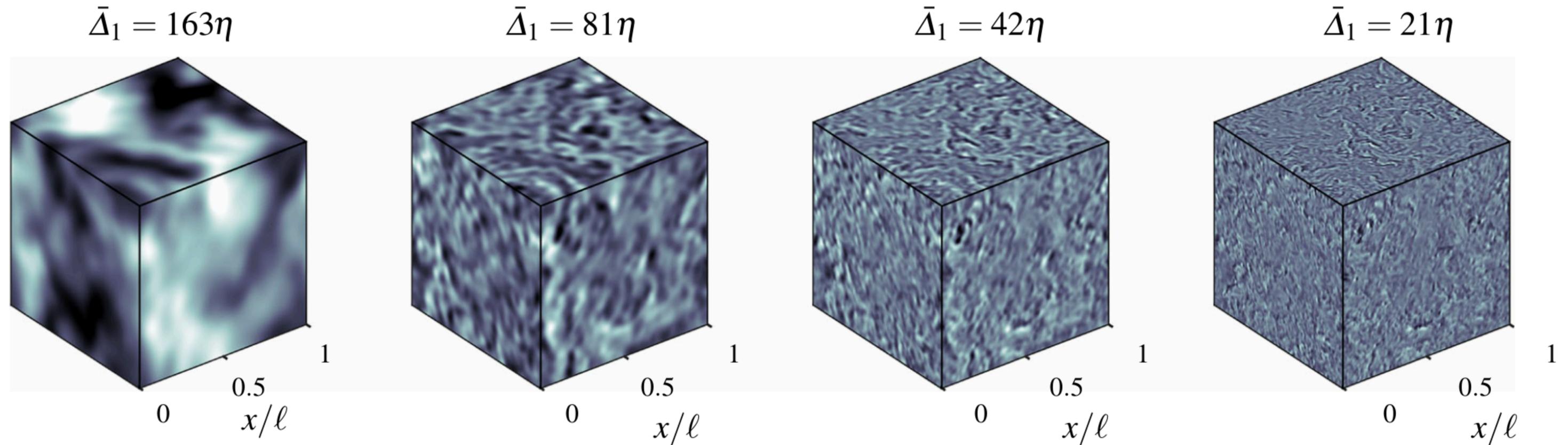


Average causality: Application



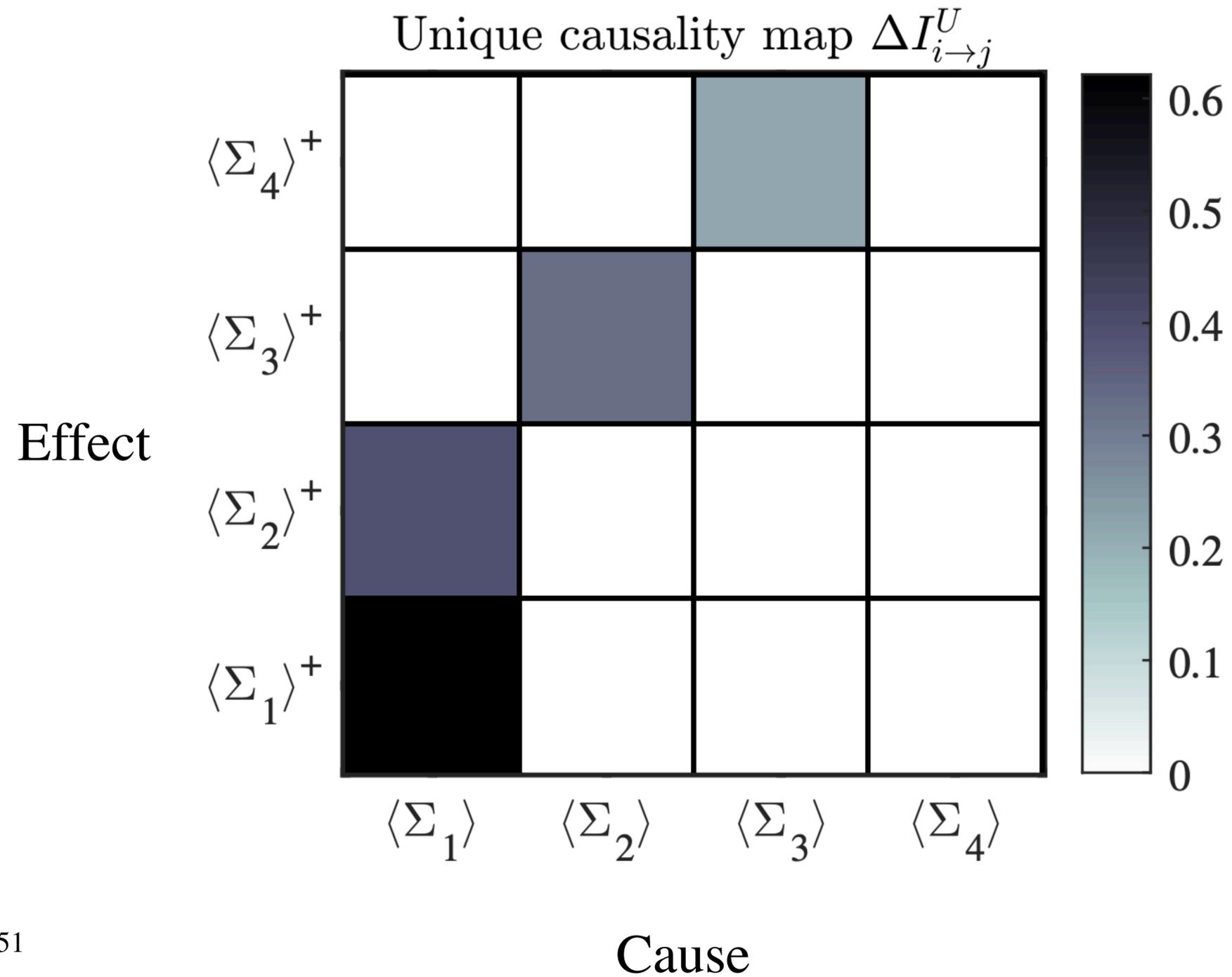
$$H(Q_j^+) = \underbrace{\Delta I_{i \rightarrow j}^S}_{\text{Synergistic causality}} + \underbrace{\Delta I_{i \rightarrow j}^U}_{\text{Unique causality}} + \underbrace{\Delta I_{i \rightarrow j}^R}_{\text{Redundant causality}} + \Delta I_{\text{leak} \rightarrow j}$$

