Inferring influence in a baboon troop using information theory

Carter Loftus

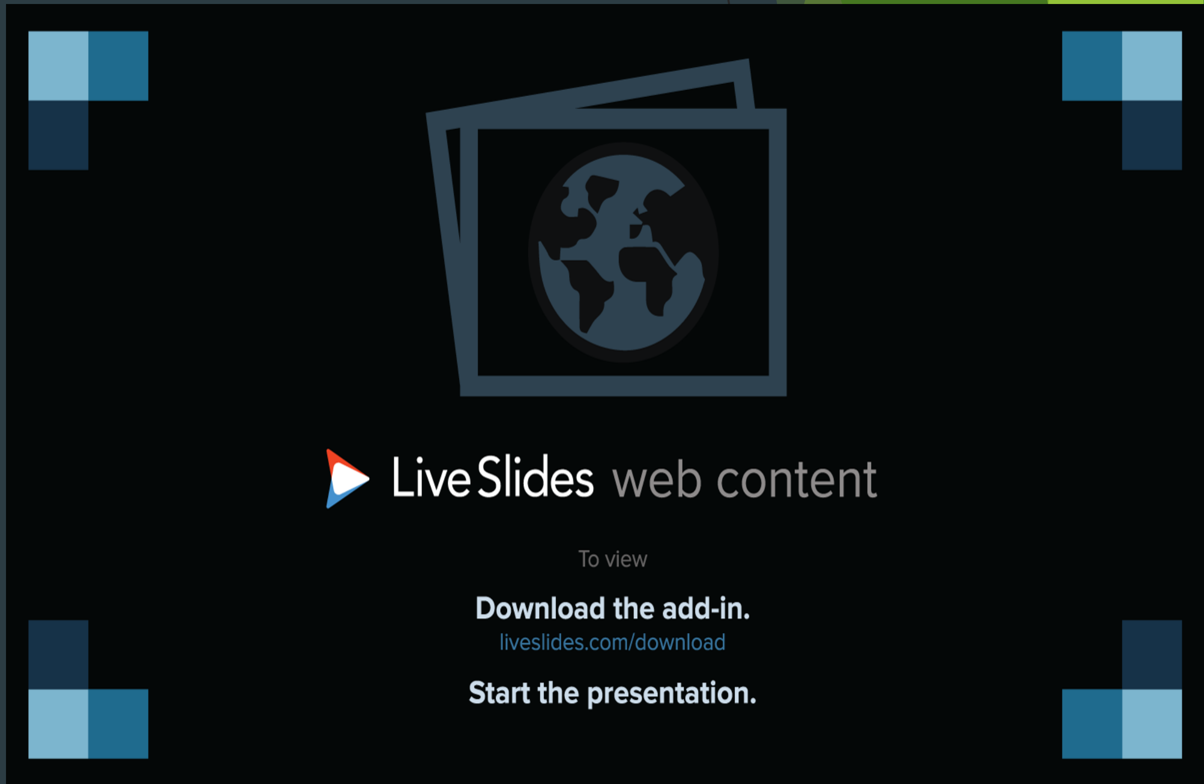
PHY 256

Outline

- Background
- Inferring influence with causation entropy
- Shortcomings of causation entropy
- Intrinsic mutual information to the rescue
- Discussion

Animal groups as complex systems

- Determining the heuristics of individuals components of a self-organized system
- BUT: animals have to do more than stick together
- AND: groupmates are **not** identical
- The cost of consensus
- **Major question: how and when do individuals mitigate consensus costs via influencing group decisions?**
- **But first: who is having influence?**



Inferring influence in a complex system

- The system:

  - 29 adult and subadult wild olive baboons (*Papio anubis*) in the troop
    - 23 collared with high-resolution GPS (1 Hz sampling rate) and triaxial accelerometers (10 Hz sampling)
    - Collars removed after 30 days
  - Mpala Research Centre in Laikipia, Kenya


Untitled
Time: 2012-08-01T10:40:10.000Z
0.02 km
ageSexNumber
1.000
5.000
travDist
0.000
63.710

Inferring influence with causation entropy

- Causation entropy (Sun & Bollt 2015):

  $$\text{Causation entropy} = I(X_{past};\, Y_{present} \mid Y_{past},\, W_{past},\, Z_{past})$$

  $$= H(Y_{present} \mid Y_{past},\, W_{past},\, Z_{past}) - H(Y_{present} \mid X_{past},\, Y_{past},\, W_{past},\, Z_{past})$$

- "How much is the uncertainty of Y's present state reduced by knowing X's previous state, given that we already know Y's, W's and Z's past state?"

- What causal relationship does X have with Y?

Inferring influence with causation entropy

- Data: Time-series of stop-go movements from accelerometers (10 Hz) for each baboon
- The alphabet for W, X, Y, and Z: binary (stopped or moving)
- (Down)sampling rate: the rate that optimizes the total information flowing in the network, given a range of allowable sampling rates
- Using one day of data

Inferring influence with causation entropy

- Only consider the 8 adults (6 females, 2 males)
- Divide the day into 10 different time periods
- Calculate the causation entropy matrix for each time period (at the sampling rate that optimizes the flow of influence for that given time period)

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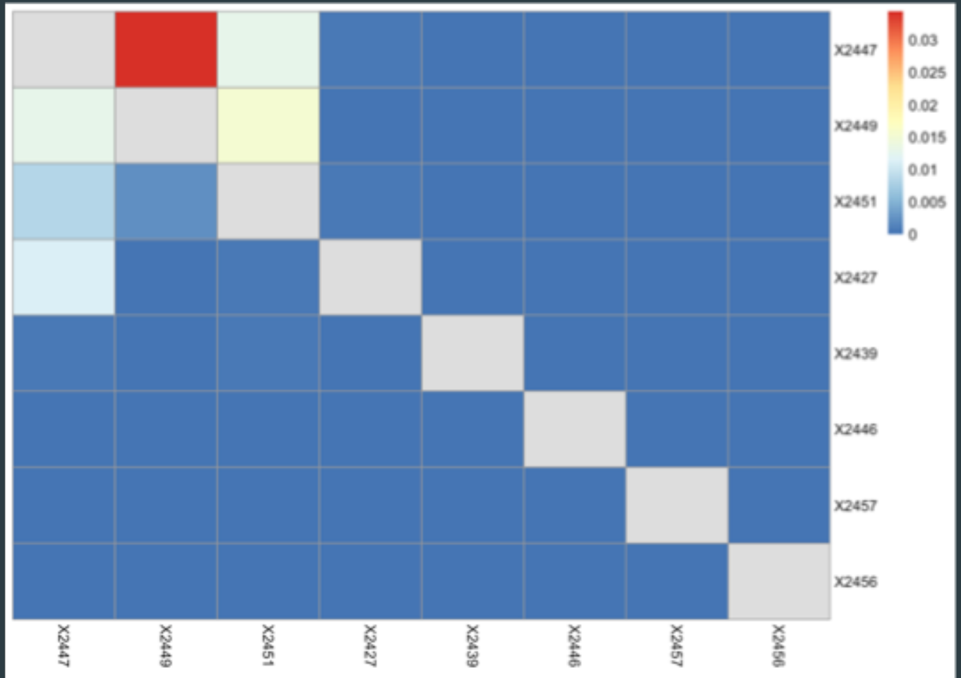

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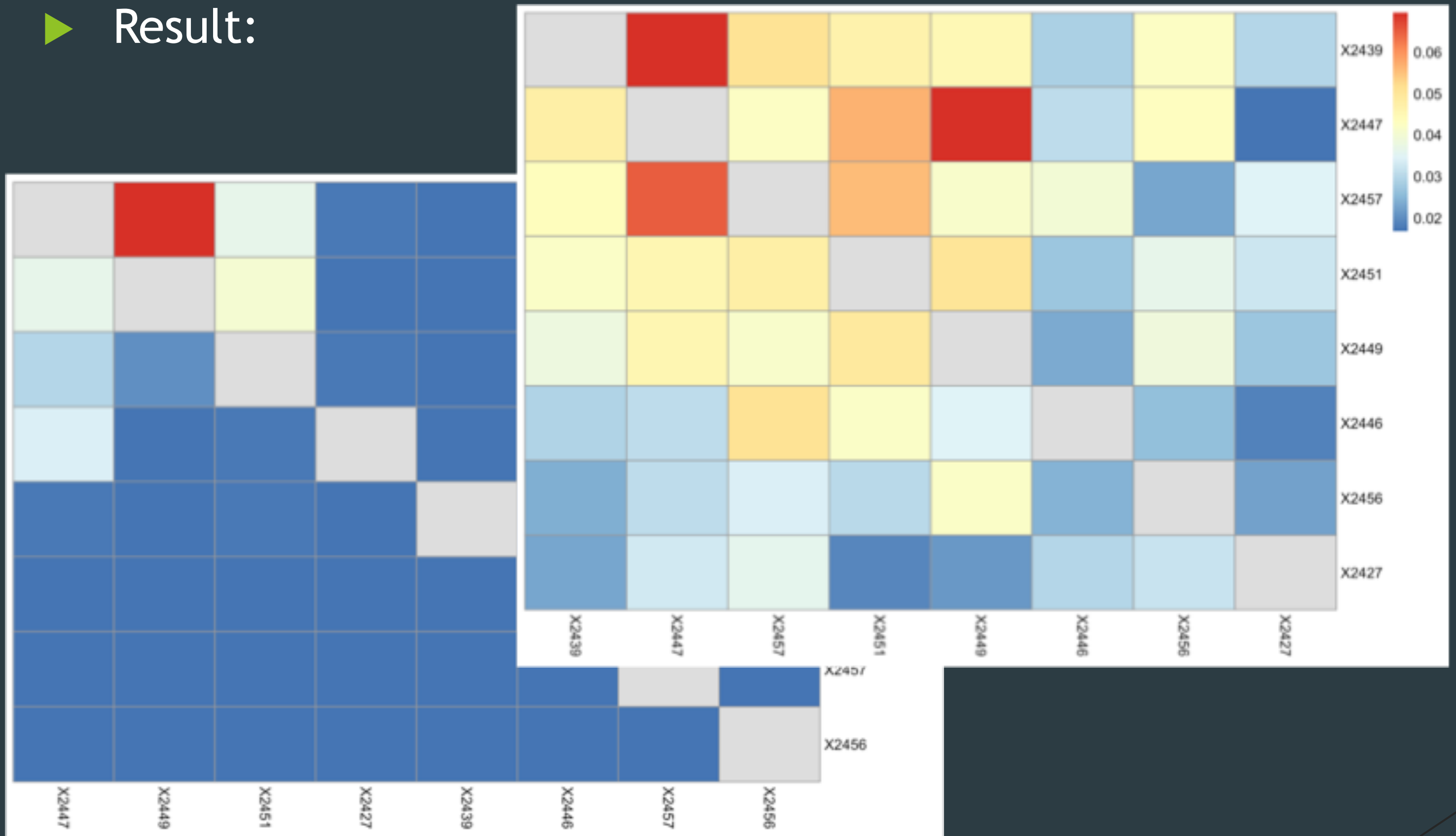

