

Auto-information in non-Markovian diffusion systems.

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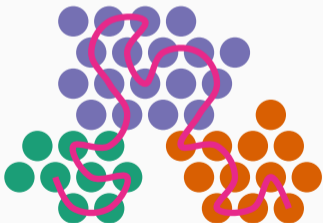
 icteam, UCLouvain, Belgium

Intro



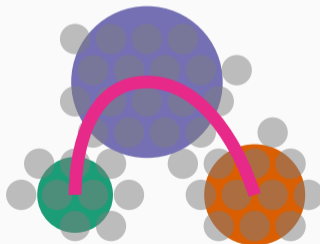
A markov chain

$\dots, X_{\text{past}}, X_{\text{now}}, X_{\text{future}}, \dots$



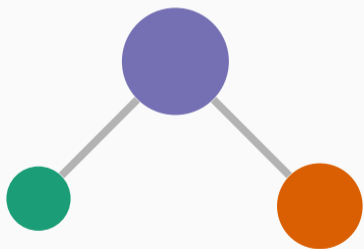
Its projection

$\dots, Y_{\text{past}}, Y_{\text{now}}, Y_{\text{future}}, \dots$



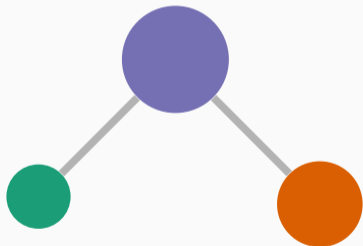


Where did the complexity go?





Where did the complexity go?



Part of the complexity is now hidden in the [projected] dynamics.

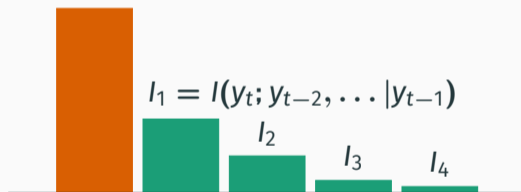
Emergence of **effective memories**.

The Entrogram



Information flowing from the PAST toward the FUTURE.

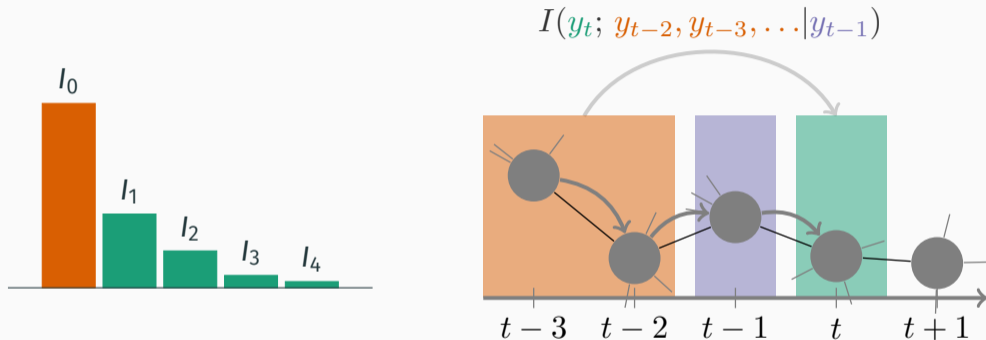
$$I_0 = I(y_t; y_{t-1}, \dots)$$



where $I(X; Y) = H(X) - H(X|Y)$ is the Mutual Information

Faccin, Schaub, Delvenne Journal of Complex Networks, 6(5), 2018, p661-678

Entrogram: Information flowing from the PAST to the FUTURE

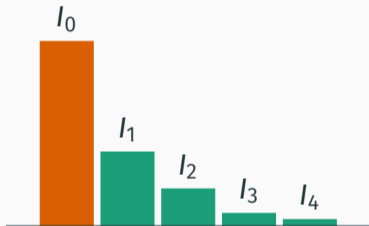


Faccin, Schaub, Delvenne Journal of Complex Networks, 6(5), 2018, p661-678

Crutchfield and Young (1989) PRL, 63, 105.

Crutchfield and Feldman (2003) Chaos, 13, 25-54.

Entrogram: a compact description of the system complexity



■ [Total] Predictability, how the dynamics are aligned to the partition.

■ Emergent effective memory

■ + ■ Overall complexity (excess entropy) of the dynamical process

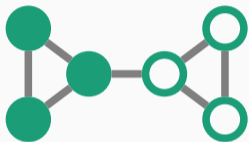
Faccin, Schaub, Delvenne *Journal of Complex Networks*, 6(5), 2018, p661–678