Average causality: Application

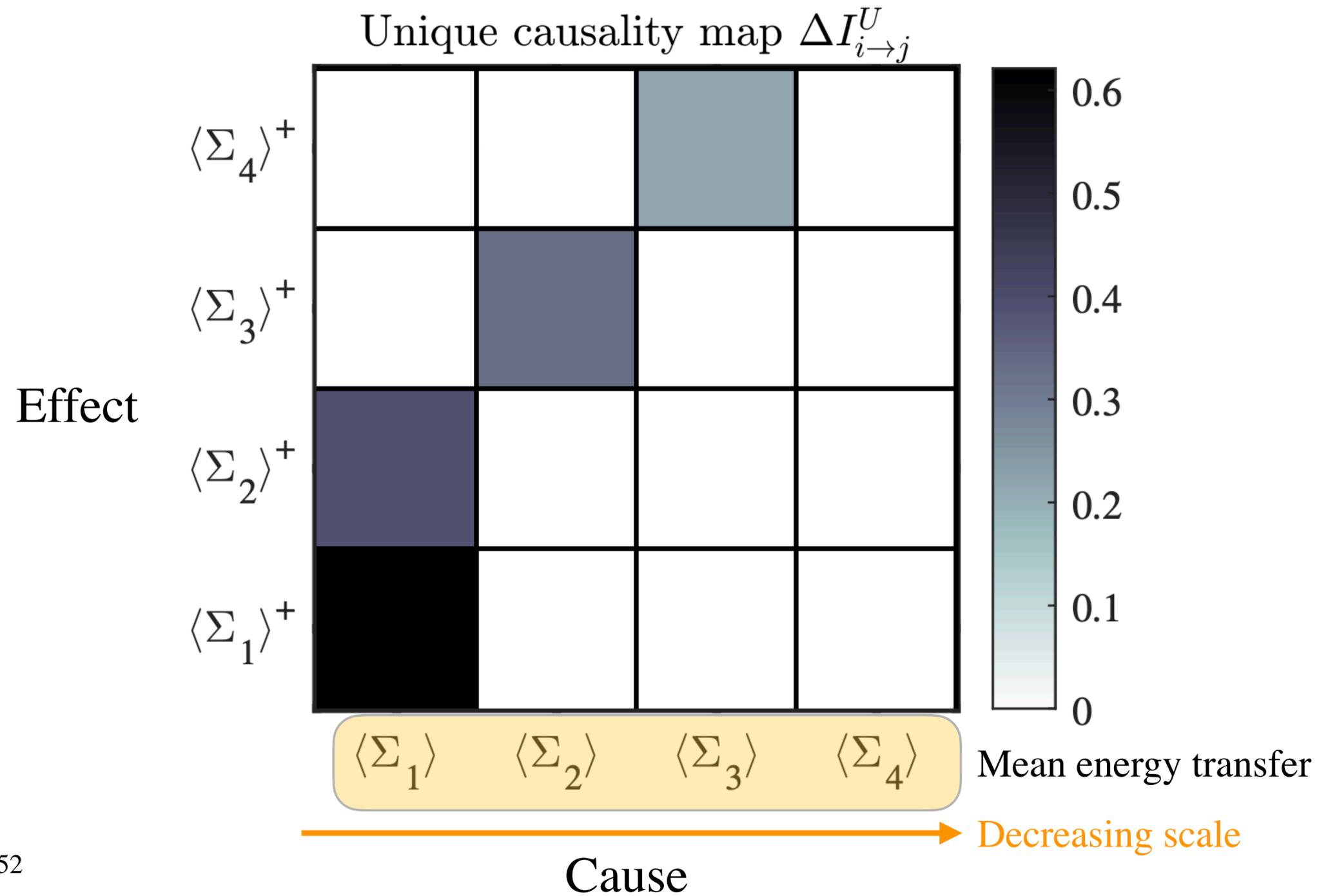


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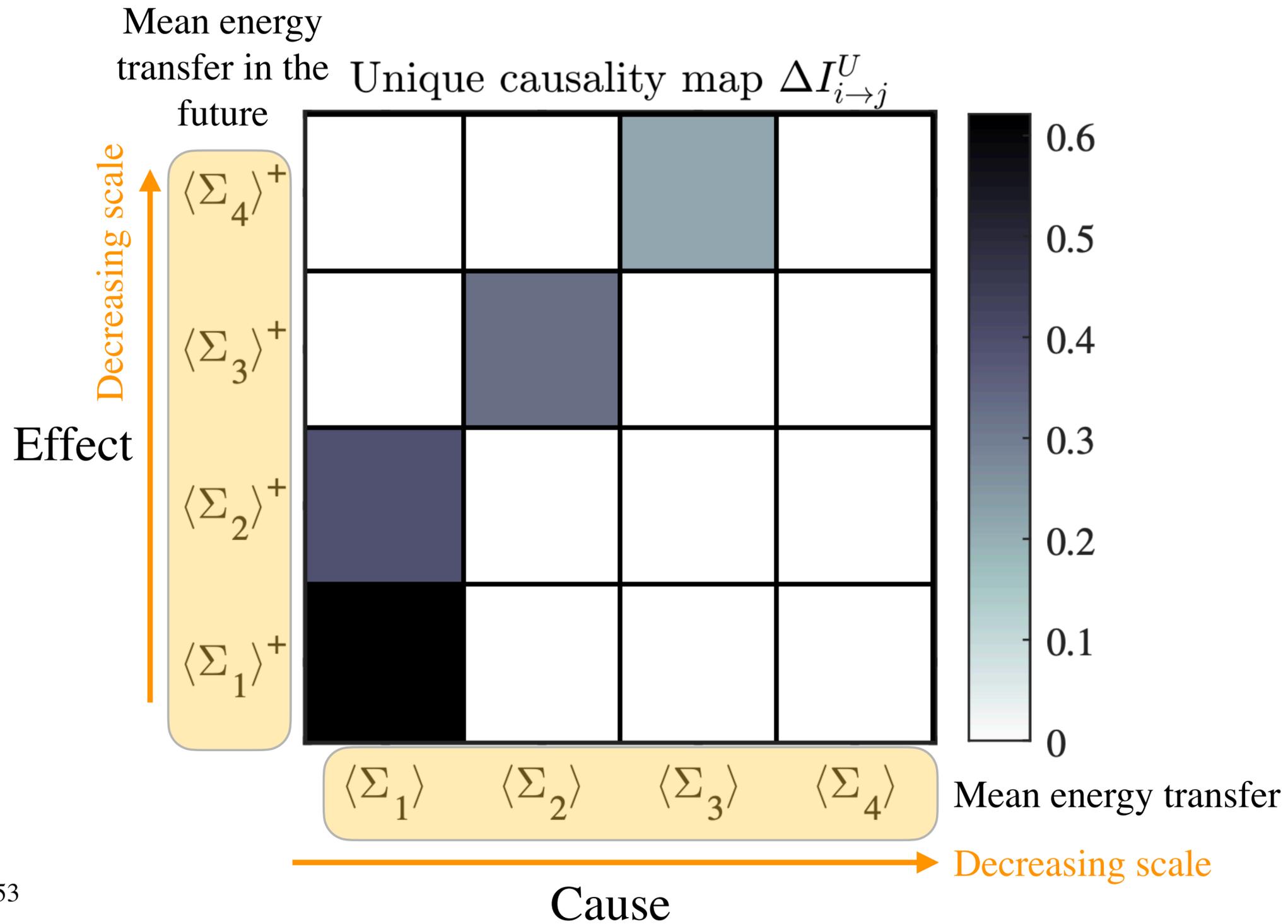
Average causality: Application



