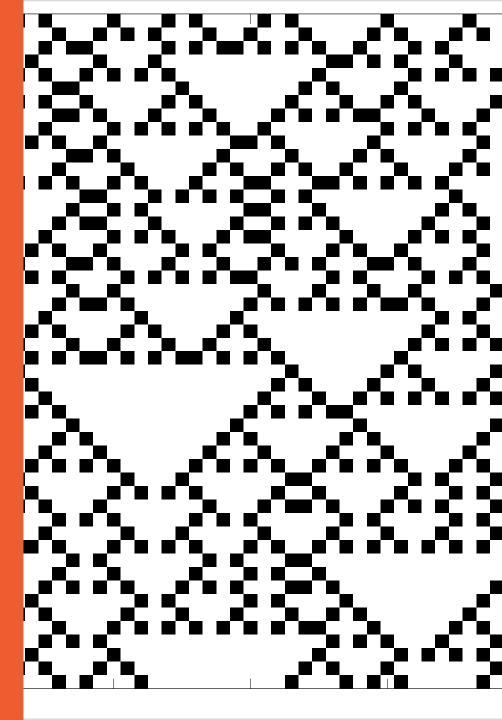
Lecture 7 — Information dynamics — part II

Dr. Joseph Lizier





COMMONWEALTH OF AUSTRALIA

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Information dynamics Part I: session outcomes

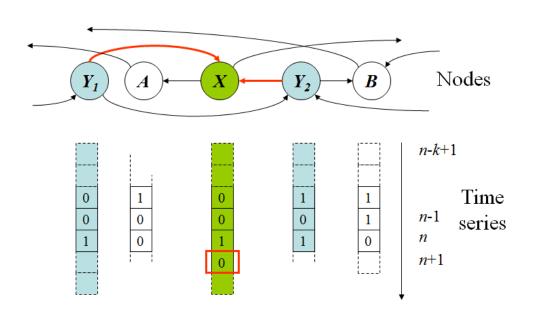
- Understand philosophy behind information storage and transfer components of information dynamics and how they are related.
- Apply JIDT using AutoAnalyser and extensions of code it produces to analyse information transfer in complex systems data sets.

Primary references:

- J.T. Lizier, "JIDT: An information-theoretic toolkit for studying the dynamics of complex systems",
 Frontiers in Robotics and Al, 1:11, 2014; appendix A.2 and A.3
- J.T. Lizier, "The local information dynamics of distributed computation in complex systems", Springer:
 Berlin/Heidelberg, 2013; chapter 3, 4
- Bossomaier, Barnett, Harré, Lizier, "An Introduction to Transfer Entropy: Information Flow in Complex Systems", Springer, Cham, 2016; chapter 4 (sections 4.1-4.3); section 5.1

Information dynamics

– Key question: how is the next state of a variable in a complex system computed?



Complex system as a multivariate time-series of states

Q: Where does the information in x_{n+1} come from, and how can we measure it? (Where might we look?)

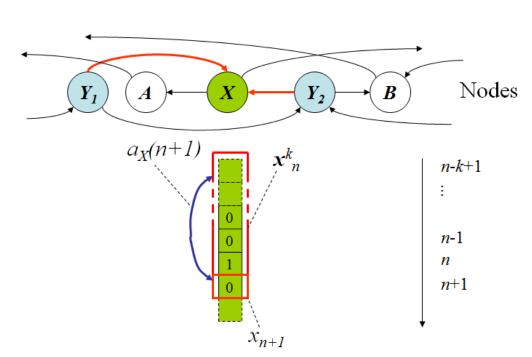
Q: Can we model the information processing in X in terms of:

- how much information was stored?
- how much was transferred?

Q: Can we partition them, do they overlap? etc.

Active information storage

- How much information about the next observation X_n of process X can be found in its past state $X_n^{(k)}=\{X_{n-k+1},\dots,X_{n-1},X_n\}$?