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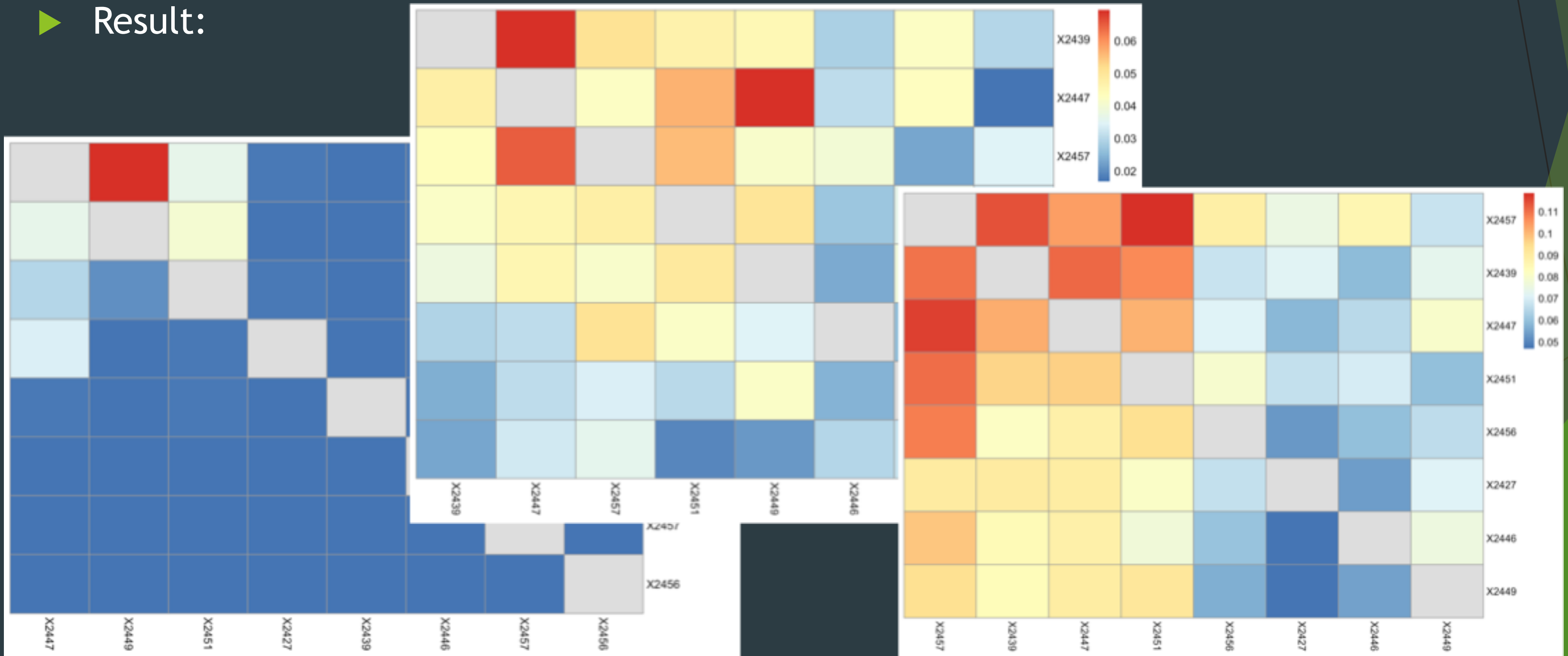

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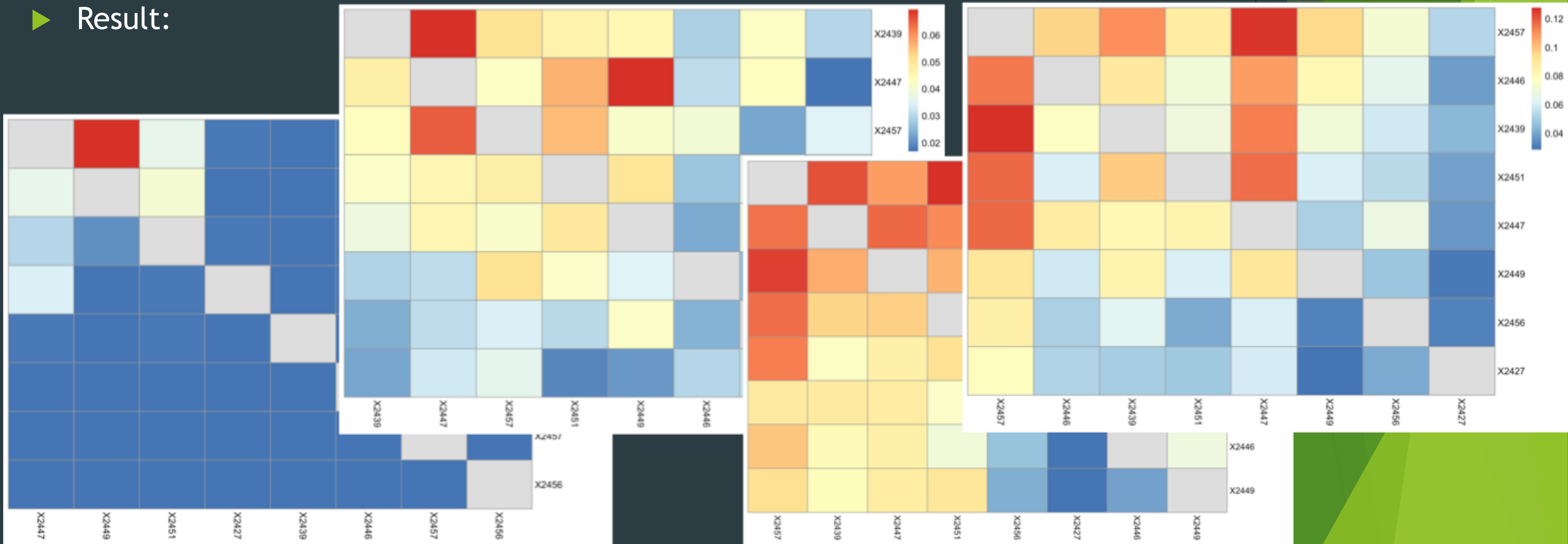
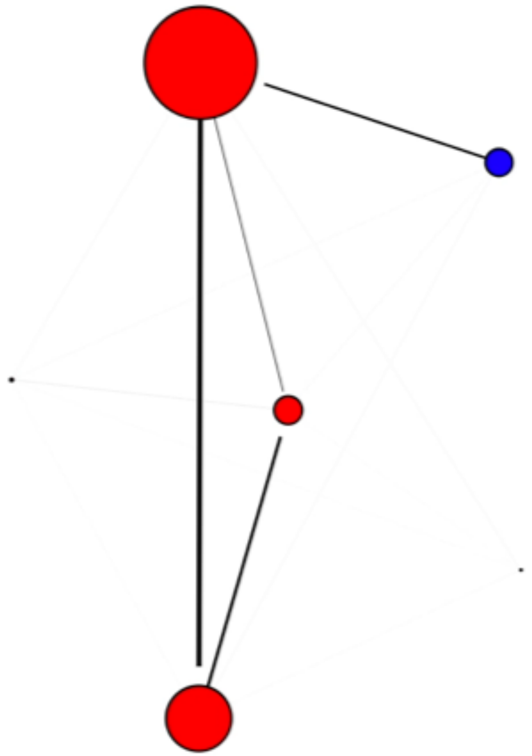
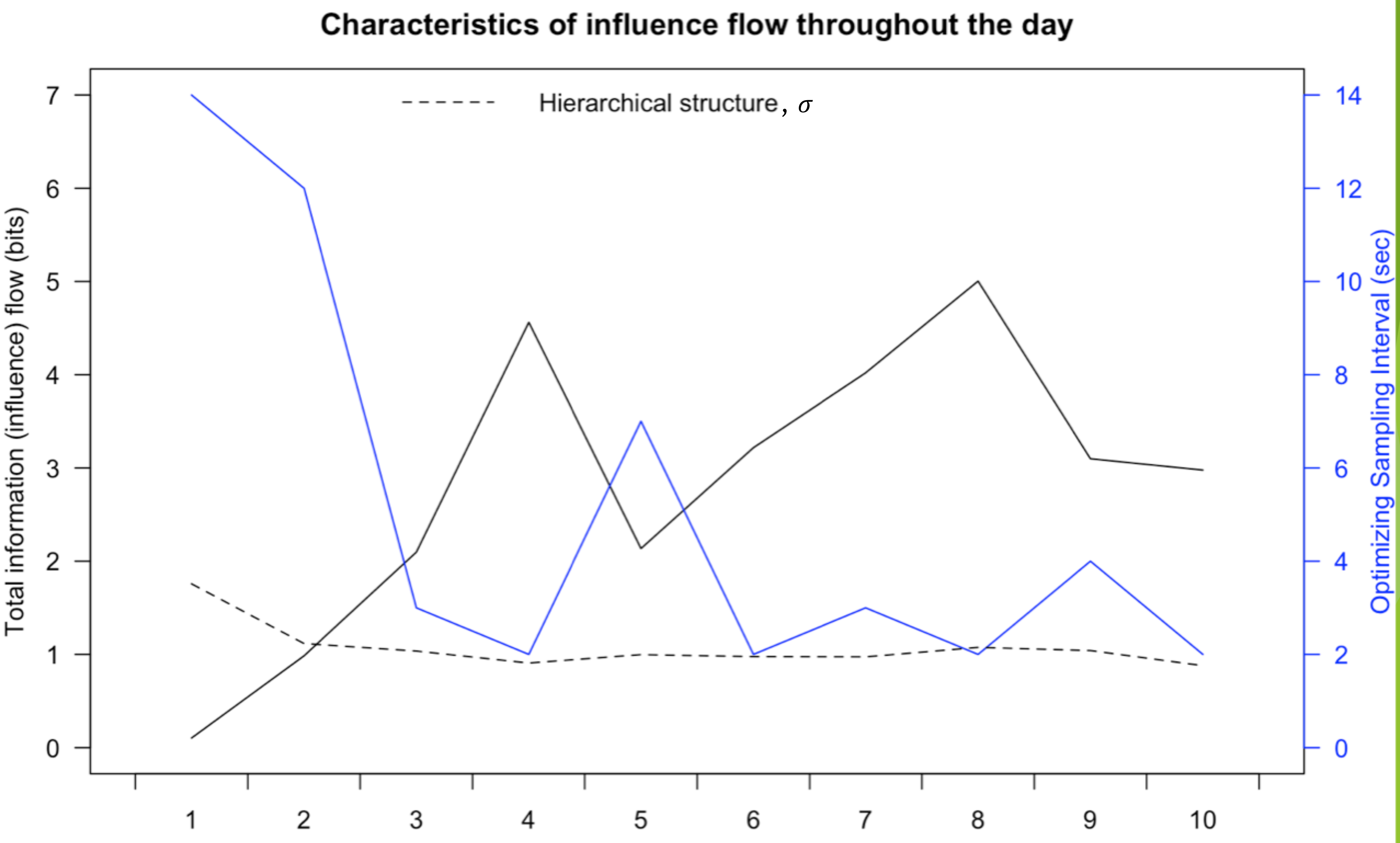


