

# The Life and Death of Social Networks: A network formation model for opinion dynamics

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One of the most robust effects governing social life is homophily and triadic closure. We like people similar to ourselves, and we find new connections through our existing connections. These two effects can combine to self-reinforcing processes of shaping both social networks of social agents as well as their opinions. Here I investigate a stylized agent-based model of opinion dynamics. I find that the model can generate realistic social networks while simultaneously producing realistic opinion distributions.

opinion dynamics | computational social science | agent-based modeling

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## Sections: Theory, Methods, Results, Discussion...

### 1. Theory

One of the most robust mechanisms governing social networks is the tendency of similarity to breed connection. This effect is often characterized as homophily. The effect of homophily results in neighbourhoods within social networks, which are homogeneous with regard to sociodemographic, behavioral and political characteristics. This has dramatic implications as one's social world defines what pieces of information, opinions and interactions that an individual have. The most clear example is echo chambers in social media networks. In echo chambers, homophily can lead to a distortion of what kind of information is presented to each individual.

It is examples like those from echo chambers that clearly illustrates that the principles of homophily not only influences who we make connections with, but also how we think. Several studies have pointed to the fact that one's peer group is an important influence on one's behavior. For instance, shared political beliefs predict more behavioral involvement with one another.

Homophily and its effects become especially potent as they can create self-reinforcing mechanisms when combined with tie-formation principles such as triadic closure. Triadic closure refers to tie formation between "friends of friends" in a network. For instance, if  $A \leftrightarrow B$  and  $B \leftrightarrow C$ , then this small system would achieve triadic closure by forming the edge  $C \leftrightarrow A$ . When new ties are found via triadic closure,

To see why homophily and triadic closure can create self-

reinforcing homophily effects, notice the following. Due to homophily, the probability of  $A$  being similar to  $B$  will be higher than when they find new connections via triadic closure i.e. "friends of friends". In such cases, any social agent will have a propensity to like agents which are more similar to themselves. Moreover, they find new connections primarily by finding them via "friends of their friends".

Homophily and its effects become especially potent when social agents can be influenced by their peers. This social influence can potentially explain how

### A. Network Formation.

**A.1. Social Networks.** Social networks differ in key ways to more idealized networks. Here I outline the most important characteristics, which have been found across many different domains and networks.

The first of which is that the average path length in social networks tends to be small. This is best exemplified by the idea of "six degrees of separation", which refers to the notion that you are never more than five intermediaries away from any other person on the planet. Average path length is as the average of all shortest paths between nodes. CITE (Meeting strangers and friends) Recently, this notion has been studied empirically on social media networks, including 721 million people. They found that the average shortest path length was 4.74, corresponding to closer to four degrees of separation CITE (four degrees of separation). This feature is in part also the claim to fame of small-world networks. Simple lattice networks can be modified with random rewiring of connections, making some connections act as shortcuts across the network. CITE (small world)

The second characteristic is the fact that social networks tend exhibit clustering behavior. Small hubs of the network are well-connected locally, while often having limited connections to other hubs of the network. The level of clustering is

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often quantified with a clustering coefficient. Here, different coefficients can be used, but arguably the most common is the average clustering coefficient proposed by Watts and Strogatz in the seminal paper on small-world networks CITE(small world). The basic intuition is that with higher clustering coefficients, an agent's connections tend to be connected to each other. This is the reason why the literature often includes triangles and closed triangles in their terminology. A triangle is a set of three nodes, where either two of them are connected or three of them are connected. When all three are connected, the resulting set is a closed triangle. Clustering can also be thought of as the ratio between all closed triangles of the graph and all the triangles of the graph.

The third characteristic is that the degree distributions of networks tend to have "fat tails". In this case, the degree distribution refers to the probability distribution of degrees in a network. What is meant when degree distributions are described as having fat tails, is essentially two attributes. The distributions tend to have relatively few nodes with the average degree of the distribution, but instead have many low and high degree nodes. These degree distributions are also referred to as being "scale-free" or following a power-law distribution. In other words, most nodes have relatively few connections, but a few of them have disproportionally many connections compared to all the other nodes.