Active information storage

$$A_{X} = \lim_{k \to \infty} I(X_{n}^{(k)}; X_{n+1})$$

$$A_{X}(k) = I(X_{n}^{(k)}; X_{n+1})$$

$$A_{X} = H(X_{n+1}) - H_{\mu X}$$

$$A_{X}(k) = \left\{ \log_{2} \frac{p(x_{n+1} | x_{n}^{(k)})}{p(x_{n+1})} \right\}$$

$$a_{X}(k) = \log_{2} \frac{p(x_{n+1} | x_{n}^{(k)})}{p(x_{n+1})}$$

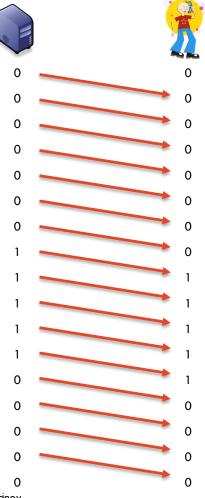
- AIS: Average information from past state that is in use in predicting the next value
- Local AIS: information from a specific past state in use in predicting specific next value

Information transfer

- Recall we're building a model of the dynamics of the target variable
 - And we've already accounted for the past of the target (Information storage).
- How much information from the past of a source variable helps
 us predict the next state of the target ...
- Or, in modelling the dynamics of the variable, how much information transfer would we include in that model by accounting for the past influence of the source ...
- Given that we've already considered the past of the target.

Information transfer — using our intuition

- Simple example: heartbeat messages
 - Target copying simple (Poisson transitioning) messages from source



	$s_n = 0$	$s_n = 1$
$s_{n+1} = 0$	$1-\lambda_1$	λ_0
$s_{n+1} = 1$	λ_1	$1-\lambda_0$

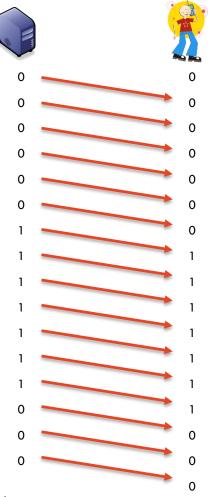
- $t_{n+1} = s_n$
- Transition rates small (<0.5), and $\lambda_1 < \lambda_0$ so values are normally 0.

- E.g.
$$\lambda_1 = 0.05$$
, $\lambda_0 = 0.2$

- Try to predict the next values.
- Where did you take the information from?

Information transfer – using our intuition

- Simple example: heartbeat messages
 - Target copying simple (Poisson transitioning) messages from source



	$s_n = 0$	$s_n = 1$
$s_{n+1} = 0$	$1-\lambda_1$	λ_0
$s_{n+1} = 1$	λ_1	$1-\lambda_0$

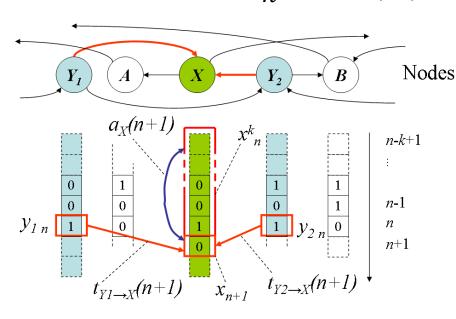
- $t_{n+1} = s_n$
- Transition rates small (<0.5), and $\lambda_1 < \lambda_0$ so values are normally 0.

- E.g.
$$\lambda_1 = 0.05$$
, $\lambda_0 = 0.2$

- Now: you are (modelling) the destination.
- At each step, model your prediction of the next value.
 - Write down your prediction based on past and how sure you are (scale of 1 to 10).
 - Update your prediction based on source, and evaluate how much source adds (scale 1 to 10) Page 8
- Where did source add most/least? Why?

Transfer entropy

- How much information about the next observation X_n of process X can be found in observation Y_n of process Y, in the context of the past state $\boldsymbol{X}_n^{(k)} = \{X_{n-k+1}, \dots, X_{n-1}, X_n\}$?



Transfer entropy

$$T_{Y \to X} = \lim_{k \to \infty} I\left(Y_n; X_{n+1} \middle| \boldsymbol{X}_n^{(k)}\right)$$

$$T_{Y \to X}(k) = I\left(Y_n; X_{n+1} \middle| \boldsymbol{X}_n^{(k)}\right)$$

$$T_{Y \to X}(k) = \left|\log_2 \frac{p\left(x_{n+1} \middle| \boldsymbol{x}_n^{(k)}, y_n\right)}{p\left(x_{n+1} \middle| \boldsymbol{x}_n^{(k)}\right)}\right|$$

$$t_{Y \to X}(k) = \log_2 \frac{p\left(x_{n+1} \middle| \boldsymbol{x}_n^{(k)}, y_n\right)}{p\left(x_{n+1} \middle| \boldsymbol{x}_n^{(k)}, y_n\right)}$$

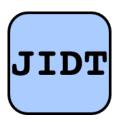
- TE: Average info from source that helps predict next value in context of past.
- Local AIS: info from a specific source value to predict specific next value in context of past.

T. Schreiber, "Measuring Information Transfer", Physical Review Letters, 85(2), pp. 461-4, 2000.

J. T. Lizier, M. Prokopenko, & A. Y. Zomaya. "Local information transfer as a spatiotemporal filter for complex systems". Physical Review E, 77(2):026110, 2008.

