



Beyond Communities: Dynamical Markov Modules

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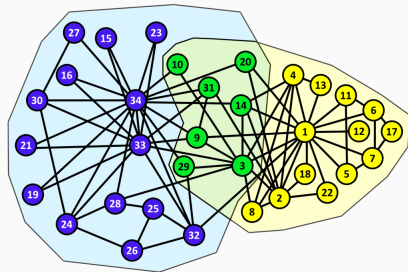
CCS 2106 - Amsterdam

Partitioning Problem



Why should we care

- A simple description of the structure
- A model for the system dynamics
- Insight





What about other link patterns?

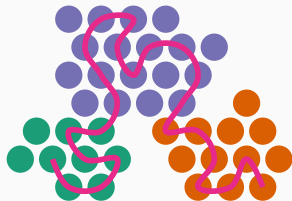
Modules defined by dynamics

Projected Markov Chain



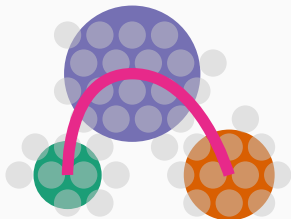
Markov Chain

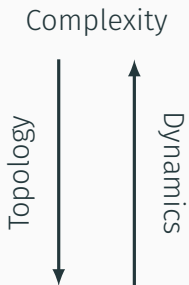
$\dots, x_{\text{past}}, x_{\text{now}}, x_{\text{future}}, \dots$

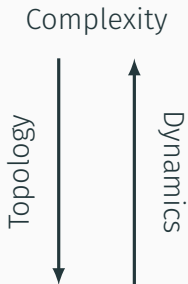


Projection

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







Memories



Projected Markov Chain:

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

Maximize predictability:

$$I(Y_{\text{future}}; Y_{\text{past}})$$

amount of information
flowing from *past* to *future*.

$$I(Y_{\text{future}}; Y_{\text{past}}) \leq I(x_{\text{future}}; x_{\text{past}})$$

- Increases predictability of future with knowledge of past;
- Favors heterogeneous module-linking;
- Favors homogeneous module size;
- $I(\cdot; \cdot)$ is Mutual Information



Projected Markov Chain:

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

Minimize memories:

$$I(Y_{\text{future}}; Y_{\text{past}} | Y_{\text{now}})$$

higher order memory
embedded into the process.

$$I(Y_{\text{future}}; Y_{\text{past}} | Y_{\text{now}}) \geq I(x_{\text{future}}; x_{\text{past}} | x_{\text{now}}) = 0$$

- Higher compression can require knowledge of the past dynamics (memories);
- Projected dynamics could differ from dynamics on the projected topology;
- $I(\cdot; \cdot)$ is Mutual Information

Put together:

$$\mathcal{F} = \alpha I(Y_{t+1}; Y_t, Y_{t-1}, \dots) - I(Y_{t+1}; Y_{t-1}, \dots | Y_t)$$

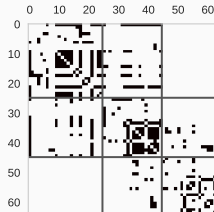
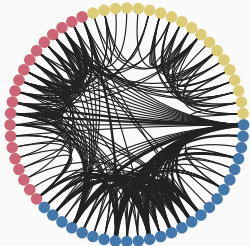


$$\mathcal{F} = \alpha I(Y_{t+1}; Y_t, Y_{t-1}, \dots) - I(Y_{t+1}; Y_{t-1}, \dots | Y_t)$$

nice behavior for $\alpha = 1$:

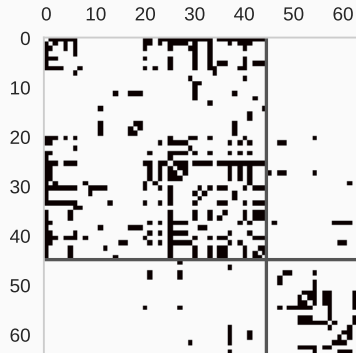
$$\mathcal{F}_P = I(Y_{t+1}; Y_t)$$

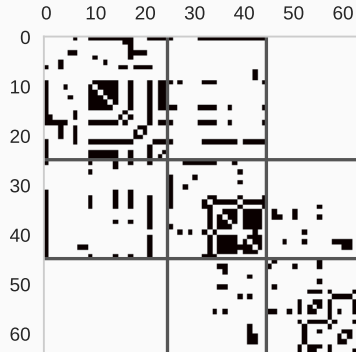
- Easy to compute
- Under some conditions is the same as DCSBM
- Plenty of algorithms

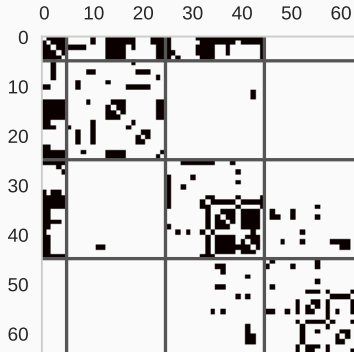


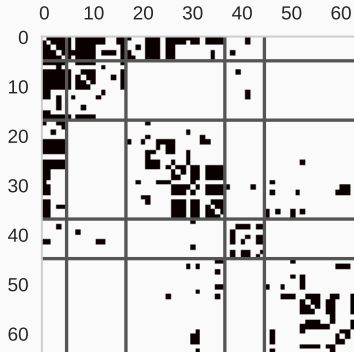
Contacts between suspect terrorists involved in the attack to Madrid station (2004).¹