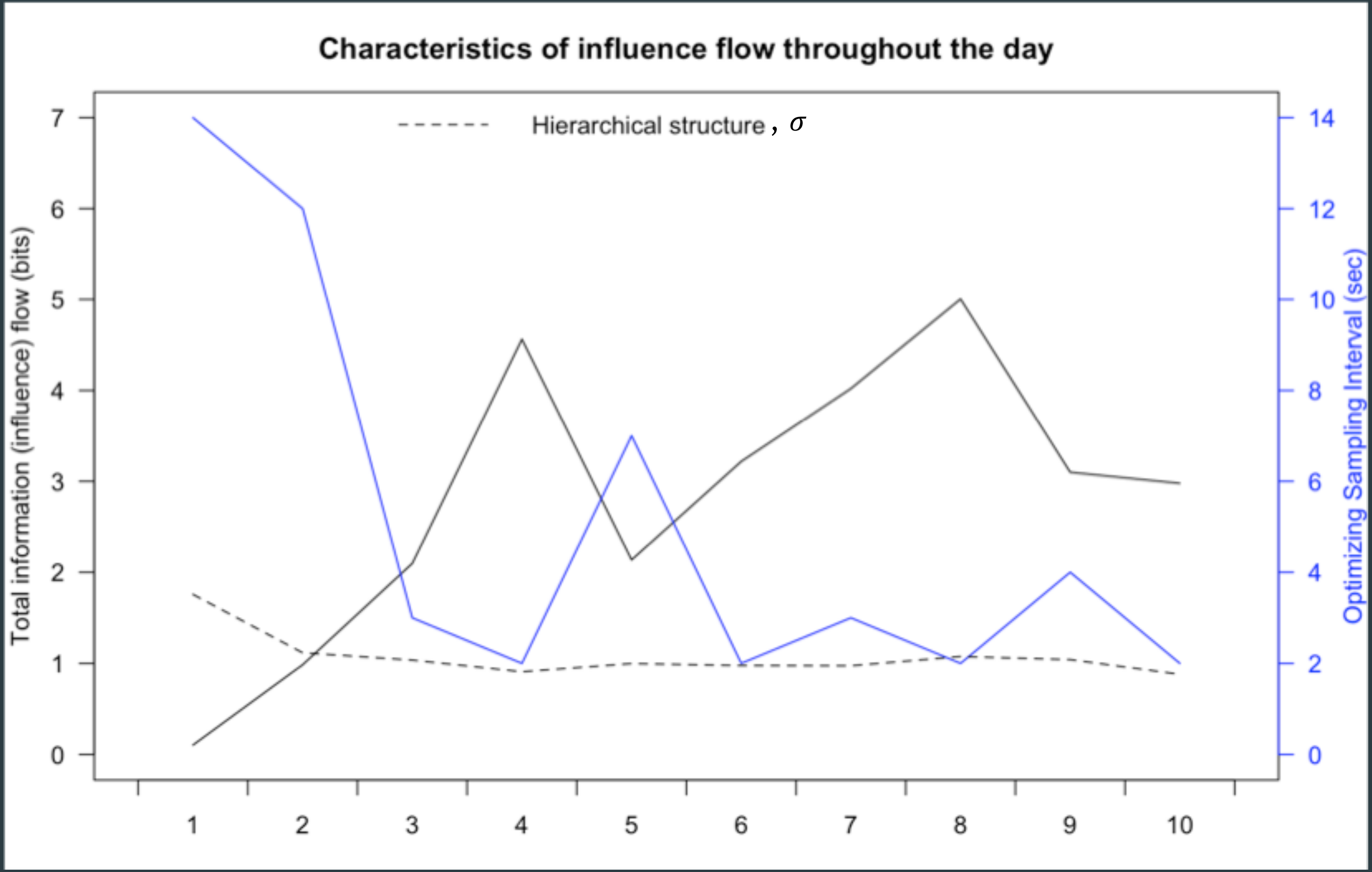


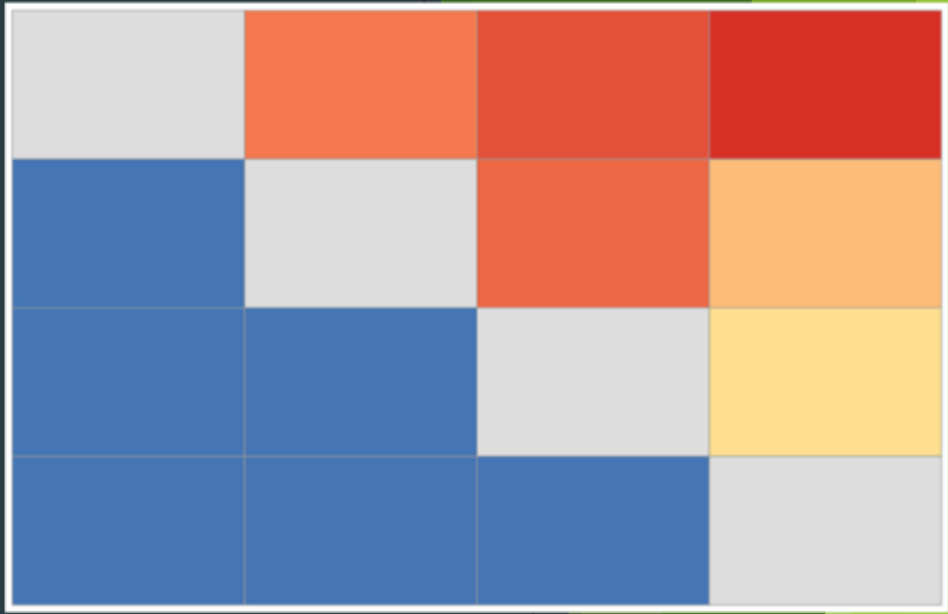
t=0-1

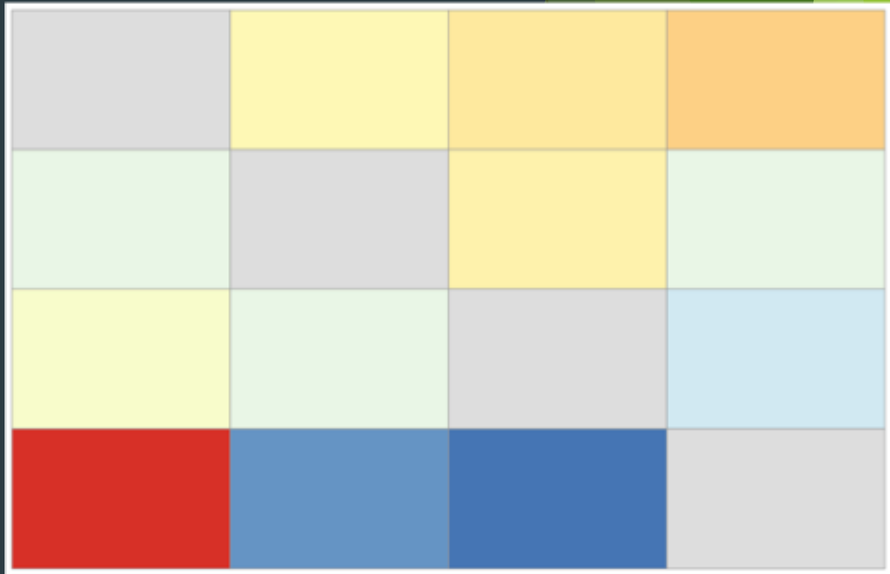
Not a clear answer as to who is having the most influence in the group


Characteristics of influence flow throughout the day
Hierarchical structure, σ
Total information (influence) flow (bits)
Optimizing Sampling Interval (sec)
0
1
2
3
4
5
6
7
0
2
4
6
8
10
12
14
1
2
3
4
5
6
7
8
9
10

σ approaches infinity







$\sigma \approx 1$

Shortcomings of causation entropy

- James et al. 2016
- Conditional dependence!!!
  - Remember RRXOR: $I(X;Y) = 0$, $I(X;Z) = 0$ and $I(Y;Z) = 0$, but $I(X;Y|Z) = 1$
- Interpretation: could baboon A be getting credit for influencing baboon B, even though it could not have done so without baboon C?