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Transfer entropy in JIDT

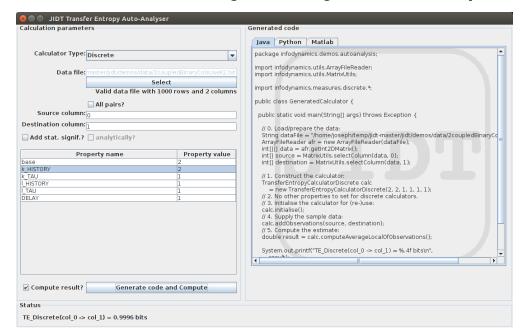


- Start TE AutoAnalyser
- Notice the important embedding parameters (e.g. k_HISTORY)

 Has all types of underlying CMI estimators available, same parameters as each &features (e.g. statistical significance, local)

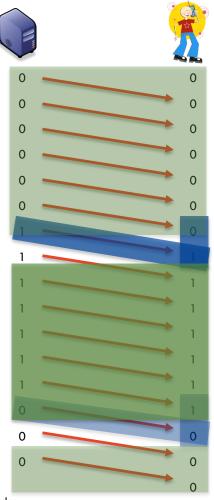
Using Gaussian model amounts to measuring Granger causality

(factor of 2)



Transfer entropy on heartbeat messages

Examine local transfer entropy using JIDT on this example

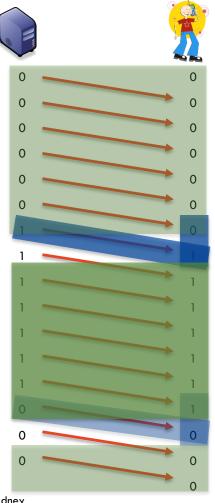


	$s_n = 0$	$s_n = 1$
$s_{n+1} = 0$	$1-\lambda_1$	λ_0
$s_{n+1} = 1$	λ_1	$1-\lambda_0$

- See tutorial activity with $\lambda_1 = 0.05$, $\lambda_0 = 0.2$, N = 100000
- Where did source add most?
 - Why?
- Where did source add the least?
 - Why?

Transfer entropy vs (lagged) mutual information

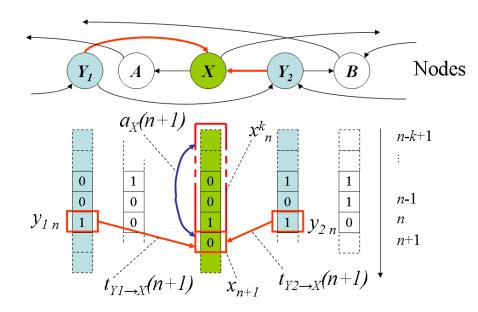
- How does $I\left(Y_n; X_{n+1} \middle| \boldsymbol{X}_n^{(k)}\right)$ contrast to $I(Y_n; X_{n+1})$?



- Both are directed, but conditioning on past makes TE dynamic
- Recall the effect of conditioning in a CMI:
 - Reduces MI in removing redundancies between the source and the target past
 - Increases MI in including synergies
 (where the source became more informative in the context of the past)
- Challenge: compute local Mls to compare
- These differences directly relate to our intuition about information transfer here!

Role of conditioning on history for TE

- Provides a contrast to information storage
 - Removes any information storage from being considered as transfer. (removes redundant information in past and source)
 - Transfer is defined in juxtaposition to storage.
 - 2nd step in our modelling process of the computation of the target, after first considering the information that was already present in the target state.



$$H(X_{n+1}) = I(X_n^{(k)}; X_{n+1}) + I(Y_n; X_{n+1} | X_n^{(k)}) + H(X_{n+1} | X_n^{(k)}, Y_n)$$

Bossomaier, Barnett, Harré, Lizier, "An Introduction to Transfer Entropy: Information Flow in Complex Systems", Springer, Cham, 2016; section 4.2.2

J.T. Lizier, M. Prokopenko, & A. Y. Zomaya. "Local information transfer as a spatiotemporal filter for complex systems". Physical Review E, 77(2):026110, 2008.