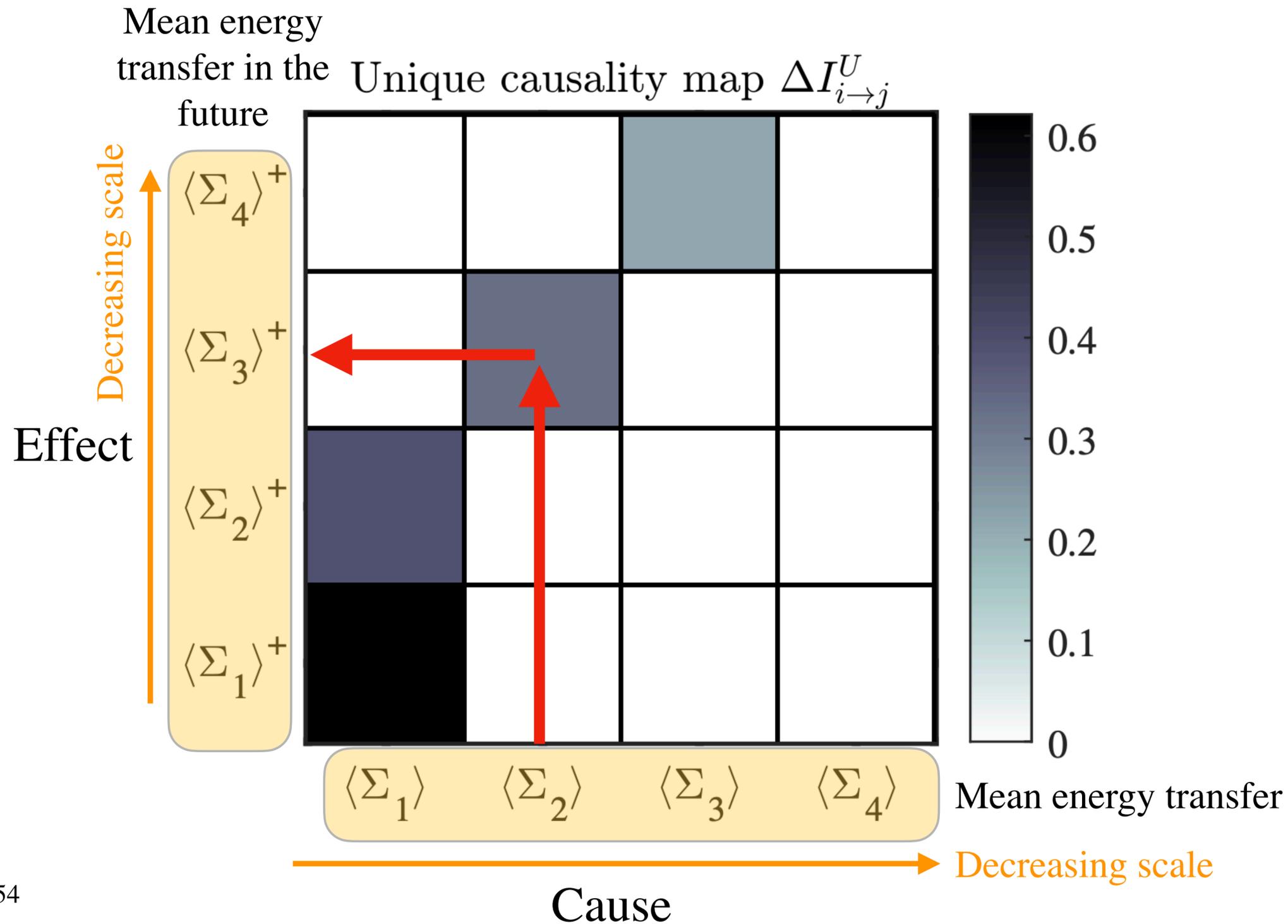
Average causality: Application



Average causality: Application

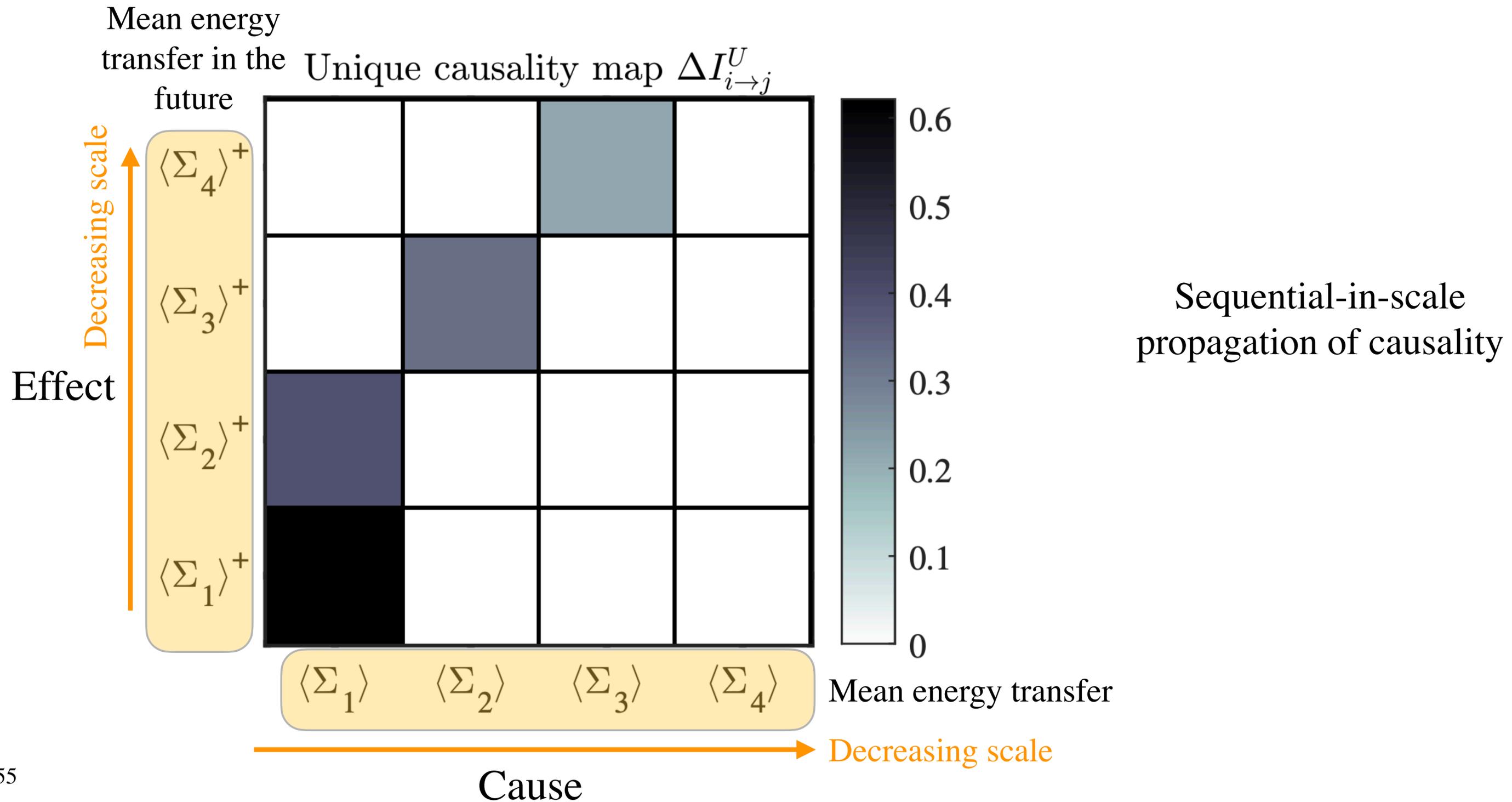


Average causality: Application

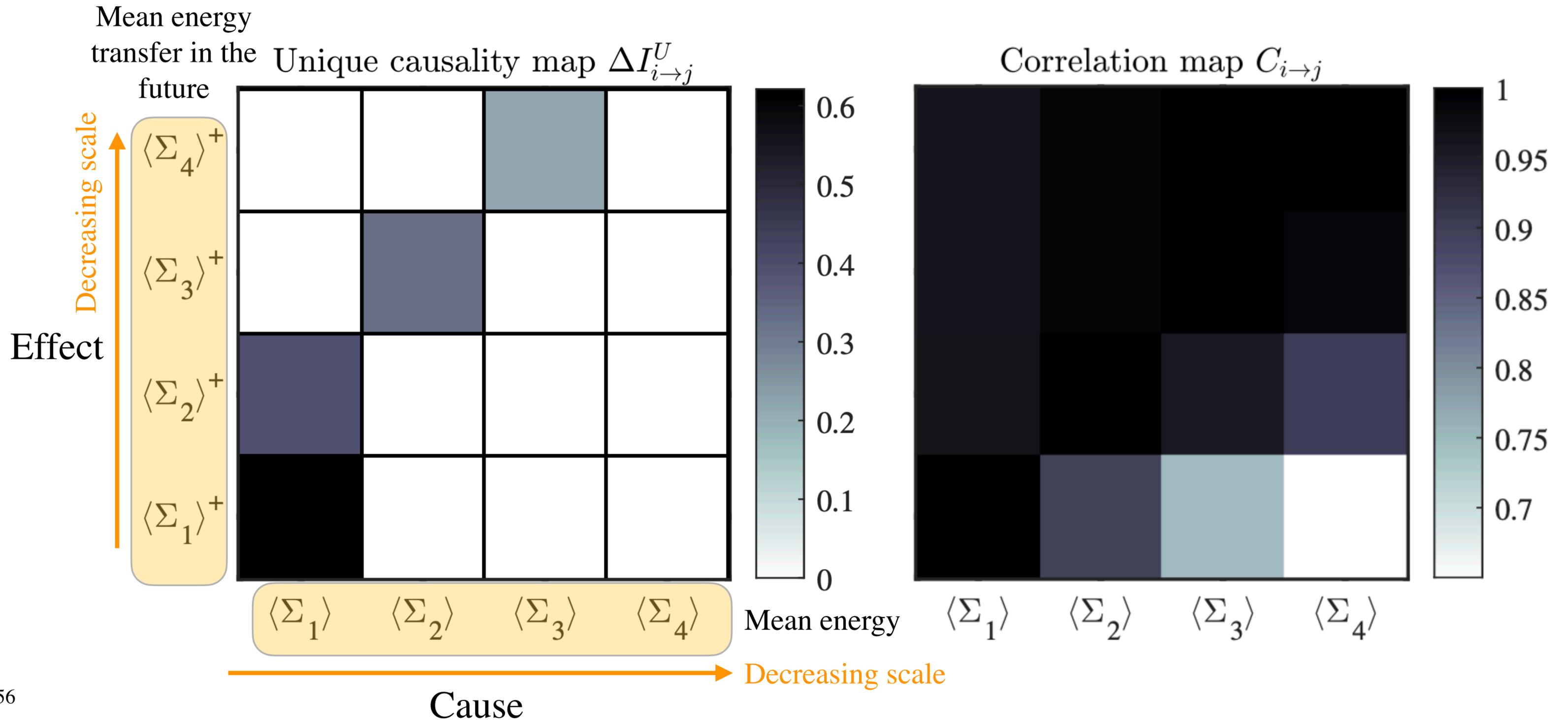


$$\langle \Sigma_2 \rangle \rightarrow \langle \Sigma_3^+ \rangle$$

Average causality: Application



Average causality: Application



Three levels of causality

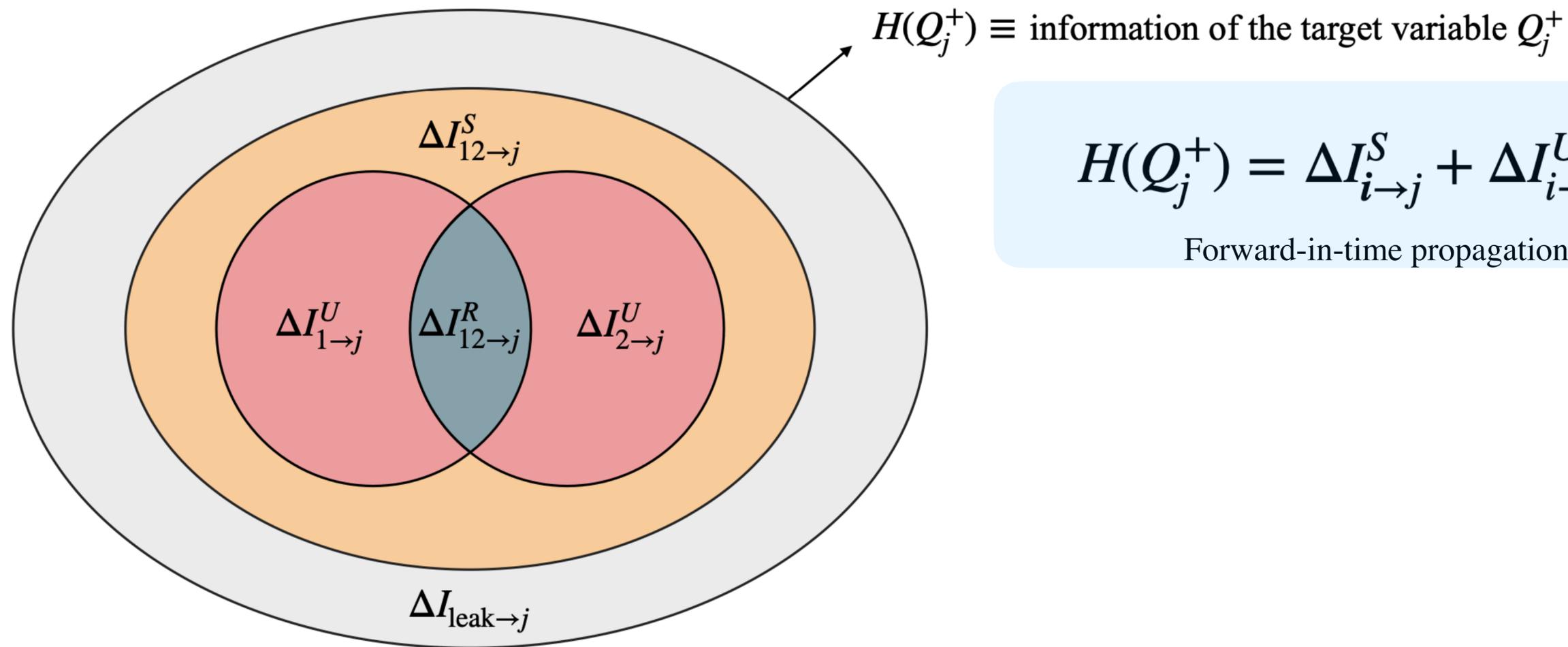
Average Causality

State-dependent Causality

Space-time Causality

State-dependent causality: Method

Quantify the causality from observed variables $\mathbf{Q} = [Q_1, Q_2]$ to target variable $Q_j^+ = Q_j(t + \Delta T)$