- Synergisms can occur between the “influencer” and any other individual, or combination of individuals in the baboon troop, and even the “influencee’s” past

Intrinsic mutual information

- James et al. 2018

- Intrinsic Mutual Information:

$$= \min I(X; Y \mid f(Z))$$

$$= \min I(X_{past}; Y_{present} \mid f(Y_{past}, W_{past}, Z_{past}))$$

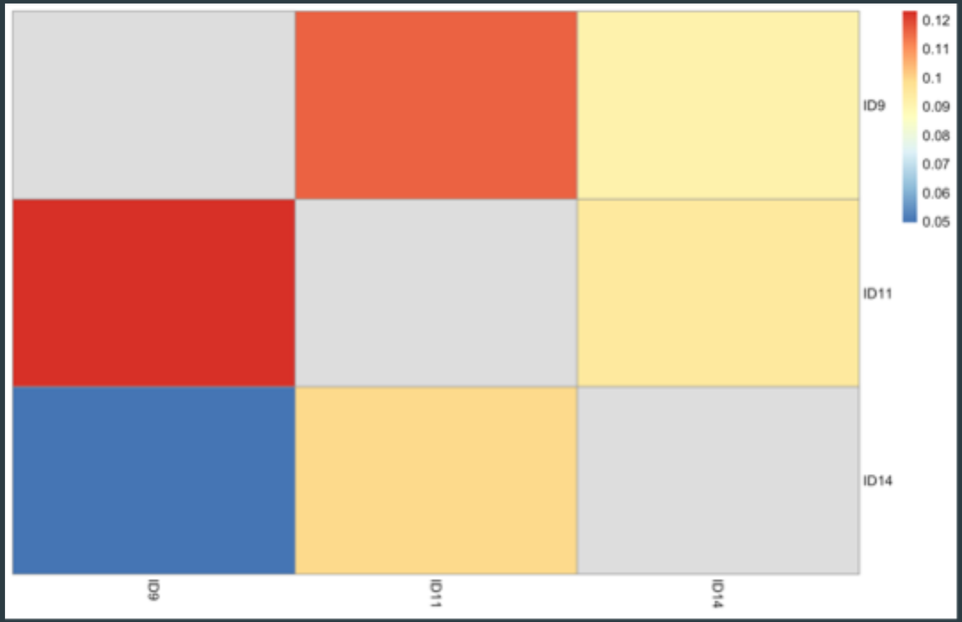
- Determines the influence on $Y_{present}$ that came <u>exclusively</u> from X_{past}

- Cryptographic roots

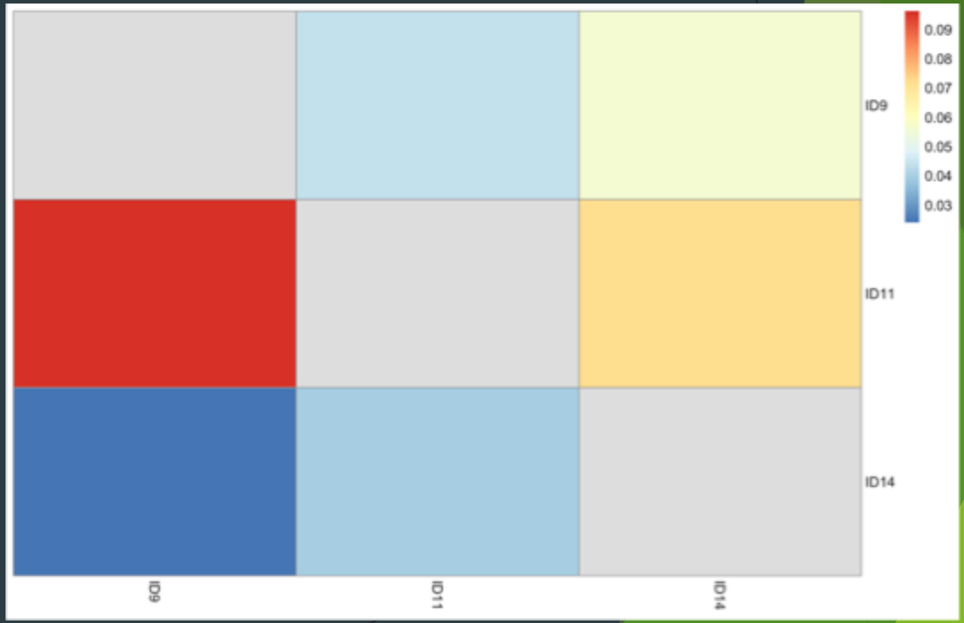
Intrinsic mutual information

- Subgroup of three individual baboons traveling alone

Causation Entropy Matrix



Intrinsic Mutual Information Matrix



Intrinsic mutual information

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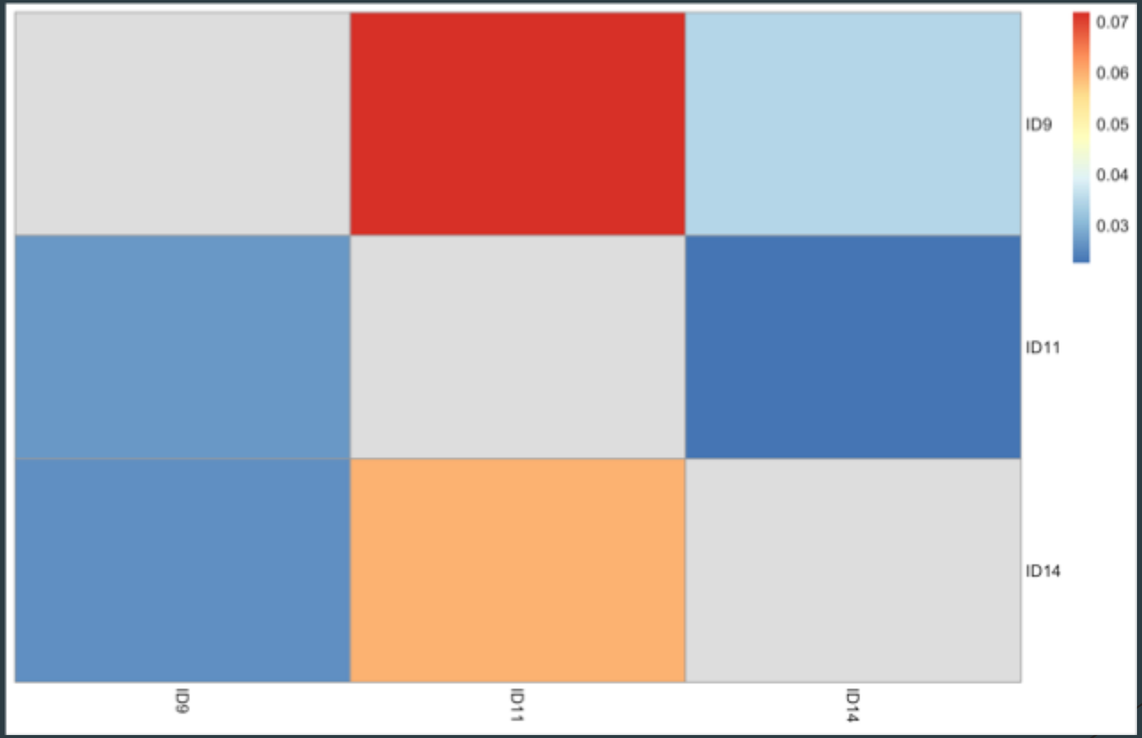
Synergism Matrix