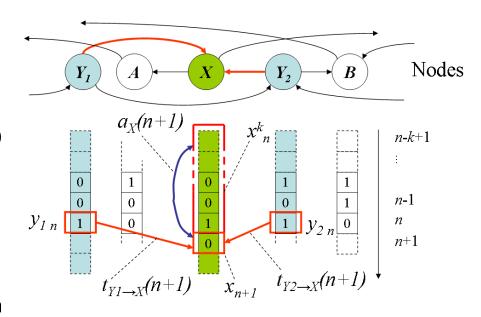
J.T. Lizier and J.R. Mahoney, "Moving frames of reference, relativity and invariance in transfer entropy and information dynamics", Entropy, 15(1), p. 177-197, 2013.

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Role of conditioning on history for TE

TE examines state transitions in the target

- Recall the interpretation of $x_n^{(k)}$ as a Takens' embedding of the underlying state of the target.
- We are examining the state transition $x_n^{(k)} o x_{n+1}$ (or including redundant information $x_n^{(k)} o x_{n+1}^{(k)}$)
- TE is information provided by source about this dynamic state transition in the target.



T. Schreiber, "Measuring Information Transfer", Physical Review Letters, 85(2), pp. 461-4, 2000.

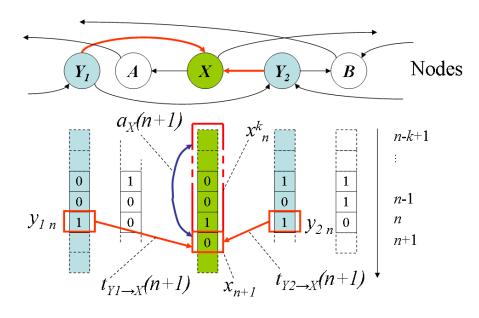
Bossomaier, Barnett, Harré, Lizier, "An Introduction to Transfer Entropy: Information Flow in Complex Systems", Springer, Cham, 2016; section 4.2.2

J.T. Lizier, M. Prokopenko, & A. Y. Zomaya. "Local information transfer as a spatiotemporal filter for complex systems". Physical Review E, 77(2):026110, 2008.

J.T. Lizier and J.R. Mahoney, "Moving frames of reference, relativity and invariance in transfer entropy and information dynamics", Entropy, 15(1), p. 177-197, 2013.

Role of conditioning on history for TE

- TE examines contribution from source in the context of the target history
 - The target past does not only "condition out" redundant information, but
 - Allows TE to include synergistic information from source and target past.
 - Think of our modelling process as including the target past $x_n^{(k)}$ as context to consider other sources.



Differentiating information transfer and causal effect

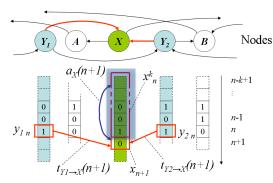
- <u>Heartbeat example</u>: what were the differences?
- Causality is about the effect of interventions; Information transfer is about modelling dynamics as computation.
- Information transfer does not directly measure causal effect:
 - Causal sources may serve information storage only
 - Non-causal sources (e.g. hidden common drivers) can have transfer
 - One should restrict analysis to causal sources where possible.
- Information transfer measures emergent computational structure that causality does not, e.g.:
 - Transitions in Heartbeat example
 - Gliders in cellular automata

J.T. Lizier and M. Prokopenko, "Differentiating information transfer and causal effect", European Physical Journal B, vol. 73, no. 4, pp. 605-615, 2010

Bossomaier, Barnett, Harré, Lizier, "An Introduction to Transfer Entropy: Information Flow in Complex Systems", Springer, Cham, 2016; section 4.2.2.1

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Using transfer entropy in practice



1. Set the target embedding

 Similar concerns as per the active information storage (see previous lecture), and can include an embedding delay:

$$T_{Y\to X}(k,\tau_X) = I\left(Y_n; X_{n+1} \middle| \boldsymbol{X}_n^{(k,\tau_X)}\right)$$

- Set in the same manner to minimise stored information being counted as transfer, i.e.:
 - Max bias-corrected AIS or Ragwitz criteria or non-uniform.
 - First two options are available in JIDT

– Caveats:

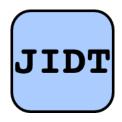
- Must embed target first for proper interpretation as information transfer! (Rather than embedding source-target together)
- Additional target past values could be missed here which add synergistic information with source.