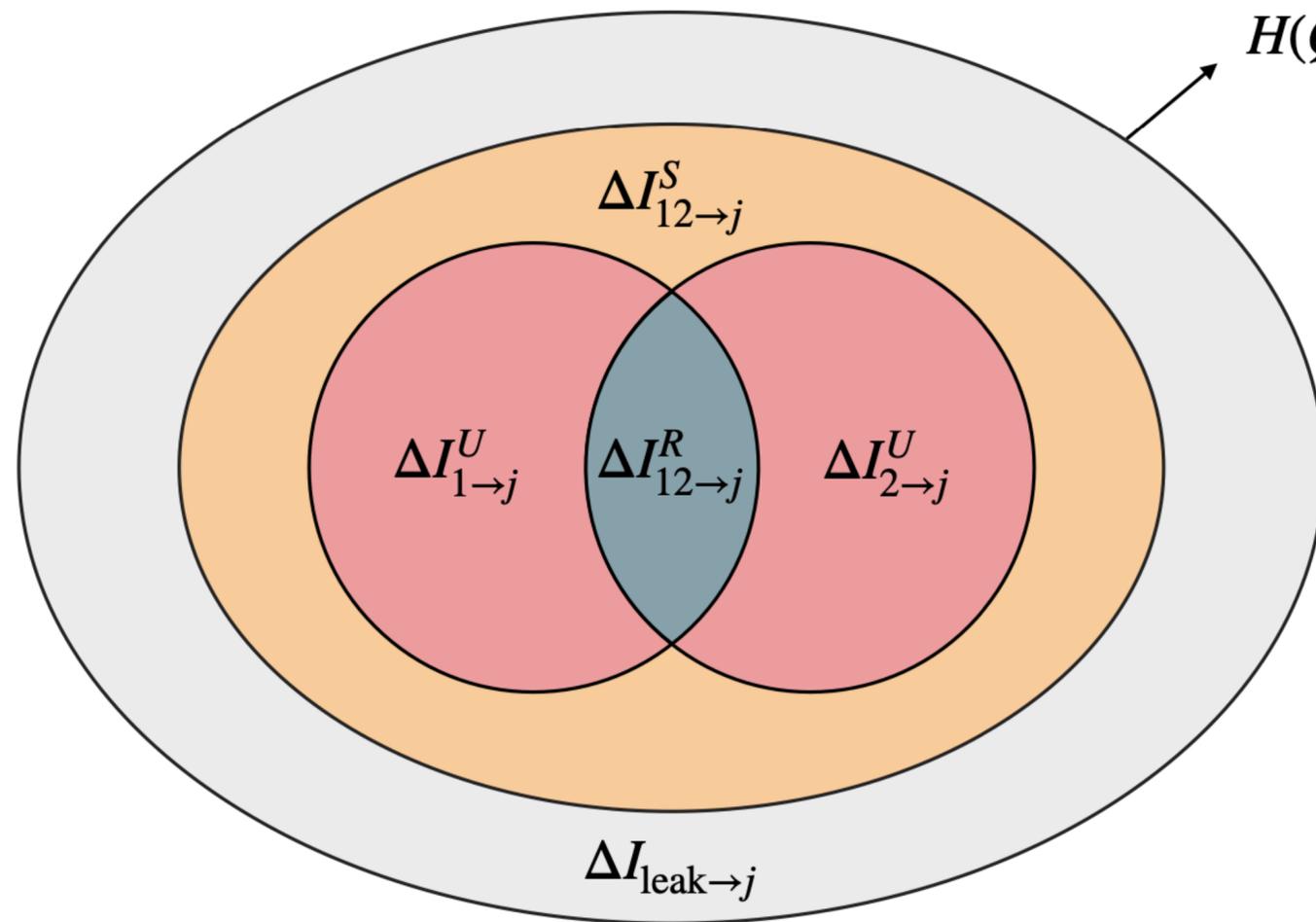


$$H(Q_j^+) = \Delta I_{i \rightarrow j}^S + \Delta I_{i \rightarrow j}^U + \Delta I_{i \rightarrow j}^R + \Delta I_{\text{leak} \rightarrow j}$$

Forward-in-time propagation of information equation

State-dependent causality: Method

Quantify the causality from observed variables $\mathbf{Q} = [Q_1, Q_2]$ to target variable $Q_j^+ = Q_j(t + \Delta T)$



$H(Q_j^+) \equiv$ information of the target variable Q_j^+

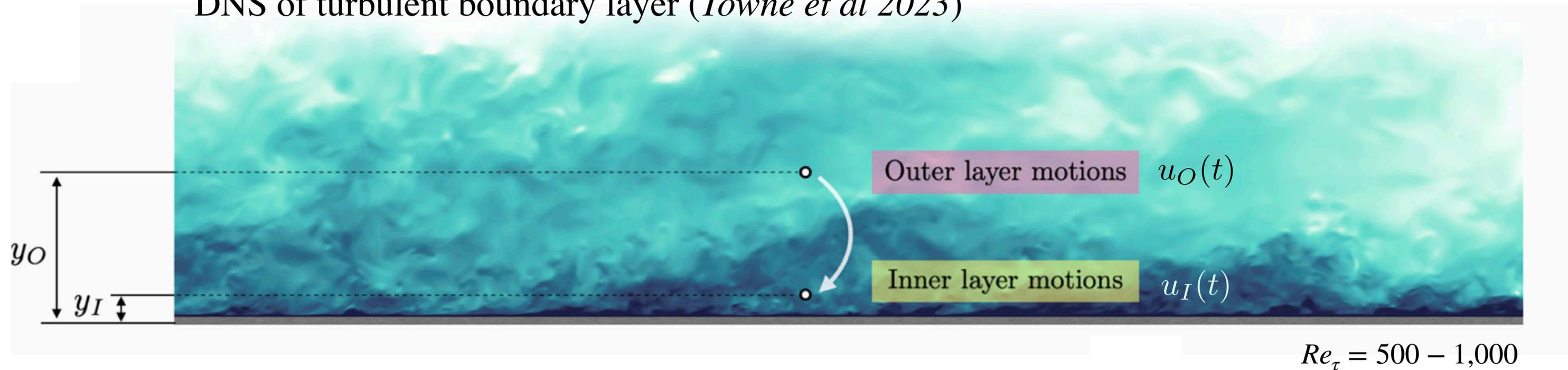
$$H(Q_j^+) = \Delta I_{i \rightarrow j}^S + \Delta I_{i \rightarrow j}^U + \Delta I_{i \rightarrow j}^R + \Delta I_{\text{leak} \rightarrow j}$$

Forward-in-time propagation of information equation

$$\Delta I_{i \rightarrow j}^\alpha = \sum_{q_j^+ \in Q_j^+} \sum_{q \in Q} \Delta C_{i \rightarrow j}^\alpha + \dots$$

State-dependent causality: Application

DNS of turbulent boundary layer (*Towne et al 2023*)



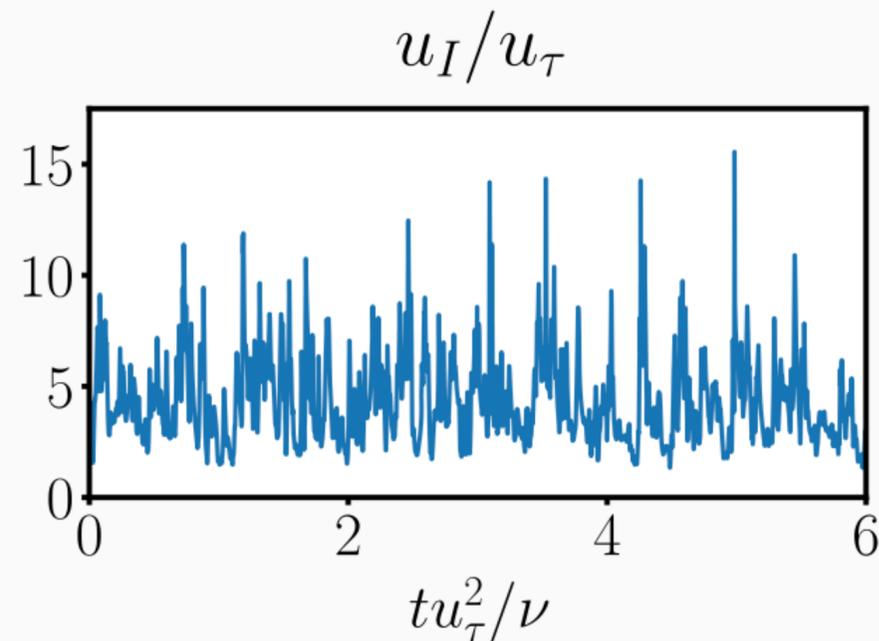
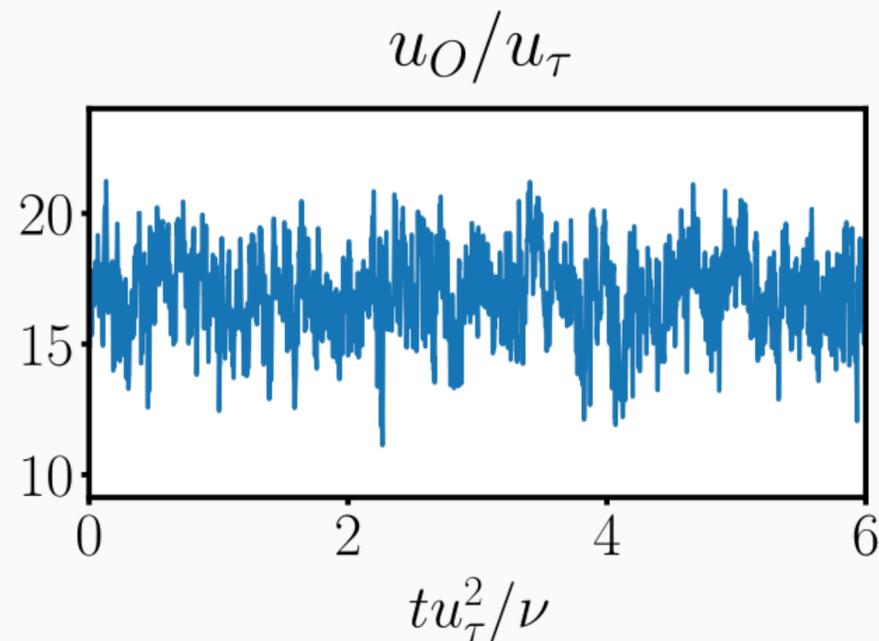
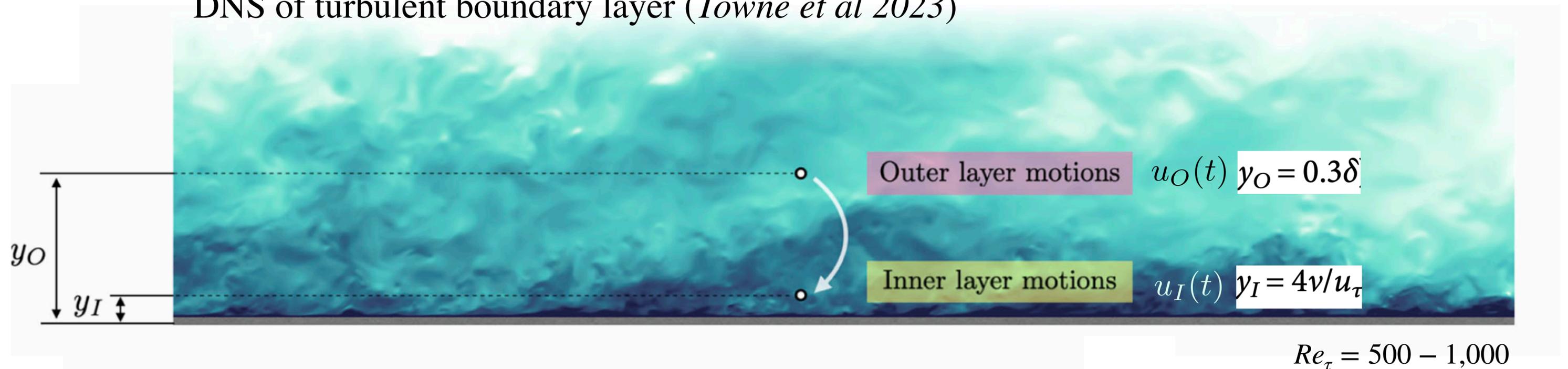
Question: Is there causality of outer layer velocity to the inner layer velocity?