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Assortative partition



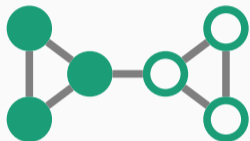
Equitable partition



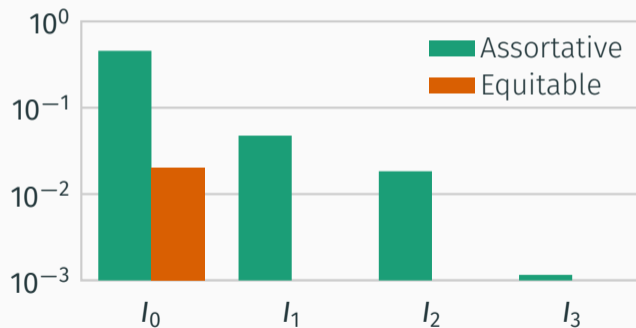
An Example: the Bow-tie



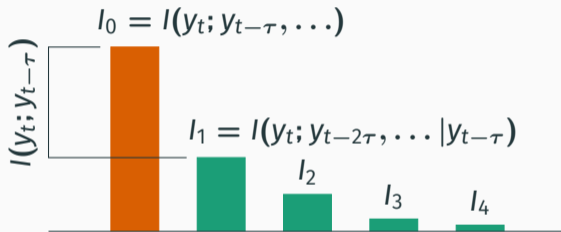
Assortative partition



Equitable partition



Auto-information



where τ represents a time-scale parameter.



Modularity:

$$Q = \frac{1}{2m} \sum_{ij} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j)$$

χ_c characteristic variable of partition c

$$Q \propto \sum_c \mathbf{Cov}(\chi_c(t), \chi_c(t+1))$$

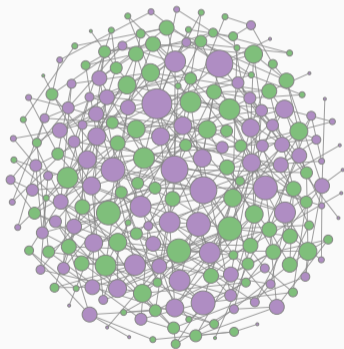
Modularity can be interpreted as **auto-covariance** of the dynamics (linear dependence of consecutive time-steps).

Blocks and NON-Markovian dynamics

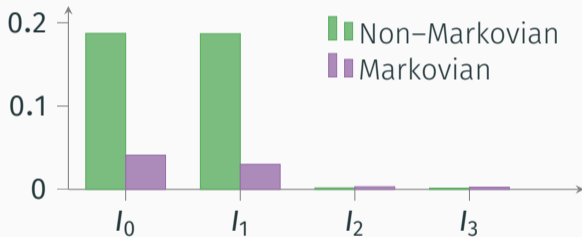
Example: Backtracking



Erdős-Rényi with nodes of two different classes.



Walkers have higher probability to *go back* to a visited class (second order memory).

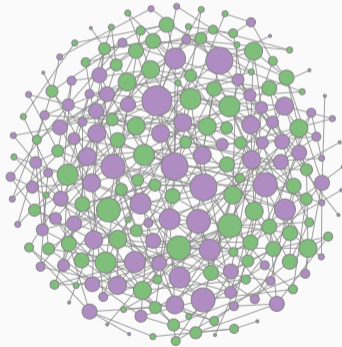


The complexity of the system resides on the dynamics.

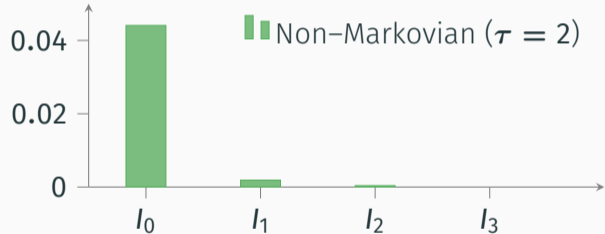
Example: Backtracking



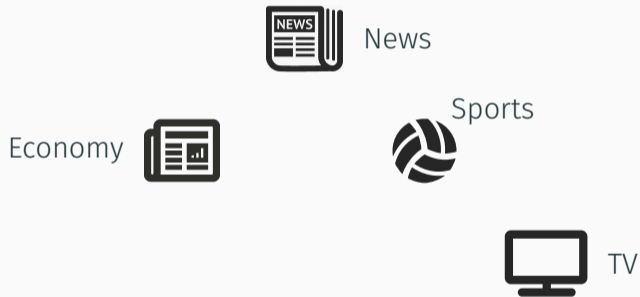
Erdős-Rényi with nodes of two different classes.



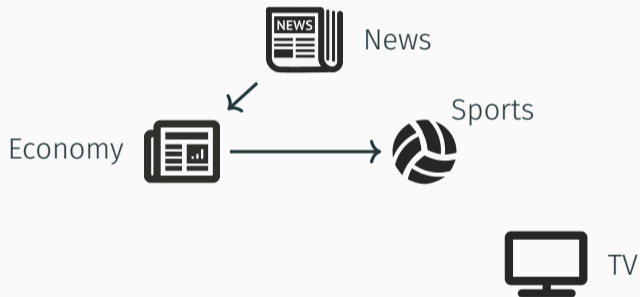
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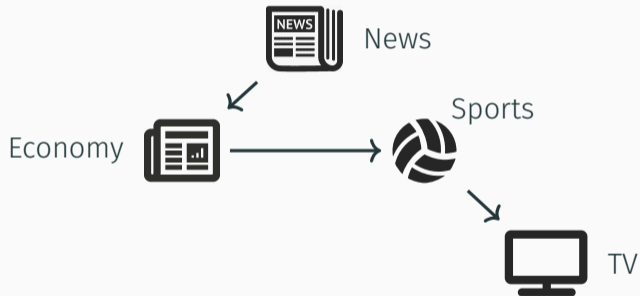


The complexity of the system resides on the dynamics.