Bossomaier, Barnett, Harré, Lizier, "An Introduction to Transfer Entropy: Information Flow in Complex Systems", Springer, Cham, 2016; section 4.2 M. Wibral, R. Vicente, and M. Lindner. "Transfer entropy in neuroscience". In M. Wibral, R. Vicente, and J. T. Lizier, editors, Directed Information Measures in Neuroscience, pp. 3–36. Springer, Berlin/Heidelberg, 2014

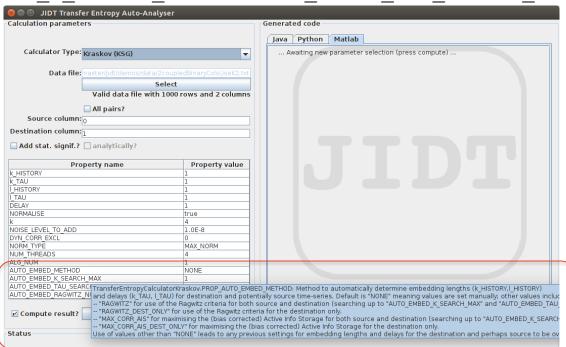
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TE: setting embedding parameters in JIDT

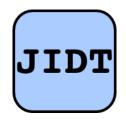


- Select KSG estimator
- Hover on AUTO EMBED METHOD property to see options:
 - NONE: set k_HISTORY and TAU manually.
 - RAGWITZ:* optimal parameters to minimise prediction error scanned up to
 AUTO_EMBED_K_SEARCH_MAX and AUTO_EMBED_TAU_SEARCH_MAX
 - MAX_CORR_AIS:* optimal parameters to max. bias-corrected AIS scanned up to
 AUTO EMBED K SEARCH MAX and AUTO EMBED TAU SEARCH MAX

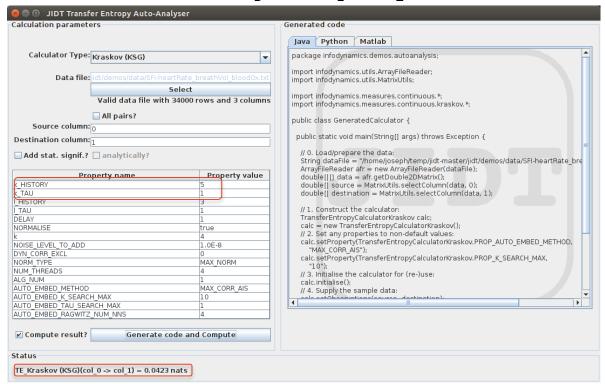


* Note clarification on these parameters re source embedding later!

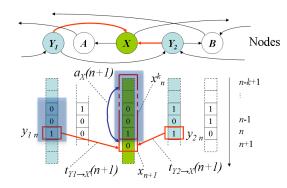
TE: setting embedding parameters in JIDT



- Select the SFI-heartRate_breathVol_bloodOx.txt data set
- Set AUTO_EMBED_METHOD to MAX_CORR_AIS and
 AUTO_EMBED_K_SEARCH_MAX to 10 and AUTO_EMBED_TAU_SEARCH_MAX to 1.
- Click Compute
- The result is returned with optimal parameters shown in $k_HISTORY$ and TAU. You can retrieve them in code via a getProperty() call.



Using transfer entropy in practice



2. Set the source embedding

- I gave you the simple TE definition earlier!
- More general including source embedding:

$$T_{Y\to X}(k, l, \tau_X, \tau_Y) = I\left(\mathbf{Y}_n^{(l,\tau_Y)}; X_{n+1} \middle| \mathbf{X}_n^{(k,\tau_X)}\right)$$

- When to use source state $y_n^{(k,\tau_Y)}$ directly instead of scalar y_n :
 - If observations y_n masks hidden Markov process
 - ullet If multiple past values of Y are causal to X
 - Otherwise we can build a set of contributors from Y via non-uniform embedding (see next lecture).

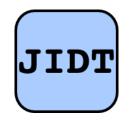
Bossomaier, Barnett, Harré, Lizier, "An Introduction to Transfer Entropy: Information Flow in Complex Systems", Springer, Cham, 2016; section 4.2.1.2

J. T. Lizier. "Measuring the dynamics of information processing on a local scale in time and space". In M. Wibral, R. Vicente, and J. T. Lizier, editors, Directed Information Measures in Neuroscience, pp. 161–193. Springer, Berlin/Heidelberg, 2014.