$$y_O = 0.3\delta$$

$$y_I = 4\nu/u_\tau$$

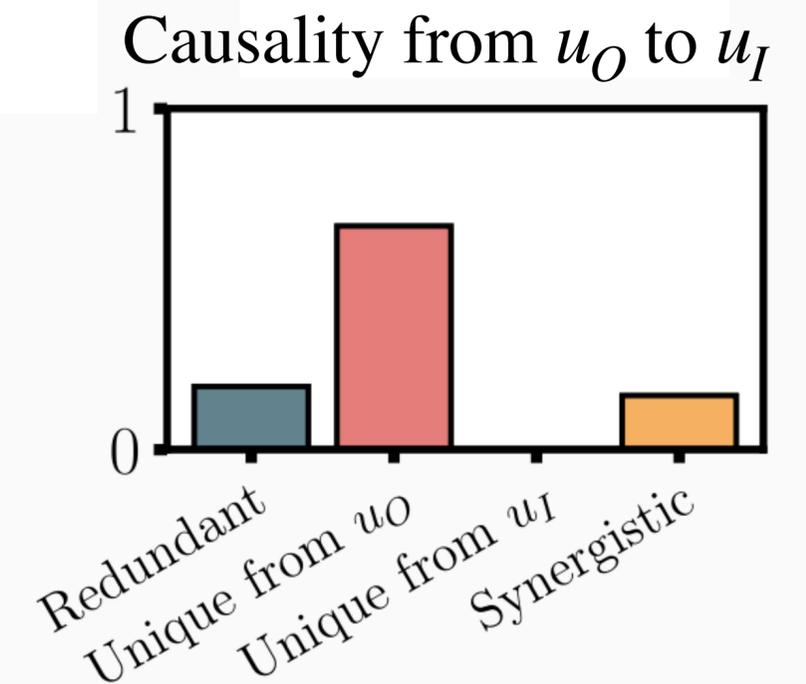
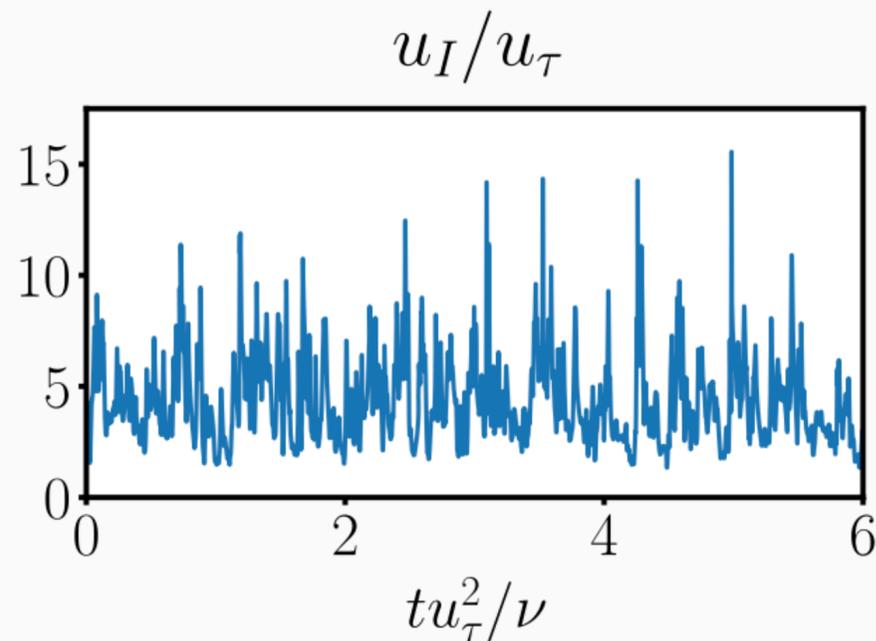
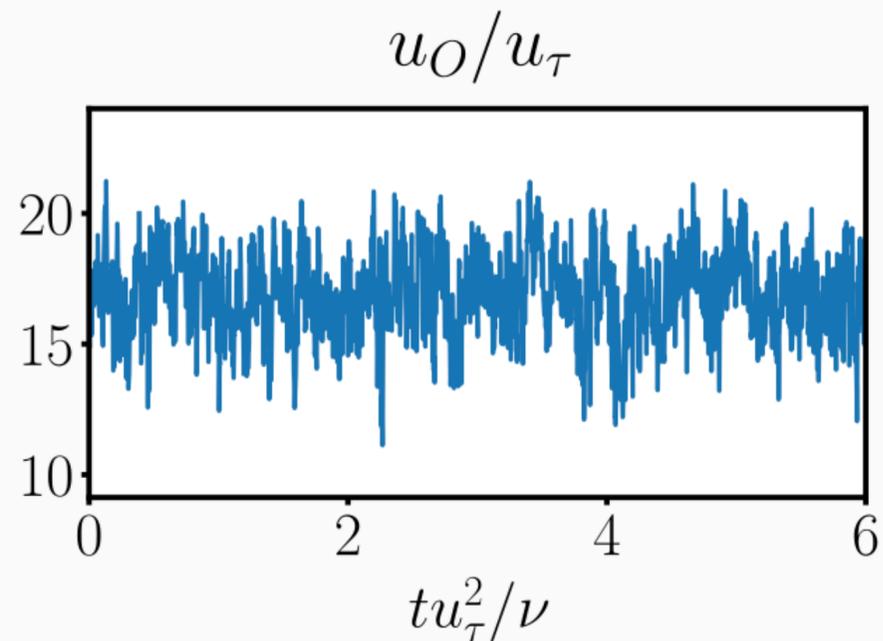
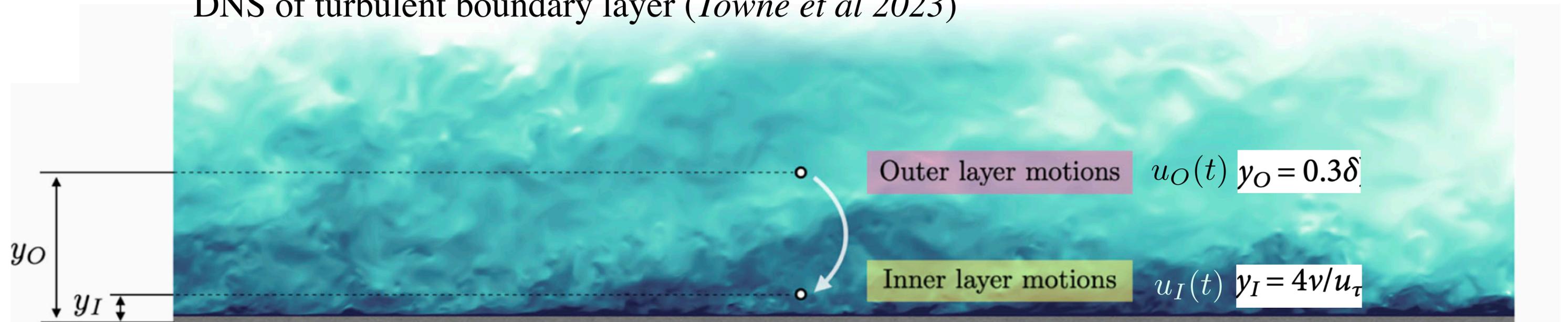
State-dependent causality: Application

DNS of turbulent boundary layer (*Towne et al 2023*)