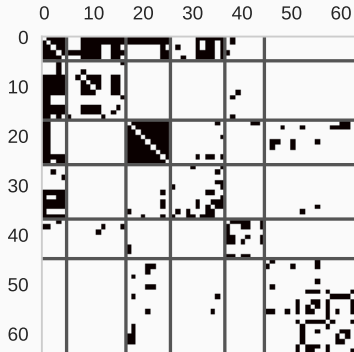
¹ *The March 11th Terrorist Network: In its weakness lies its strength*, José A. Rodríguez













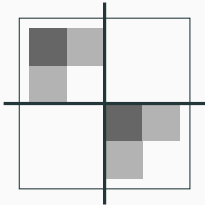
$$\mathcal{F} = \alpha I(Y_{t+1}; Y_t, Y_{t-1}, \dots) - I(Y_{t+1}; Y_{t-1}, \dots | Y_t)$$

A bit harder with $\alpha = 0$:

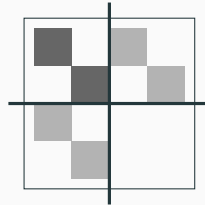
$$\mathcal{F}_M = -I(Y_{t+1}; Y_{t-1}, \dots | Y_t)$$

- Markovian model dynamics
- Not biased toward predictable models
- Harder to compute but easy to implement with actual algorithms

What's the best model?



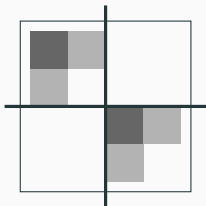
Better predictability of the dynamics



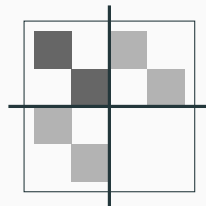
Also this is a perfect description of the system

$$\mathcal{F}_P(C) > \mathcal{F}_P(CP)$$

What's the best model?



Better predictability of the dynamics

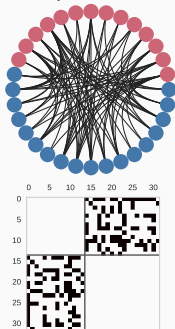


Also this is a perfect description of the system

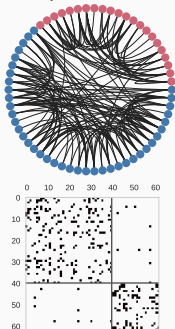
$$\begin{aligned}\mathcal{F}_P(C) &> \mathcal{F}_P(CP) \\ \mathcal{F}_M(C) &= 0 = \mathcal{F}_M(CP)\end{aligned}$$



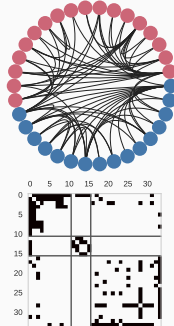
DeepSouth



Dolphins



Karate



Concluding



- Dynamics define partitioning

Concluding



- Dynamics define partitioning
- Predictability vs Markovianity

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- Dynamics define partitioning
- Predictability vs Markovianity
- Only needs dynamics (topology not necessary)

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- Dynamics define partitioning
- Predictability vs Markovianity
- Only needs dynamics (topology not necessary)
- Extends DCSBM to weighted graphs



- Dynamics define partitioning
- Predictability vs Markovianity
- Only needs dynamics (topology not necessary)
- Extends DCSBM to weighted graphs
- Non-Markovian Systems



See you on Wednesday at:



Coarse-graining of Complex Systems

CCS@CCS'16

[CCS 2016](#) [Invited Speakers](#) [Call for Abstracts](#)

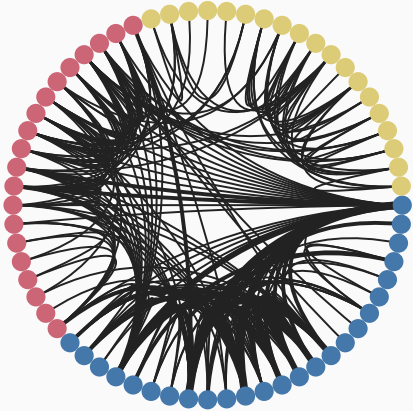
Summary

A fundamental issue in the field of complex systems is to identify the most important interactions or processes within a system so that we may better understand them. Coarse-graining methods attempt to abstract away unnecessary details, leaving behind a simplified interpretable representation of the system. Coarse-graining approaches are well-established in many different

Full day workshop

http://michaelschaub.github.io/ccs_at_ccs_2016/

Questions?



Joint work with:

JC Delvenne

@ ICTEAM and BigData Group,
UCLouvain.

*Good partitioning is the one leading to
an interesting reduced model*