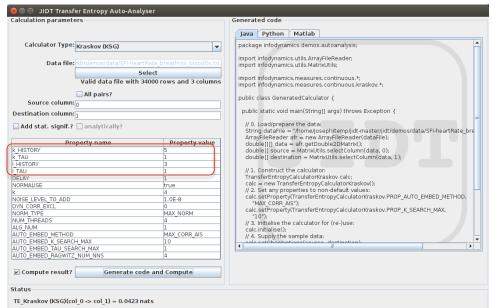
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TE: setting source embedding parameters in JIDT

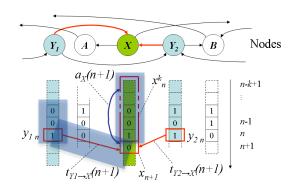


- Select KSG estimator
- Hover on AUTO EMBED METHOD property to see options:
 - NONE: set target and source embeddings manually.
 - RAGWITZ: set target and source embeddings to minimise prediction error
 - RAGWITZ_DEST_ONLY: for target only
 - MAX_CORR_AIS: set target and source embeddings to max. bias-corrected AIS
 - MAX_CORR_AIS_DEST_ONLY: for target only
 - All scan up to AUTO_EMBED_K_SEARCH_MAX and AUTO_EMBED_TAU_SEARCH_MAX



* Notice the slight change in these options compared to AIS, because we're dealing with source + target

Using transfer entropy in practice



- 3. Set the source-target delay
 - Ok, I still gave you a simpler TE definition!
 - More general still including source-target delay:

$$T_{Y\to X}(k,l,\tau_X,\tau_Y,u) = I\left(\mathbf{Y}_{n+1-u}^{(l,\tau_Y)};X_{n+1}\middle|\mathbf{X}_n^{(k,\tau_X)}\right)$$

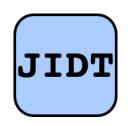
- Set u to maximise $T_{Y\to X}$
 - Proven to match actual causal delay under simple conditions.

M. Wibral, N. Pampu, V. Priesemann, F. Siebenh"uhner, H. Seiwert, M. Lindner, J. T. Lizier, and R. Vicente. "Measuring information-transfer delays". PLoS ONE, 8(2):e55809+, 2013.

Bossomaier, Barnett, Harré, Lizier, "An Introduction to Transfer Entropy: Information Flow in Complex Systems", Springer, Cham, 2016; section 4.2.4

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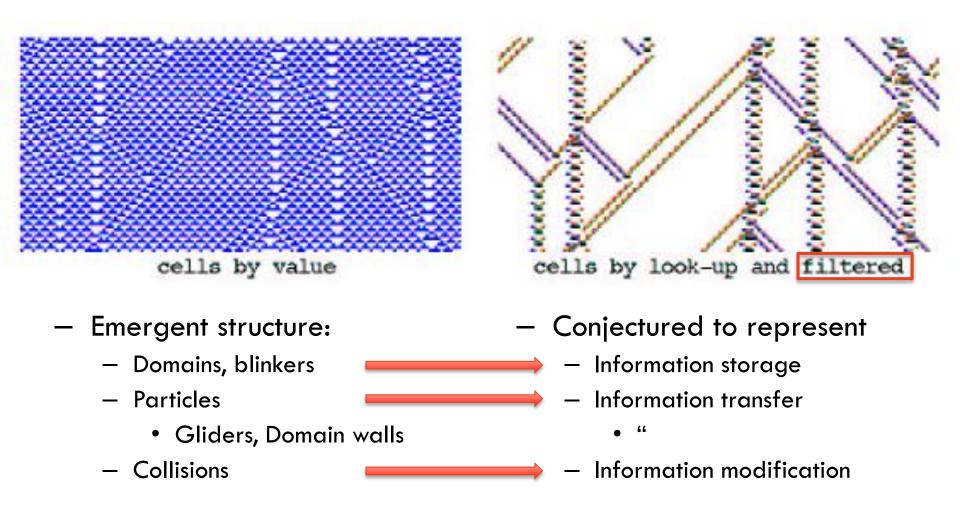
TE: setting source-target delay in JIDT



Set DELAY property (available on all except kernel estimator).

alculation parameters	Generated code
	Java Python Matlab
Calculator Type: Discrete	package infodynamics.demos.autoanalysis;
Data file: master/jidt/demos/data/2coupledBinaryColsUseK2.txt Select Valid data file with 1000 rows and 2 columns All pairs? Source column: 0 Destination column: 1 Add stat. signif.? analytically? Property name Property value lase 2 HISTORY 2 TAU 1 HISTORY 1 TAU 1 ELAY 1 ELAY 1	import infodynamics.utils.ArrayFileReader; import infodynamics.utils.MatrixUtils; import infodynamics.measures.discrete.*; public class GeneratedCalculator { public static void main(String[] args) throws Exception { // 0. Load/prepare the data: String dataFile = "/home/joseph/temp/jidt-master/jidt/demos/data/2coupledBinaryCoarrayFileReader aff = new ArrayFileReader(dataFile); int[][] data = afr.getInt2DMatrix(); int[] source = MatrixUtils.selectColumn(data, 0); int[] destination = MatrixUtils.selectColumn(data, 1); // 1. Construct the calculator: TransferEntropyCalculatorDiscrete calc = new TransferEntropyCalculatorDiscrete(2, 2, 1, 1, 1, 1); // 2. No other properties to set for discrete calculators. // 3. initialise the calculator for (re-)use: calc.initialise(); // 4. Supply the sample data: calc.addObservations(source, destination); // 5. Compute the estimate: double result = calc.computeAverageLocalOfObservations(); System.out.printf("TE_Discrete(col_0 -> col_1) = %.4f bits\n",