Discussion

- No evidence for an overt influence hierarchy, despite strong dominance hierarchy
- Even without no clear hierarchical structure, influence flows at higher quantities and at a faster rate when a baboon troop makes a collective decision
- Influence in animal groups (and likely most other systems) is non-additive!
  - Influence is context-dependent
- Summarizing dyadic relationships does not capture the group’s dynamic

Acknowledgements

- Thanks to Ryan, Danny, and Jim for all your help
- Thanks for listening!

Questions?

References

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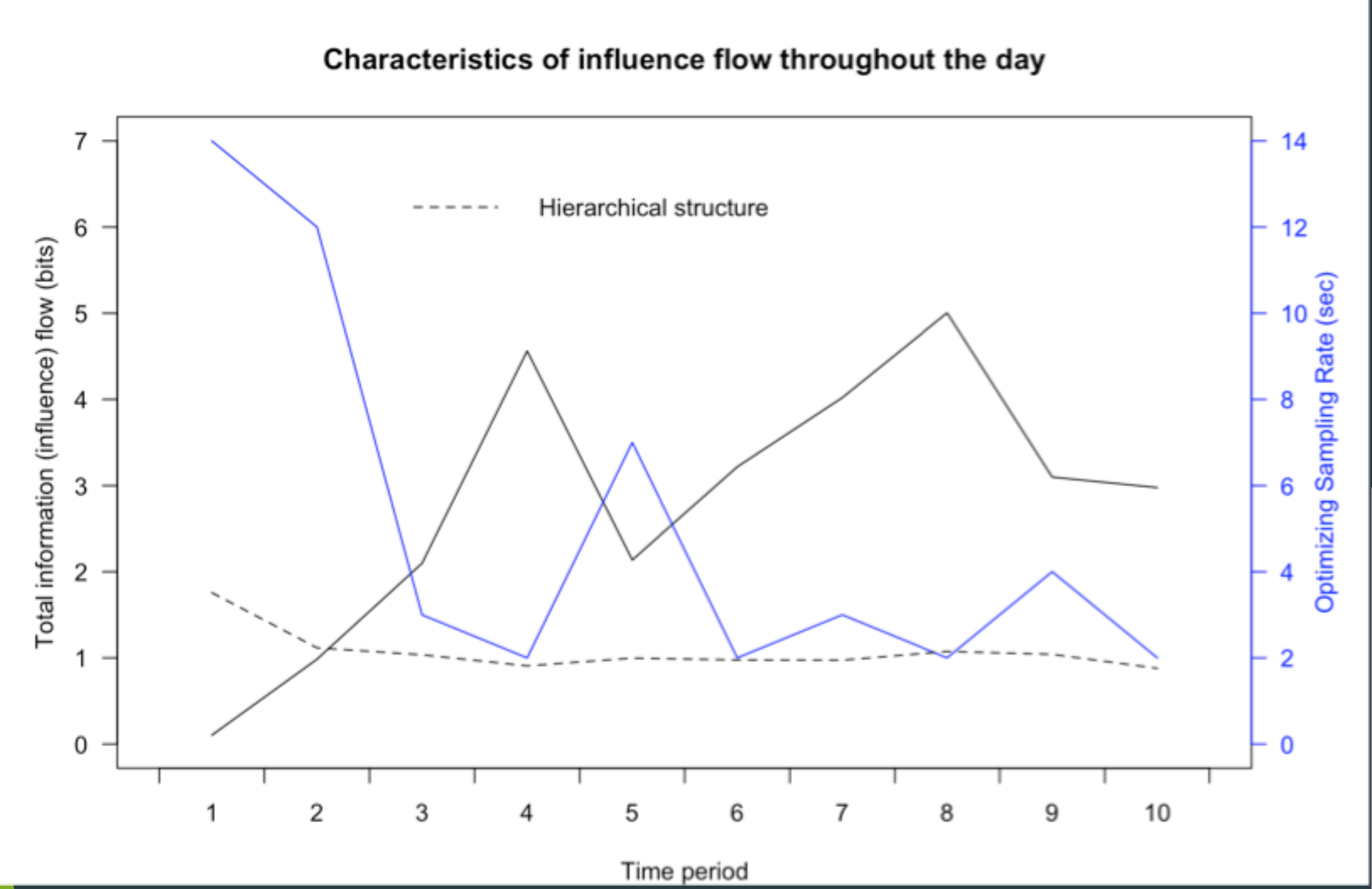
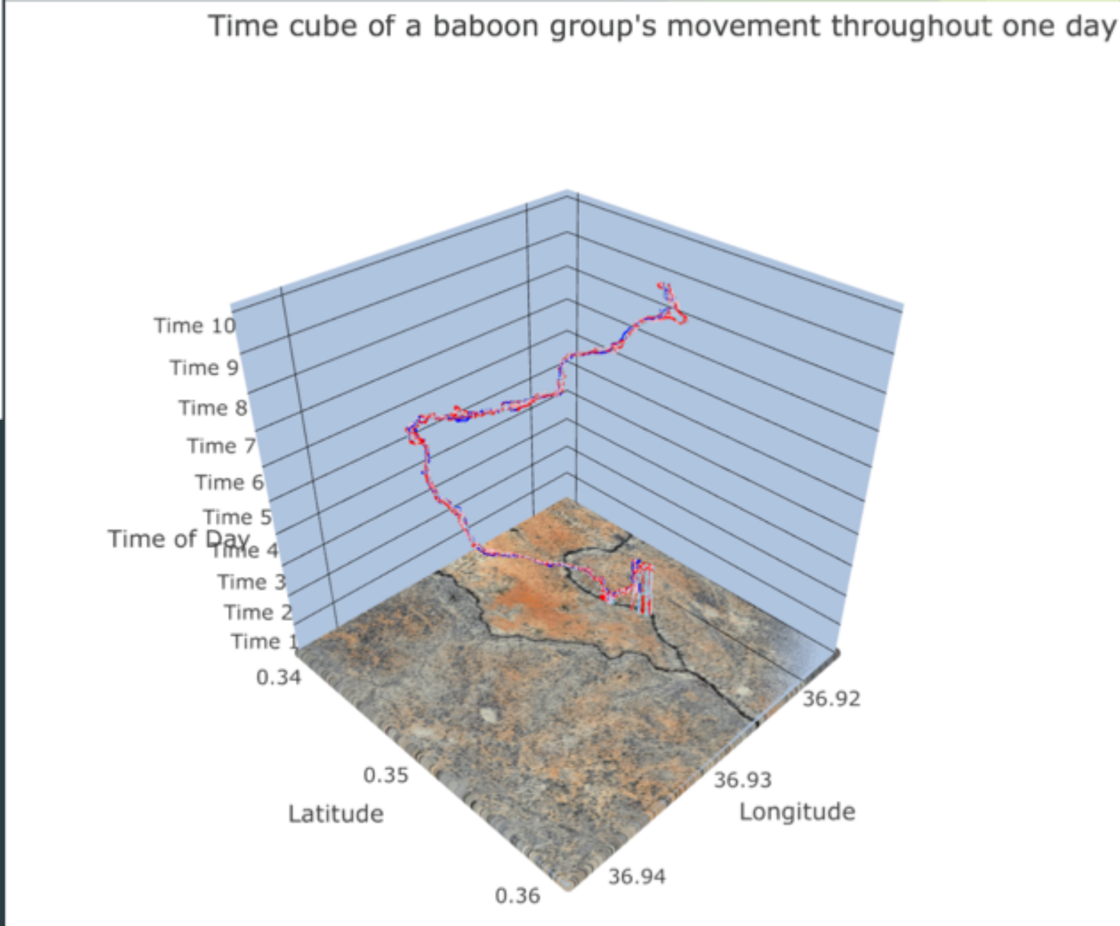
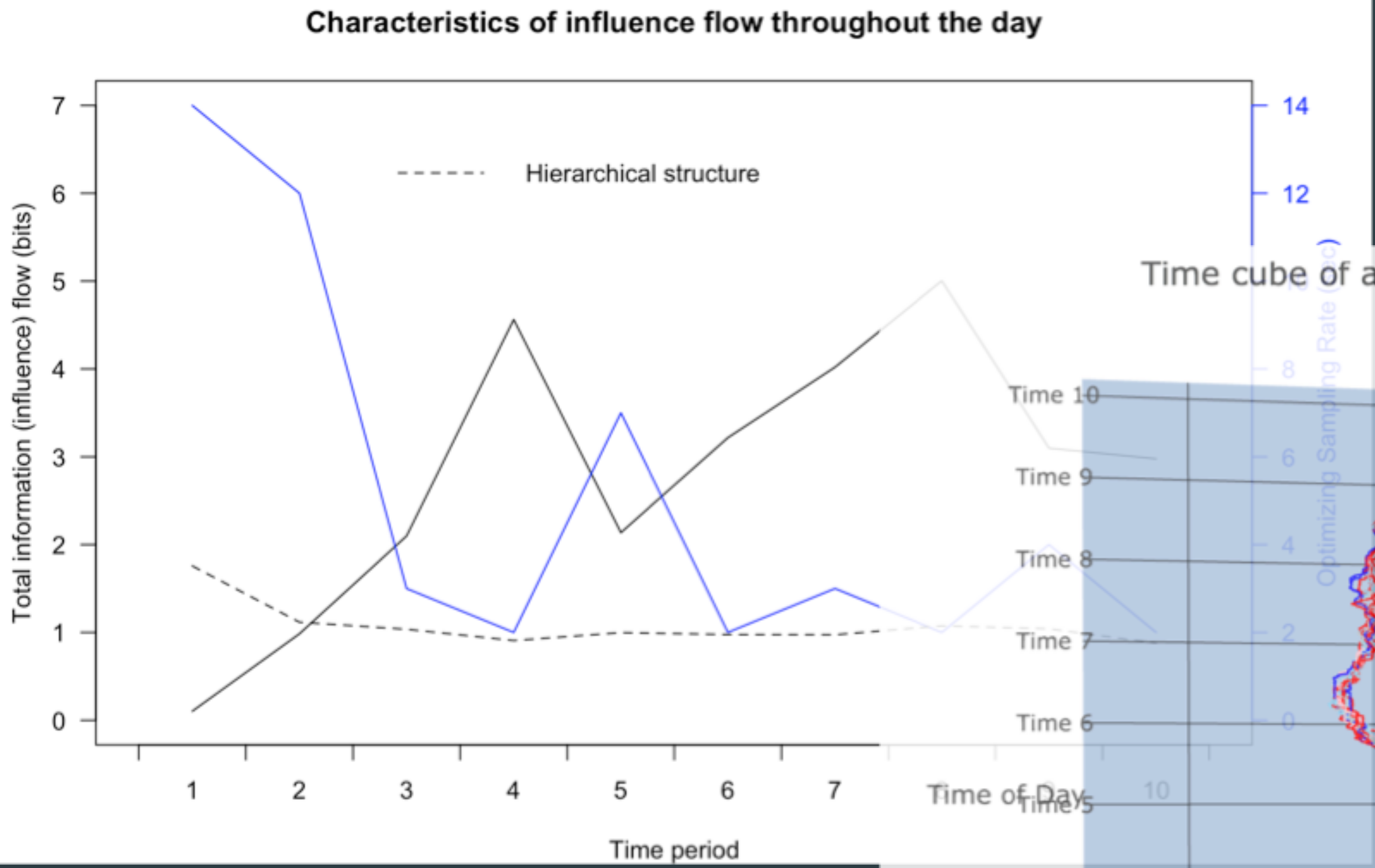
- Sun, J.,& Bollt, E. M. (2014). Causation entropy identifies indirect influences, dominance of neighbors and anticipatory couplings. *Physica D: Nonlinear Phenomena*, *267*, 49-57.