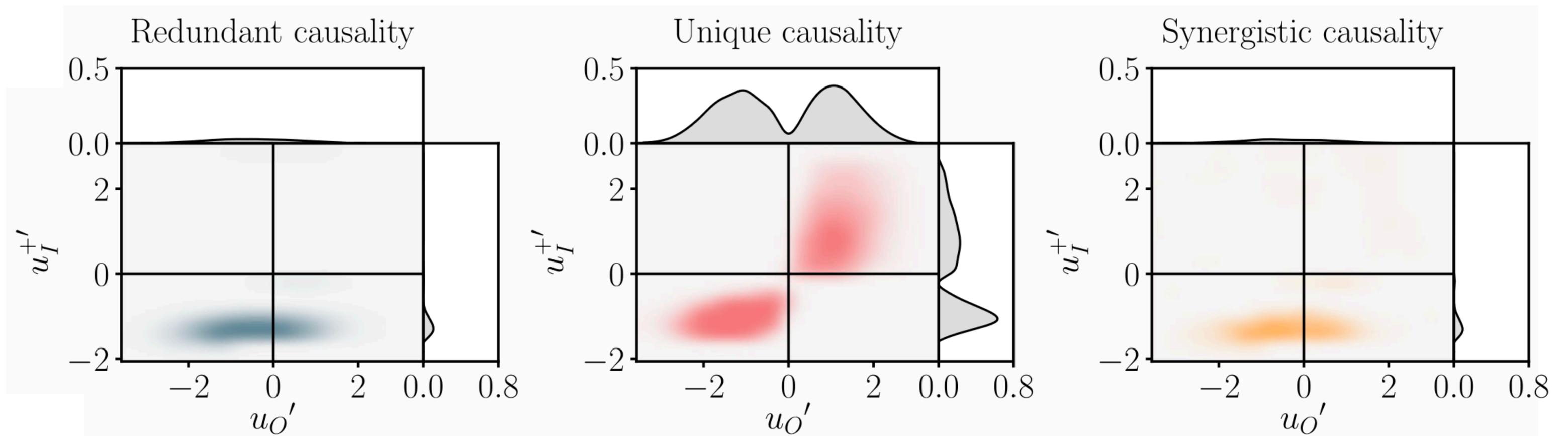


State-dependent causality: Application

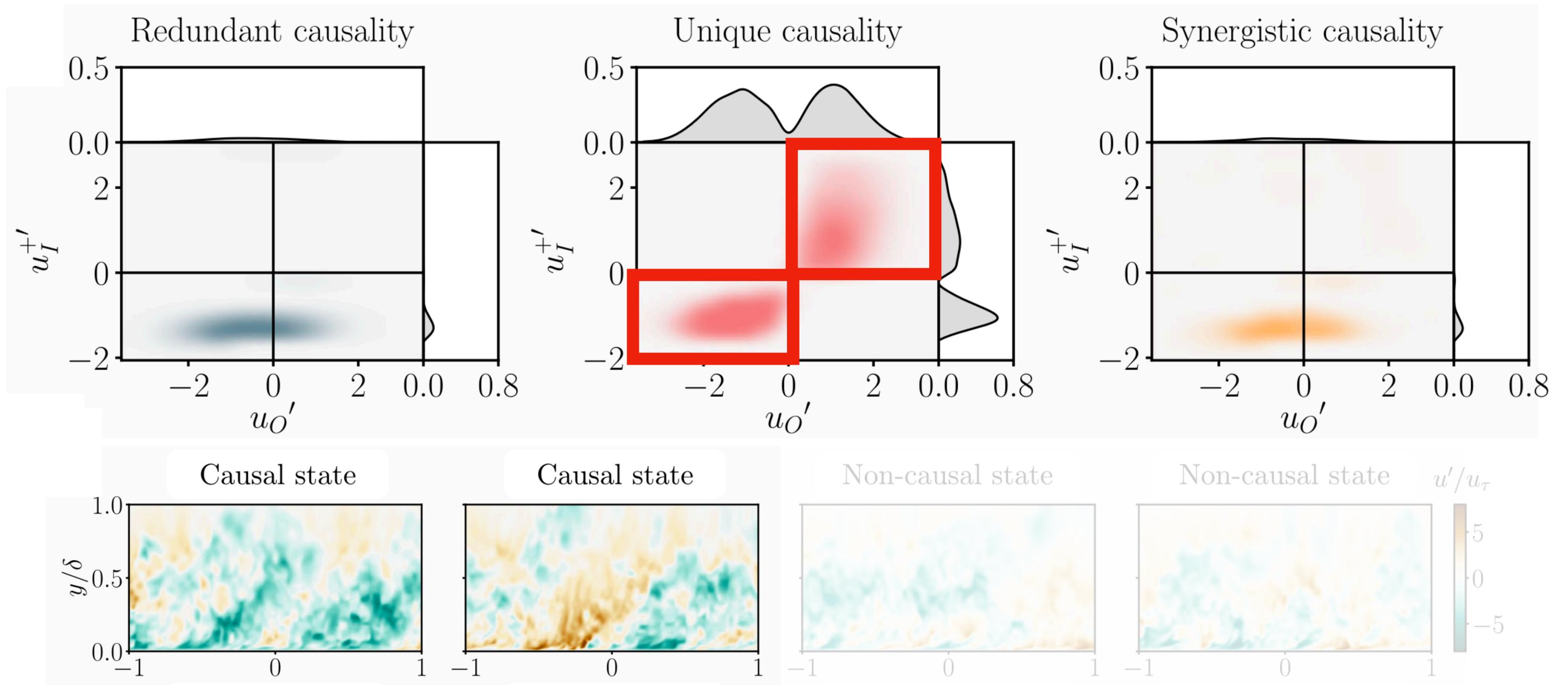
DNS of turbulent boundary layer (*Towne et al 2023*)



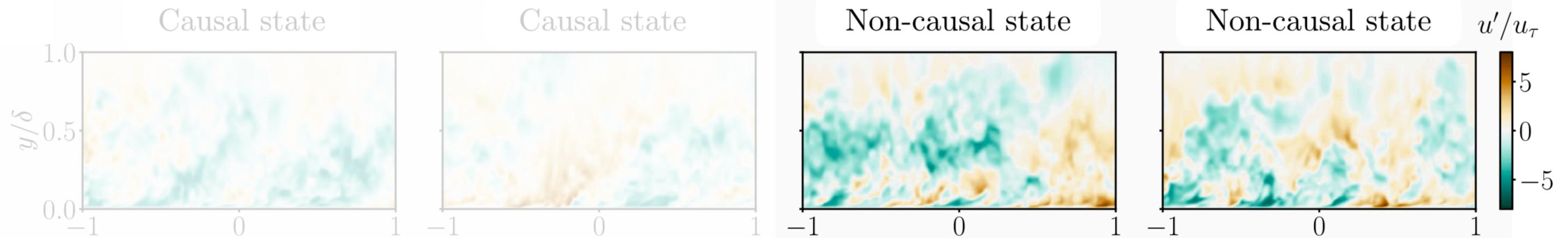
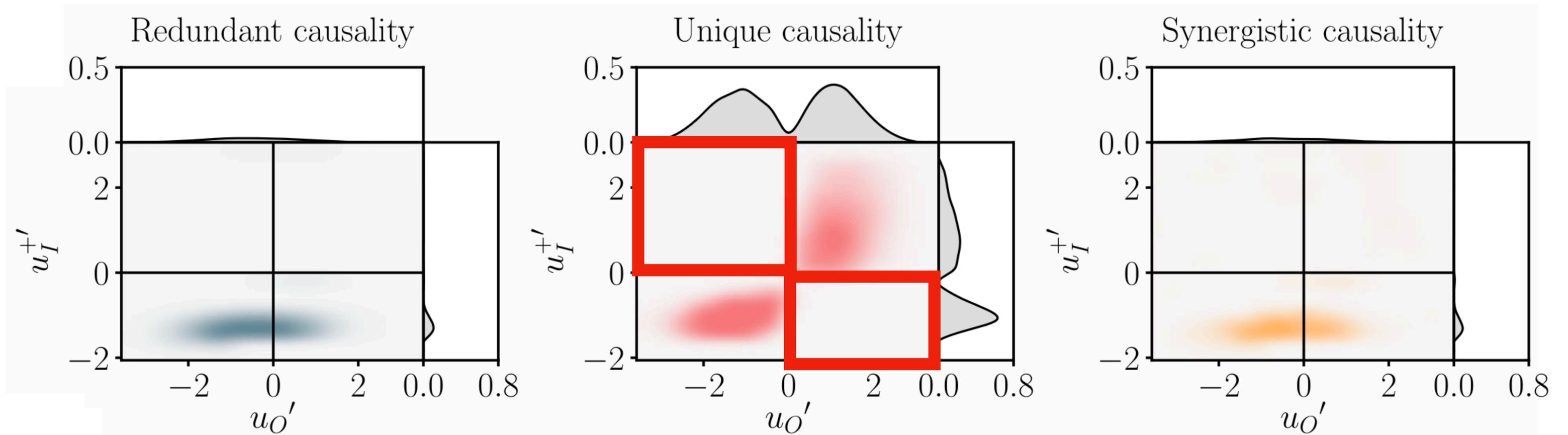
State-dependent causality: Application



