

SGN '24 - Group Project – IMSc, Chennai How to host a good party?!

Abhinav Kannan, Rubna PR, Swastik Patnaik

Mentors – Dr V Sasidevan, and Dr Soumyadeep Bhattacharya



Fundamental question: The host's dilemma

• Cannot invite everyone

• Non-friendly people might cause fights

• Want people to have more friendly interactions than non-friendly ones (strangers and enemies)

• Ideal party = Less frustration and tension among members

Rationale: Network theory to the rescue

- Natural representation of social structures
- Multi-scale analysis and emergence: Individual level
- Different network metrics for different social phenomena
 - \circ Clustering coefficient \rightarrow Friend groups or cliques
 - \circ Path length \rightarrow 'Social distance' and potential information flow
 - \circ Different probability distributions \rightarrow Different cohorts of people to sample from
- Mathematical and computational advantages
- Flexibility and extensibility

Formalism

• <u>Node-level property</u>:

Forthcomingness index (y) bounded between [0, 1]

- Edge-weight states ∈ {-1, 0, +1}: Initialised randomly with probabilities (0.25, 0.45, 0.3)
 - Enemies is represented by -1
 - Strangers as 0
 - Friends as +1

• Utilised <u>Gillespie algorithm</u> to simulate reaction dynamics

- <u>Network initialization</u>:
 - Social network of *n* nodes is generated
 - Node traits –
 Randomly sampled from a Beta distribution parameterized by α and β (Shape parameters)
 - Edge states –
 Initialized randomly with probabilities:
 - Enemy (-1): 25% or 0.25
 - Stranger (0): 45% or 0.45
 - Friend (1): 30% or 0.3

• <u>Reaction dynamics using Gillespie algorithm</u>:

- Reaction types
 - Stranger → Friend: Depends on forthcomingness of both individuals (likely to vibe if you take the plunge)
 - Enemy → Stranger : Depends on complement of forthcomingness (can't fight if you're awkward)
 - Friend \rightarrow Enemy: Depends on existing of {+1,+1,-1} triads which deteriorate with rate of Ψ = 0.5(caught in crossfire)
- Reaction selection -
 - Rates for all possible reactions computed
 - Stochastic sampling used to determine reaction and update network

- <u>Simulation execution</u>:
 - Simulation runs upto *iteration_limit* (hyperparameter) steps or until no reactions are possible

- Track network metrics at each step -
 - Proportions: Fraction of friends, enemies and strangers
 - Weight sum: Net weight of the adjacency matrix
 - Reaction rates: Average rates for each reaction type

• Parameter exploration and data aggregation:

- Varied α and β to analyze effects of personality trait distributions including Normal, left-skewed or introvert-skewed, right-skewed or extrovert-skewed, uniform, non-monotonic
- \circ Ran multiple replicates (15) for each (α, β) parameter subset for statistical robustness
- Averaged metrics across replicates to plot with mean and standard deviation for visualizations

• <u>Visualization</u>:

- Evolution of proportions over iterations Changes in friends, enemies and strangers over iterations
- Weight sum evolution Displays net weight change in network
- Reaction rate evolution Highlights dynamics of individual reaction types for a single replicate

• For $\alpha = \beta = 1$ (Uniform distribution of Forthcomingness index)



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• For $\alpha = \beta = 1$ (Uniform distribution of Forthcomingness index)











• For $\alpha = 1$, $\beta = 10$ (Left-skewed distribution of Forthcomingness index)





0.4

• For $\alpha = 1$, $\beta = 10$ (Left-skewed distribution of Forthcomingness index)







• For $\alpha = \beta = 5$ (Normal distribution of Forthcomingness index)







• For $\alpha = \beta = 5$ (Normal distribution of Forthcomingness index)







• For $\alpha = 10$, $\beta = 1$ (Right-skewed distribution of Forthcomingness index)







• For $\alpha = 10$, $\beta = 1$ (Right-skewed distribution of Forthcomingness index)







• For $\alpha = 2, \beta = 3$ (Left-skewed but non-monotonic distribution of Forthcomingness index)







• For $\alpha = 2, \beta = 3$ (Left-skewed but non-monotonic distribution of Forthcomingness index)







• For α = 3, β = 2 (Right-skewed but non-monotonic distribution of Forthcomingness index)









• For $\alpha = 3$, $\beta = 2$ (Right-skewed but non-monotonic distribution of Forthcomingness index)



Implications from simulations



Implications from simulations



Conclusion

For the given probability initialisation of (0.25, 0.45, 0.3) and the rule set we adhered to, we see relatively higher *weight sum* for distributions favoring low forthcomingness even though the network is biased towards high forthcomingness-driven interactions

We see fluctuations initially but they finally settle to either a steady state or monotonically increases/decreases

Future directions

- Exploring different edge weight initialization probabilities: We chose probabilities (0.25, 0.45, 0.3) for (-1, 0, +1) respectively but what if we chose something different?
- Exploring higher-order interactions through analyses involving information transfer about nature of relationship through path-lengths of more than 1 (By utilising powers of the adjacency matrix)
- Finding *optimal* probability distribution from which to sample forthcomingness values given a set of rules (?)

References and final acknowledgements

- <u>Gillespie Algorithm | Lewis Cole Blog</u> is a beautiful blog post by Lewis Cole which served to be very useful in trying to understand what the Gillespie algorithm is all about Worth checking out!
- ChatGPT, Claude and Gemini for wonderfully condensing vast amounts of information that we had to parse through to learn things that we had not been exposed to before this workshop

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Thank you!

Link to our code: SGN Group5 Code