Example: Computational role of emergent structure in CAs



A. Wuensche, "Classifying cellular automata automatically: Finding gliders, filtering, and relating space-time patterns, attractor basins, and the Z parameter," Complexity, vol. 4, no. 3, pp. 47–66, 1999. (plus image credit)

C. G. Langton, "Computation at the edge of chaos: phase transitions and emergent computation," Physica D, vol. 42, no. 1-3, pp. 12–37, 1990.

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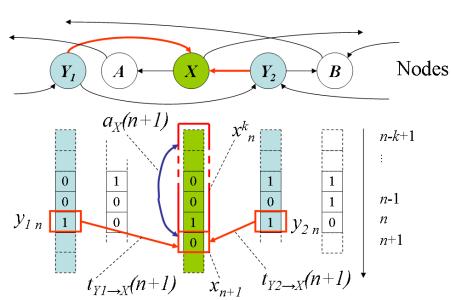


Example: Computational role of emergent structure in CAs

- Go to tutorial sheet to try out our TE calculator on CA data:
 - We'll use the appropriate embedding length determined for AIS last time.
 - We'll compute local TE values and see whether gliders do indeed have strong information transfer values.

Conditional Transfer entropy

- How much info about next observation X_n of process X can be found in observation Y_n of process Y, in context of the past state $X_n^{(k)} = \{X_{n-k+1}, \dots, X_{n-1}, X_n\}$ and observation Z_n of process Z?



$$T_{Y \to X|Z} = \lim_{k \to \infty} I\left(Y_n; X_{n+1} \middle| X_n^{(k)}, Z_n\right)$$

$$T_{Y \to X|Z}(k) = I\left(Y_n; X_{n+1} \middle| X_n^{(k)}, Z_n\right)$$

$$T_{Y \to X|Z}(k) = \left|\log_2 \frac{p\left(x_{n+1} \middle| x_n^{(k)}, y_n, z_n\right)}{p\left(x_{n+1} \middle| x_n^{(k)}, z_n\right)}\right|$$

$$t_{Y \to X|Z}(k) = \log_2 \frac{p\left(x_{n+1} \middle| x_n^{(k)}, y_n, z_n\right)}{p\left(x_{n+1} \middle| x_n^{(k)}, y_n, z_n\right)}$$

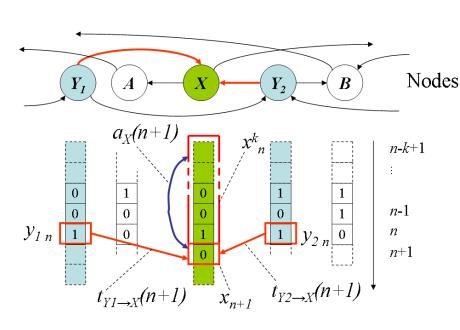
- Can add same source-target delays, conditional-target delays, embeddings, multivariate conditionals etc., all in style of such extensions for TE.
- J. T. Lizier, M. Prokopenko, & A. Y. Zomaya. "Local information transfer as a spatiotemporal filter for complex systems". Physical Review E, 77(2):026110, 2008.
- J. T. Lizier, M. Prokopenko, & A. Y. Zomaya. "Information modification and particle collisions in distributed computation", Chaos, 20(3), 037109, 2010.

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Contrasting TE and CTE

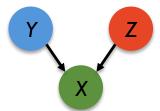
- How does extra conditioning on Z change TE?



- Removes redundancies between Y and Z, e.g.
 - Common driver effects
 Z
 X
 - Pathway effects



- Includes synergies between Y and Z, e.g.
 - Gated effects



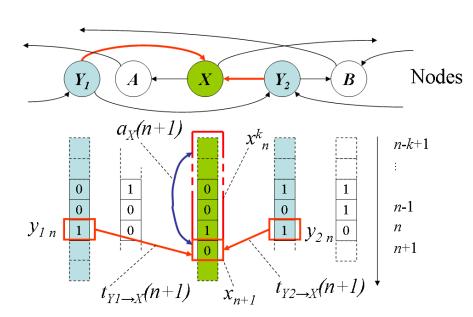
J. T. Lizier, M. Prokopenko, & A. Y. Zomaya. "Local information transfer as a spatiotemporal filter for complex systems". Physical Review E, 77(2):026110, 2008.