State-dependent causality: Application



State-dependent causality: Application



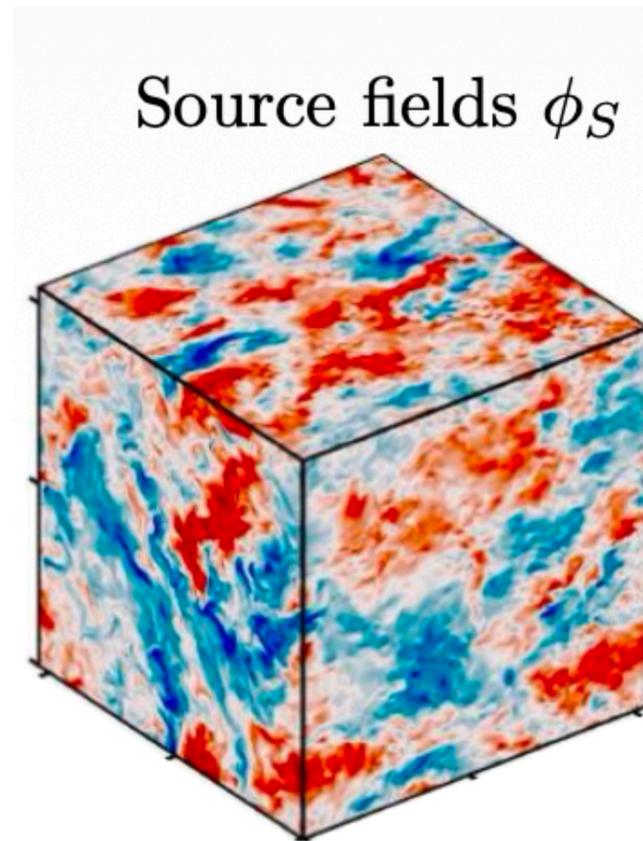
Three levels of causality

Average Causality

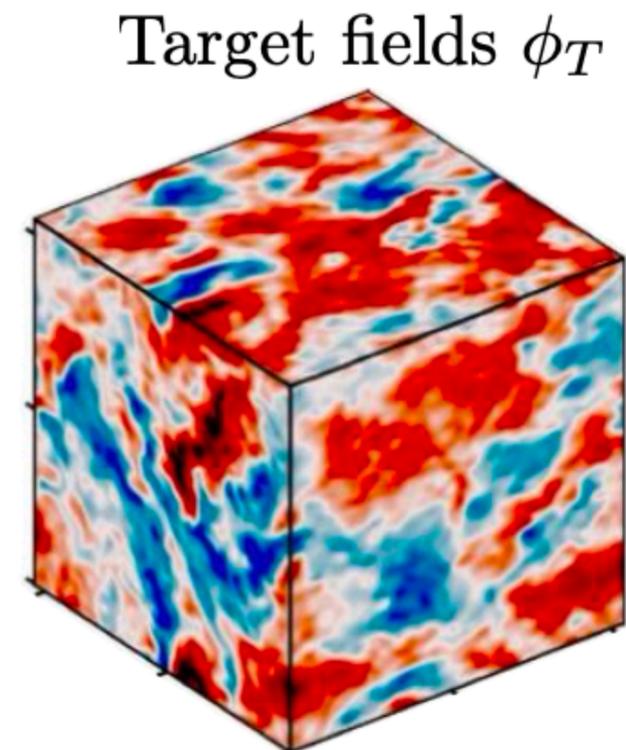
State-dependent Causality

Space-time Causality

Space-time causality: Method



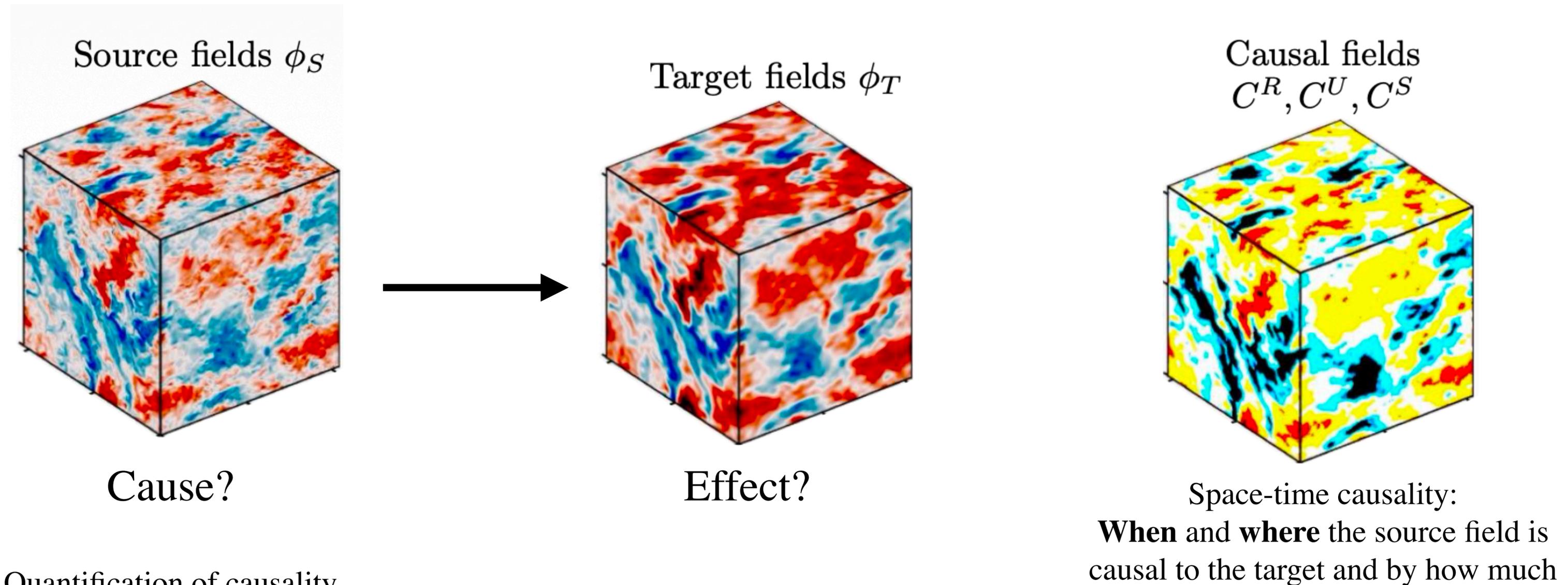
Cause?



Effect?

Space-time causality:
When and **where** the source field is
causal to the target and by how much?

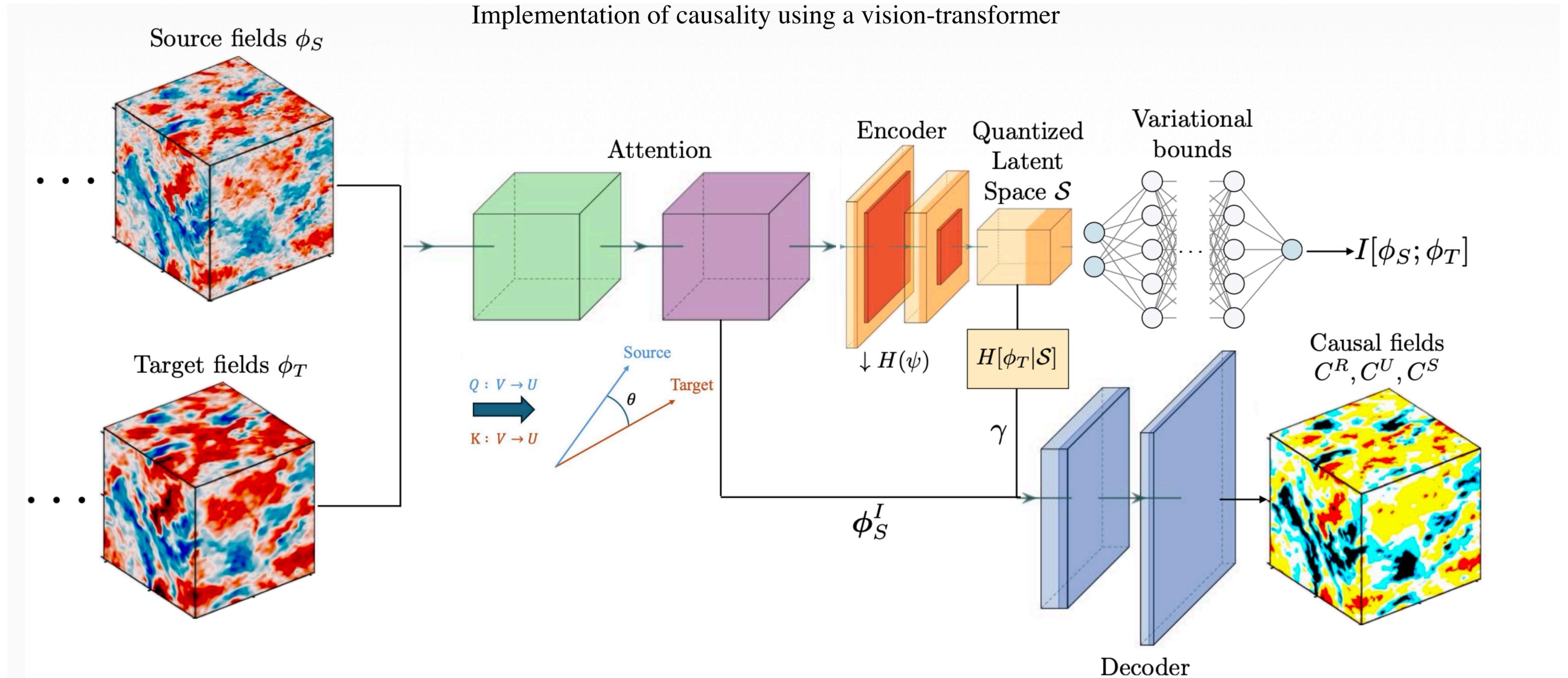
Space-time causality: Method



Quantification of causality

$$\phi_S^I(\mathbf{x}, t) = \arg \min_{\psi} \left\{ H[\psi] \mid \psi \in F(\phi_S), I[\psi; \phi_T] = I[\phi_S; \phi_T] \right\} \quad \text{with} \quad \|\phi_S - \phi_S^I\| \text{ minimized.}$$