The fourth characteristic is that high degree nodes tend to connect with other high degree nodes. This is also referred to as nodes having positive assortativity.

Idealised networks such as the small world network and the scale-free network can generate a subset of these characteristics. However, none of these models can generate networks which exhibit all features simultaneously. When evaluating good candidate models for how social networks are generated, our candidate models should be able to generate networks which exhibit all characteristics at the same time.

#### A.2. Candidate Models. For

A special focus on the Herding Friends (animal model) as well as the how random are random friends. Other papers could also be good here.

**A.3. The problems with current models.** Calibration with data and how to test models. Models with fixed networks won't cut it.

**B. Social Influence.** Including some of the basic literature (Axelrod)

**B.1. Shaping opinions.** Introduce the evidence from psychology and computational literature to show why the assumptions in the model make sense

**B.2. Models of Social Influence.** Report the evolution of models and where to place this model in all of the literature

**C. A network formation model for social influence.** Explain the importance of making both a network formation and opinion dynamics model in one go

## 2. Methods

**A. Model specification.** Explain the different parameters of the model

**B. Model fitting.** explain how the model was calibrated (Bayesian Hyperparameter Optimization)

## 3. Model investigation

Get familiar with the different parameters and their interpretations

**A. The effect of randomness.** How randomness affects the distribution of opinions, as well as the network

**B. The effect of the boundary threshold.** How the boundary threshold affects the distribution of opinions, as well as the network

**C. The effect of homophily.** How homophily affects the distribution of opinions, as well as the network

**D. Important interactions.** Point to some of the important interactions (possible Golden zones)

## 4. Results

**A. Network generation.**

**B. Opinion generation.**

## 5. Discussion

## 6. Conclusion

Use section and subsection commands to organize your document.  $\LaTeX$  handles all the formatting and numbering automatically.

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Figures and Tables should be labeled and referenced in the standard way using the `\label{}` and `\ref{}` commands.

Figure ?? shows an example of how to insert a column-wide figure. To insert a figure wider than one column, please use the `\begin{figure*}...\end{figure*}` environment. Figures wider than one column should be sized to 11.4 cm or 17.8 cm wide. Use `\begin{SCfigure*}...\end{SCfigure*}` for a wide figure with side captions.

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**Table 1. Character Level Combat Outcomes**

	<i>Dependent variable:</i>		
	Combat Amount	Combat Variability	Combat Skill
	(1)	(2)	(3)
Man - Male	0.042*** (0.002)	5.659*** (0.056)	0.031*** (0.0004)
Woman - Female	-0.026*** (0.005)	1.529*** (0.143)	0.011*** (0.001)
Woman - Male	0.010 (0.009)	0.375 (0.272)	0.005* (0.002)
Player Age	-0.077*** (0.001)		-0.003*** (0.0002)
Mil. Label	0.135*** (0.002)		0.060*** (0.0004)
Constant		-97.425*** (0.046)	
Char. Order FEs	Y	N	Y
Create Date FEs	Y	N	Y
Observations	576,430	576,430	576,430
R <sup>2</sup>	0.028	0.018	0.089

p<0.05, \*\* p<0.01, \*\*\* p<0.001

This table reports coefficients and standards errors from ordinary least squares regressions. In all models we can reject the null that *Woman - Female* and *Woman - Male* are equivalent with  $p < .01$ . In models 2 and 3 we can reject the null that the gender gaps within sex are equivalent ( $(\text{Woman} - \text{Male}) - (\text{Woman} - \text{Female}) = \text{Man} - \text{Male}$ ) with  $p < .001$ .

$$\begin{aligned}
 (x + y)^3 &= (x + y)(x + y)^2 \\
 &= (x + y)(x^2 + 2xy + y^2) \\
 &= x^3 + 3x^2y + 3xy^2 + y^3.
 \end{aligned}
 \tag{1}$$

## References

References should be cited in alphabetical order; this will be done automatically via bibtex, e.g. ?, and ?. All references should be included in the main manuscript file.

**ACKNOWLEDGMENTS.** Please include your acknowledgments here, set in a single paragraph. Please do not include any acknowledgments in the Supporting Information, or anywhere else in the manuscript.