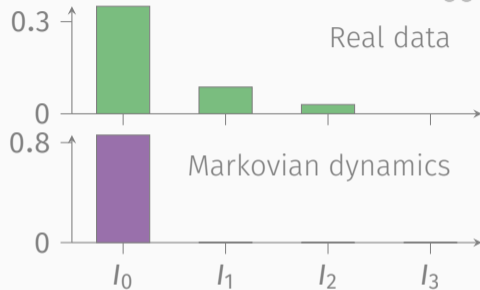
Web-portal users are non-Markovian



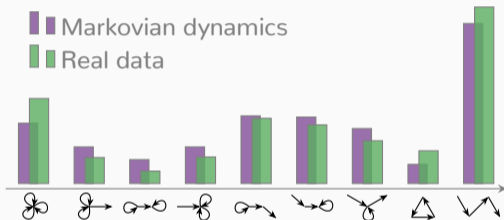
Web portal click behaviour



Single recorded path:

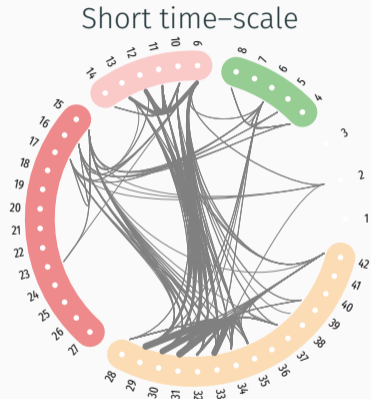


Comparison of the entrogram for the real dataset and the Markovian approximation. The former is at least Markovian of third order.

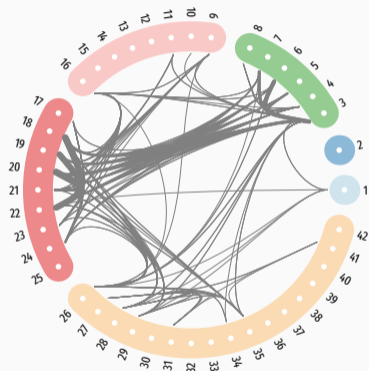


Some dynamical patterns are underestimated by the Markovian approximation.

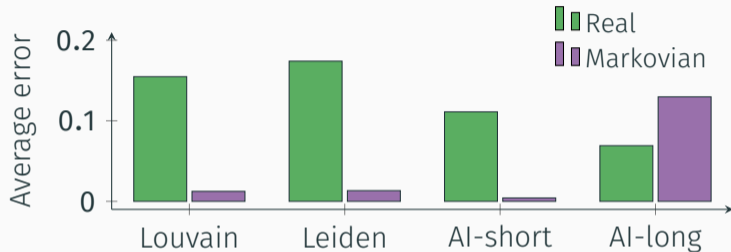
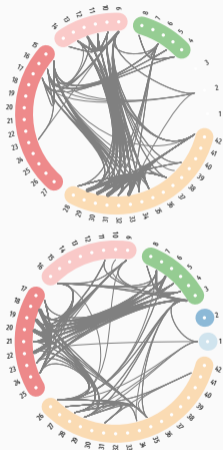
3-steps dynamical patterns of the original dataset (green) and the Markovian approximation (purple).



Longer time-scale ($\tau = 3$)



Partitions with different time-scales are slightly different.

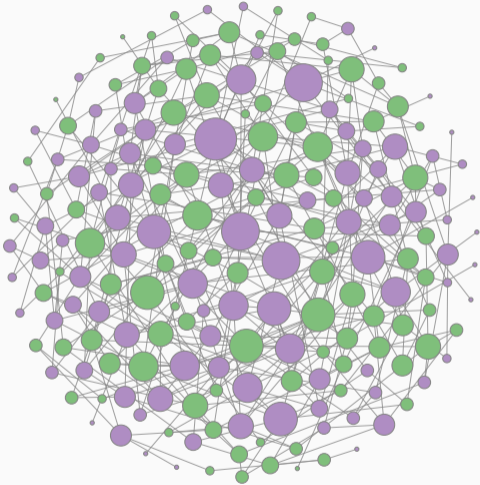


Average error after few steps (6) when using the partitions as a Markovian model.

Comparison with the original dynamics (green) and the Markovian approximation (purple).

Conclusions

Questions?



Joint work with:



JC Delvenne



UCLouvain



M Schaub



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Code at:

<https://github.com/maurofaccin/entropart>

We need a regularization term:

$$\mathcal{I}_\beta(\tau) = l(y_t, y_{t-\tau}) - \beta H(y_t)$$