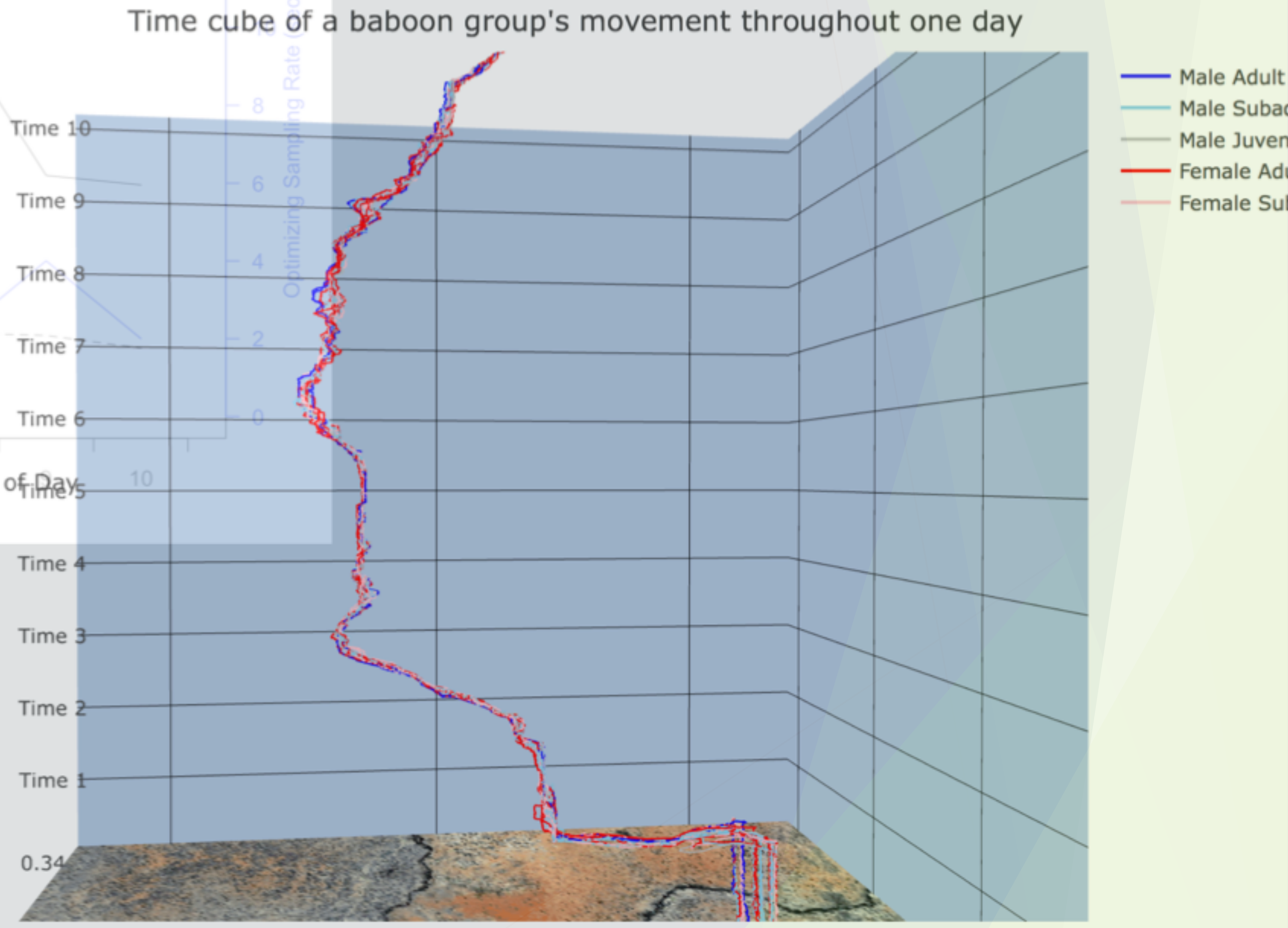
Further results and outcomes about which I did not have time to present:





Temporal structure of quantity and rate of influence flow correlate with temporal structure of baboon collective decision-making





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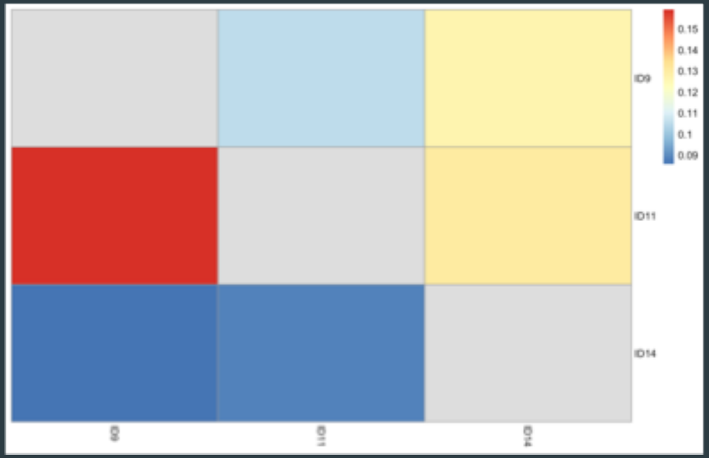
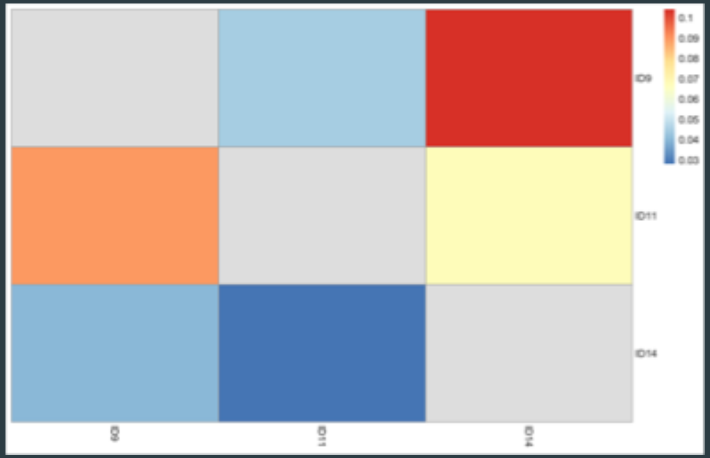
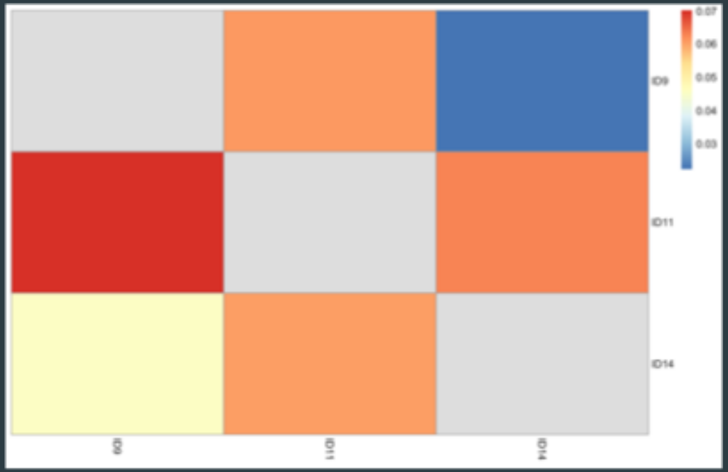
Isolating synergies