Space-time causality: Method

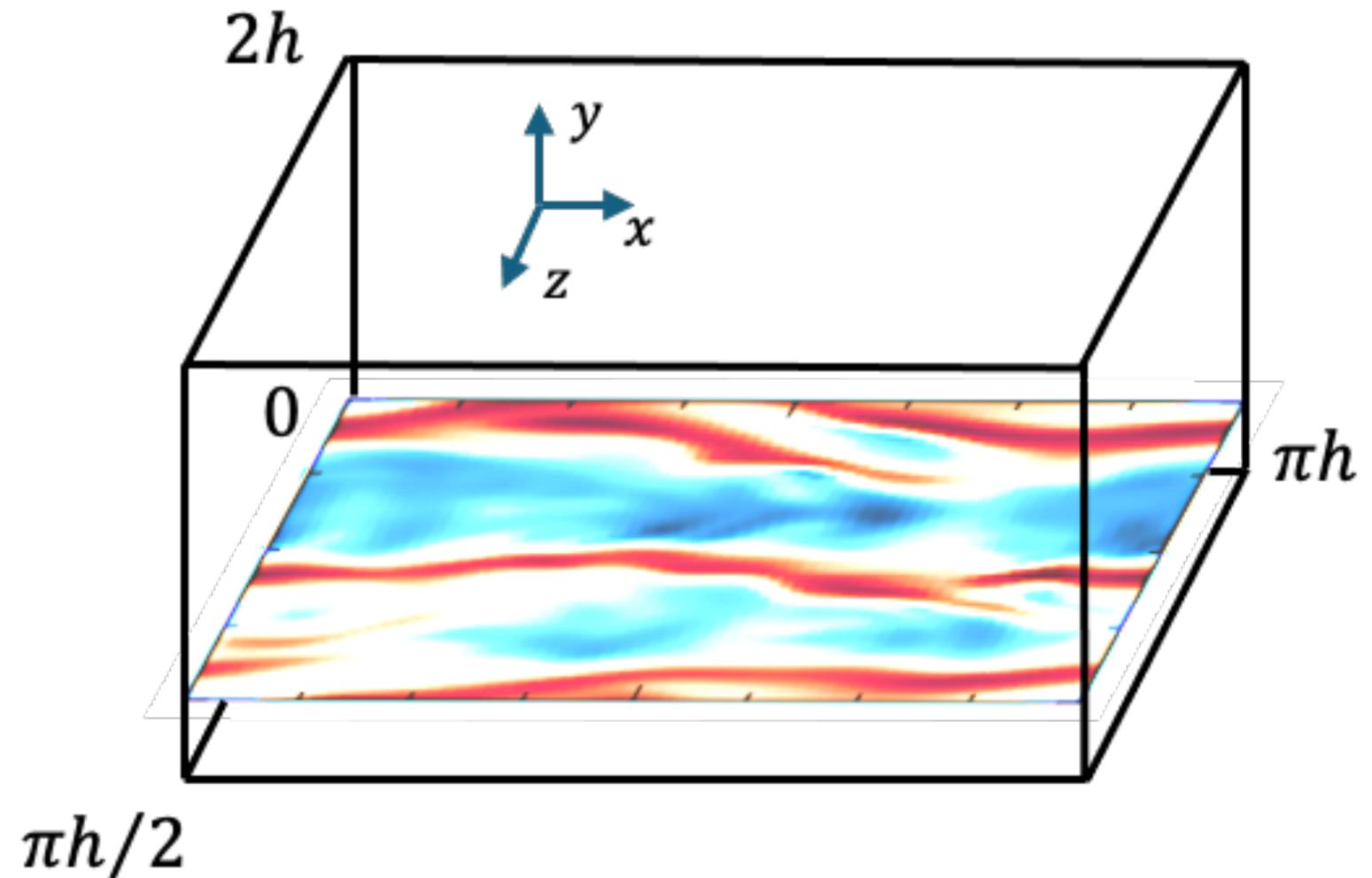


Space-time causality: Application

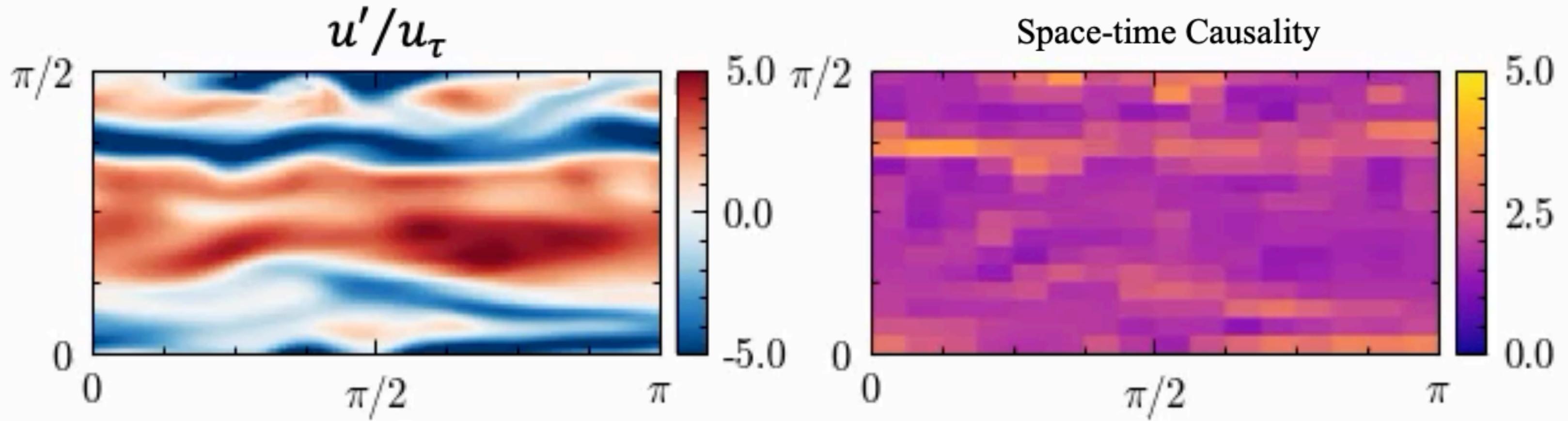
Question: When and where streamwise velocity is causal to the wall shear stress in the future?

Problem and Data:

- Turbulent Channel Flow
- DNS at $Re_\tau = 180$
- Wall-normal plane at $y^+ = 60$
- $u'(\mathbf{x}, t; y^+) \rightarrow \tau_x(\mathbf{x}, t + T)$
- $T = 10$ plus units



Space-time causality: Application



Outline

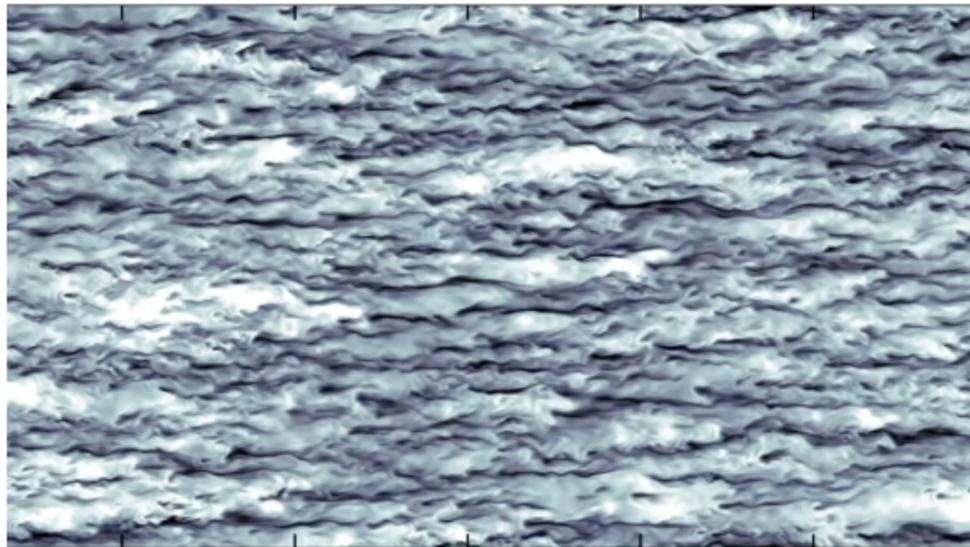
- What is causality?
- Frameworks for causal inference
 - Interventional vs. observational
- Three level of causality
 - Average causality
 - State-dependent causality
 - Space-time causality
- **Limitations**

Some limitations

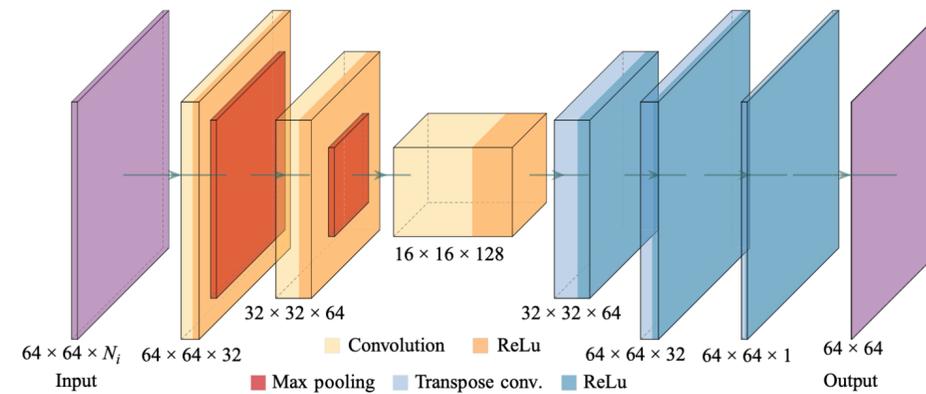
- Causal inference is just a tool. It might help to get the correct answers if the correct questions are asked
- The best definition of causality might depend on goal/application
- Some properties might be partially lost when unobserved variables play a key role in the causal network
- Only applicable to time-varying variables (not to constants/parameters of the system)
- The methods are data-hungry
- ...

Why causal analysis in fluid dynamics?

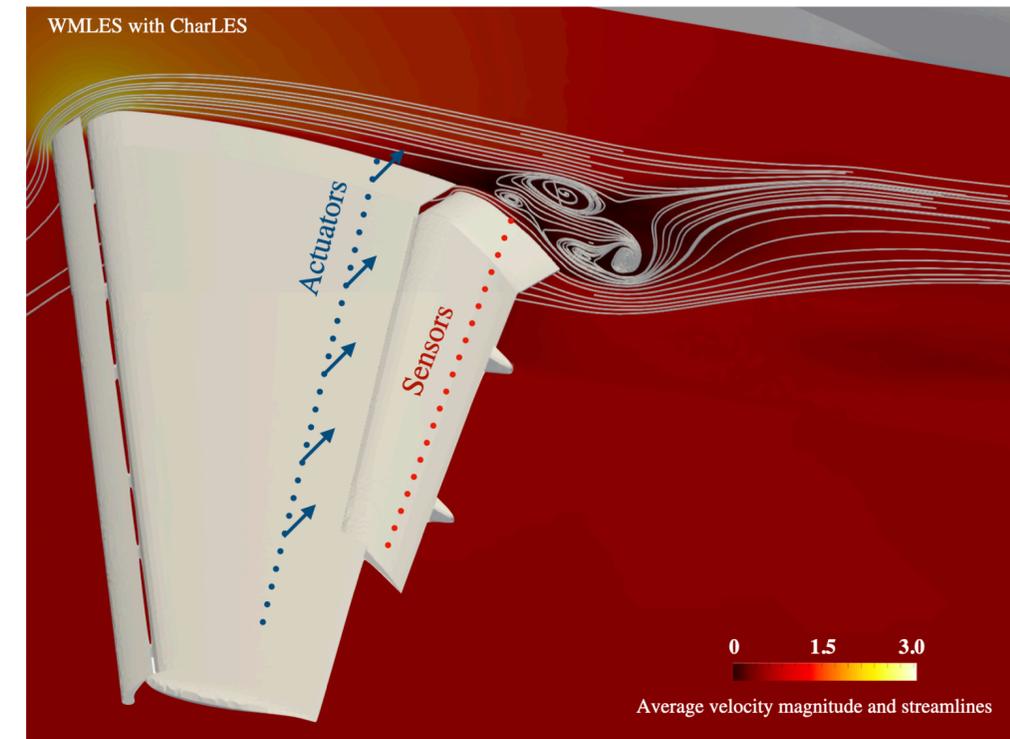
Physical insight



Causality-preserving reduced-order models



Causality-driven control



Causality map of QoIs