J. T. Lizier, M. Prokopenko, & A. Y. Zomaya. "Information modification and particle collisions in distributed computation", Chaos, 20(3), 037109, 2010.

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Relating TE and CTE

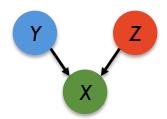
— How does extra conditioning on Z change TE? Do we need them both?



$$T_{Y\to X}(k) = I\left(Y_n; X_{n+1} \middle| \boldsymbol{X}_n^{(k)}\right)$$

$$T_{Y\to X|Z}(k) = I\left(Y_n; X_{n+1} \middle| \boldsymbol{X}_n^{(k)}, Z_n\right)$$

Information regression



- Our goal in modelling the information processing in X.
- Consider two sources to X. (General case in Lizier 2010):

$$H(X_{n+1}) = I\left(X_{n}^{(k)}; X_{n+1}\right) + I\left(Y_{n}; X_{n+1} \middle| X_{n}^{(k)}\right) + H\left(X_{n+1} \middle| X_{n}^{(k)}, Y_{n}\right)$$

$$H(X_{n+1}) = I\left(X_{n}^{(k)}; X_{n+1}\right) + I\left(Y_{n}, Z_{n}; X_{n+1} \middle| X_{n}^{(k)}\right) + H\left(X_{n+1} \middle| X_{n}^{(k)}, Y_{n}, Z_{n}\right)$$

$$H(X_{n+1}) = I\left(X_{n}^{(k)}; X_{n+1}\right) + I\left(Y_{n}; X_{n+1} \middle| X_{n}^{(k)}\right) + I\left(Z_{n}; X_{n+1} \middle| X_{n}^{(k)}, Y_{n}\right)$$

$$+ H\left(X_{n+1} \middle| X_{n}^{(k)}, Y_{n}, Z_{n}\right)$$

$$H(X_{n+1}) = I\left(X_{n}^{(k)}; X_{n+1}\right) + I\left(Z_{n}; X_{n+1} \middle| X_{n}^{(k)}\right) + I\left(Y_{n}; X_{n+1} \middle| X_{n}^{(k)}, Z_{n}\right)$$

$$+ H\left(X_{n+1} \middle| X_{n}^{(k)}, Y_{n}, Z_{n}\right)$$

1. Active information storage

2-. Collective transfer entropy

2. Pairwise/apparent transfer entropy

3+. Conditional transfer entropy

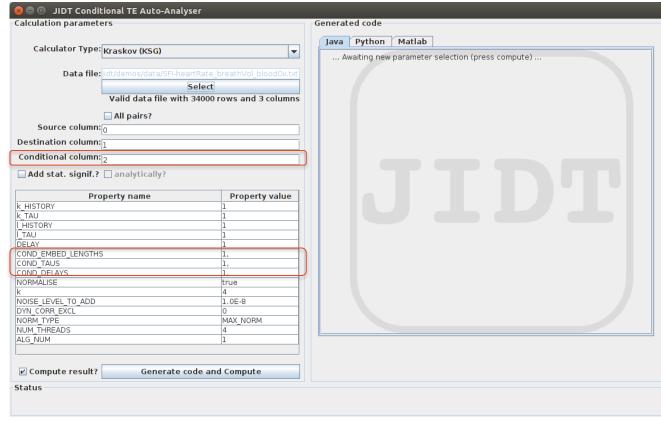
J. T. Lizier, M. Prokopenko, & A. Y. Zomaya. "Local information transfer as a spatiotemporal filter for complex systems". Physical Review E, 77(2):026110, 2008.

J. T. Lizier, M. Prokopenko, & A. Y. Zomaya. "Information modification and particle collisions in distributed computation", Chaos, 20(3), 037109, 2010. The University of Sydney Page 29

Conditional Transfer entropy in JIDT



- Start CTE AutoAnalyser
- Has all types of underlying CMI estimators available, same parameters as each & features (e.g. statistical significance, local)



Information dynamics Part II: summary

- We've looked at the philosophy behind information storage and transfer and how they are related for analysing information processing in complex systems.
- In particular, we've focussed on how information transfer is characterised.
 - How pairwise and higher order transfer entropies are related.
 - And used JIDT AutoAnalyser and extensions of code to analyse information transfer in complex systems data sets.

 Next lecture: Inferring effective networks from time-series dynamics.

Questions