Transfer Entropy



IMI (not conditioned on third parties)



Synergy between “influencer” and “influencee’s” past

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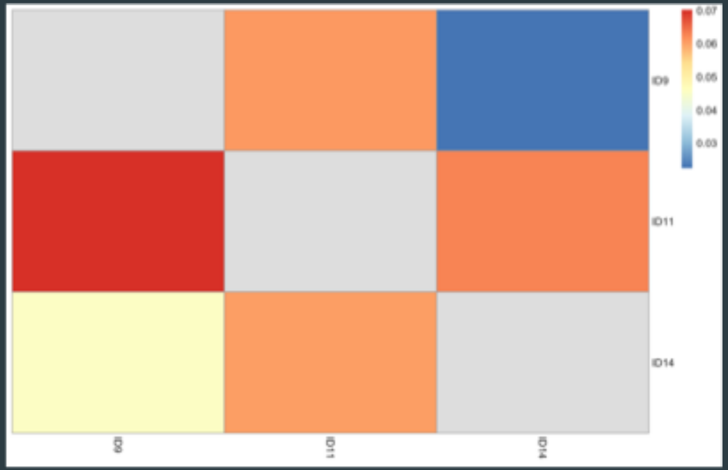

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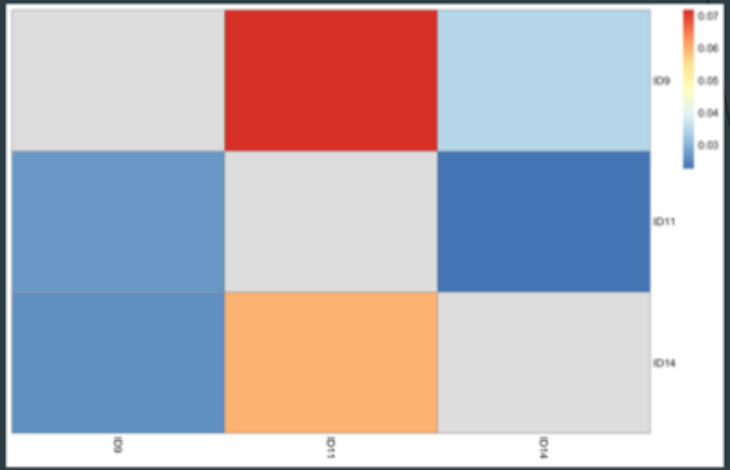
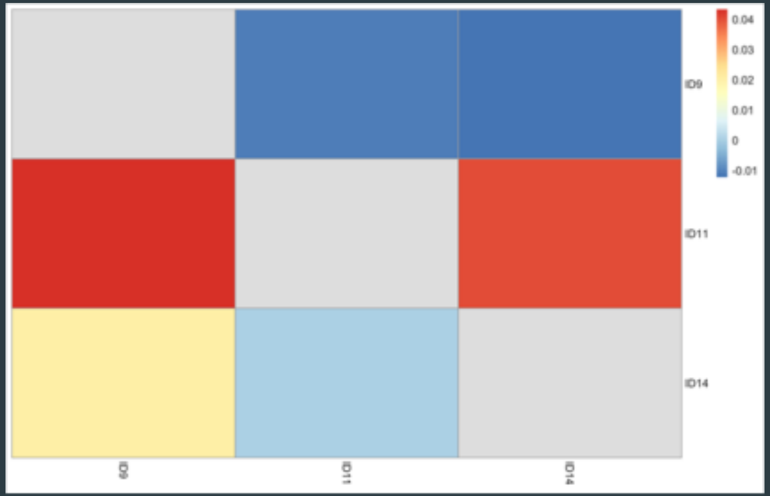


Non-isolated synergism

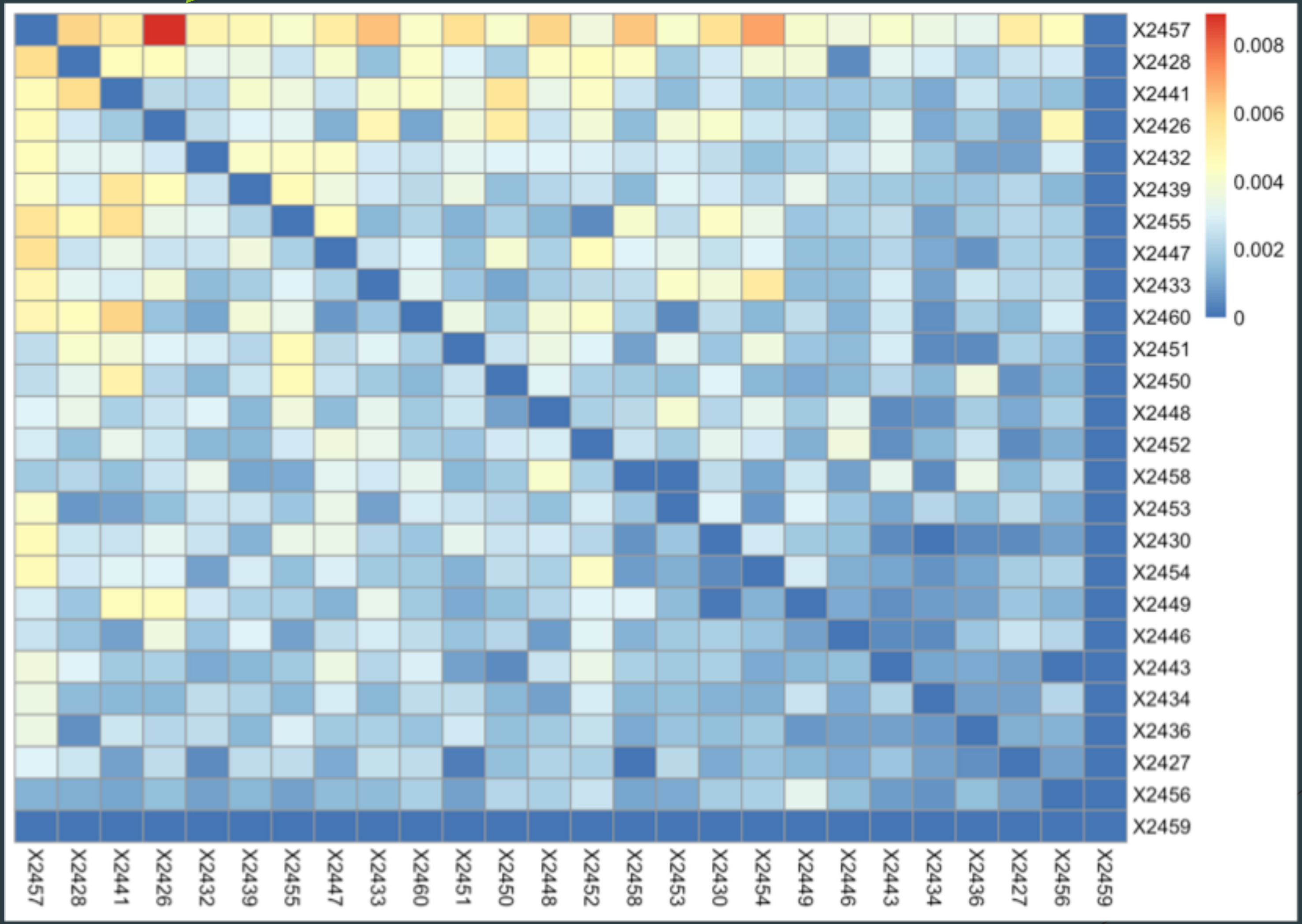


Synergism between an “influencer” and other groupmates

Inferring influence with causation entropy

ID 2457 has (relatively) strong influence over ID 2426

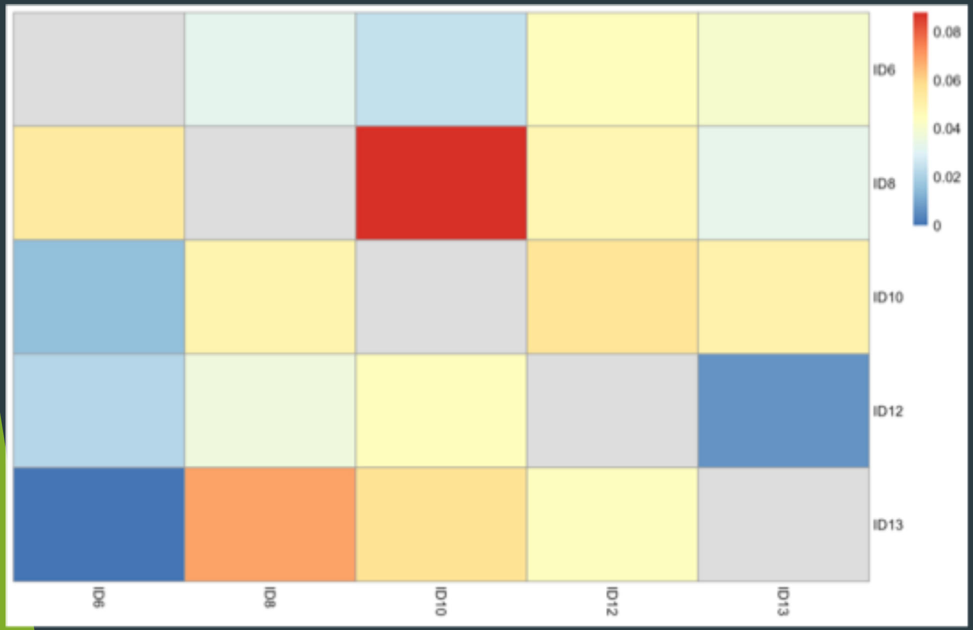
Results at the whole-group level



Intrinsic mutual information

- Subgroup of five individual baboons traveling alone

Causation Entropy Matrix



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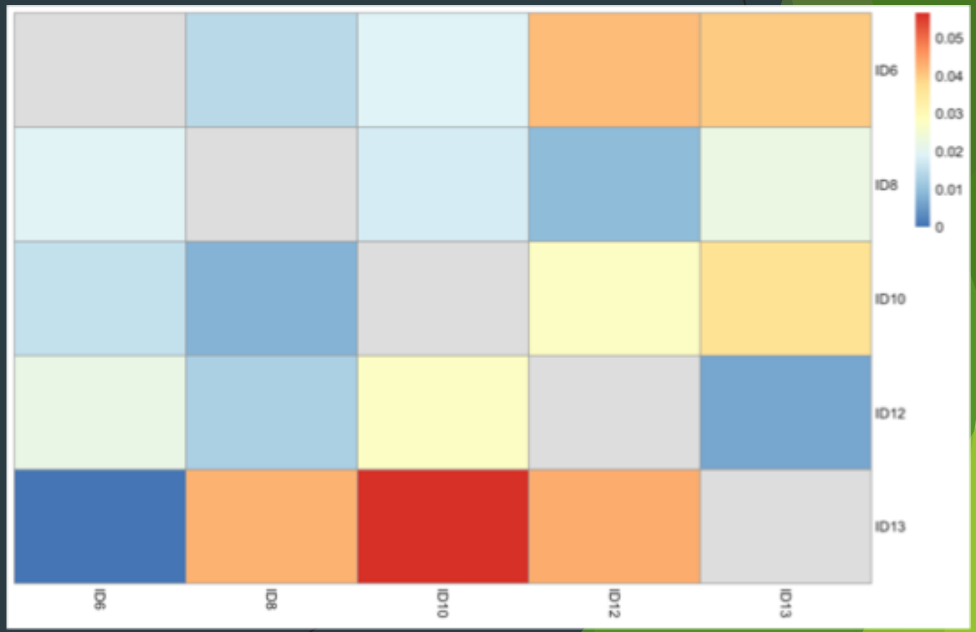

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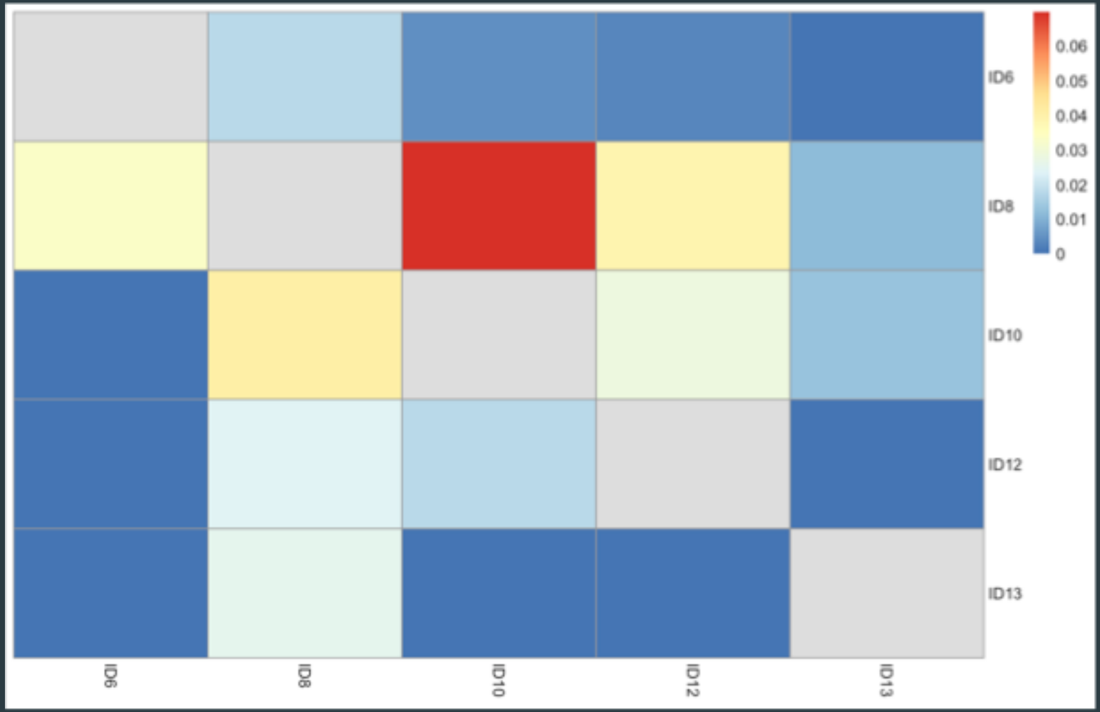

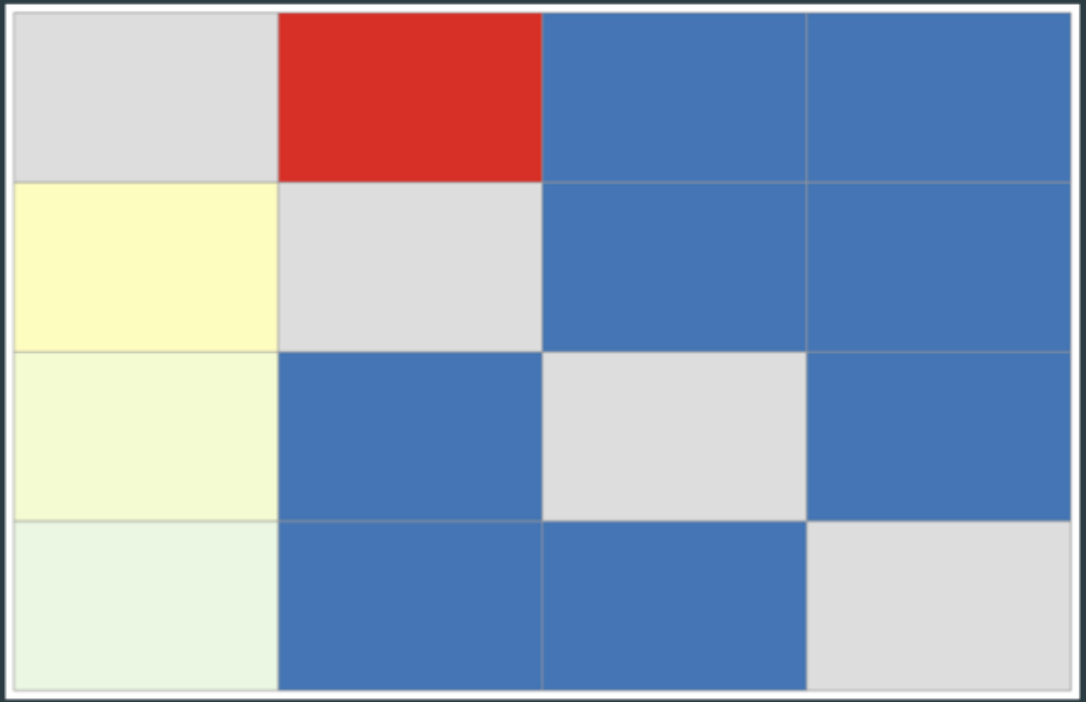

Simulated matrix showing how σ can be less than 1 in a matrix ordered by its row sums