

# Agent-Based Methods for Dynamic Social Networks

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## Outline

- Introduction
- Social Network Models
- Agent-based Models
- Our Approach
- Results
- Statistical Challenges

# Scientific Interest in Dynamic Social Networks

How do networks change over time?

How do we identify patterns?

How do we make predictions?

Examples:

- Baboon Fissions
- Antarctic Research Stations
- Terrorist Networks
- Elephants

## Scientific Questions–Baboons



- Once in a lifetime ( $\approx 10$  years) baboons will permanently fission from one group into two.
- Before the final fission baboons repeatedly split into “test” groups. After a few hours or days apart they come back together. Some time later they (temporarily) split again.
- What does this changing social structure tell us about how baboons make decisions?

## Scientific Questions—Antarctic Researchers



- How could one build cohesiveness in an Antarctic research station?
- What early characteristics of the group will lead to “perfect” clustering, cliques, loners?  
Can these aspects of the social structure be predicted or changed by studying its dynamics?
- What is the effect of having a few charismatic personalities, or someone everybody hates?

## Scientific Questions–Terrorists



- How will the structure of Al Qaeda look in the future?
- What could dynamic data tell us about characteristics of the network?
- How would the elimination of key individuals in the network affect the evolution of the network?

## Scientific Questions—Elephants



- How do changing resources affect elephant social structure (Wet Season v. Dry Season)?
- Do elephants change their preferences over time? How might this affect the social structure?
- What effect might an elephant's death have on the group structure?

## Models of Social Networks

**Social network analysis models relationships between actors.**

- The attributes of individual actors are not as important as the attributes of their relationships, or ties, with other actors.
  - Presence/absence of a friendship (0 or 1)
  - Money exchanged between actors (\$0.55)
  - a Win, Loss, or Draw (1, -1, 0) in a competition.
- A social network can be represented as a graph where the nodes are the actors and the edges represent the ties between the actors.
- A social network can also be represented by its matrix of ties:

	Amy	Ang	Ali	Ast
Amy	0	1	0	0
Ang	1	0	0	0
Ali	0	0	0	1
Ast	0	0	1	0

## Social Network Models

- Holland and Leinhardt (1981)  $p_1$  model
  - Assumes independence of dyads
  - Models the ties as functions of individual relational attributes (expansiveness, attractiveness) as well as features of the graph (density, overall tendency toward reciprocity)
- Wasserman and Pattison (1986)  $p^*$  model
  - Models the probabilities of ties conditional on all other ties in the network.
  - Explanatory variables are the differences in the network statistics (...) if a tie  $x_{ij}$  were to change from 1 to 0.
- Hoff, Raftery, and Handcock (2002)

## Hoff, Raftery, and Handcock Social Space Model

Similar to the model I use for elephants!

- Sender and receiver random effects, as well as positions in a latent social space, account for the dependence between dyads.
- $\text{logit}(p_{ij}) = \beta_0 + s_i + r_j + \beta_d X_{ij} - |z_i - z_j|$ 
  - Common intercept  $\beta_0$ , a baseline probability
  - Sender sociability or “expansiveness”  $s_i$  random effect
  - Receiver “attractiveness”  $r_j$  random effect
  - Vector of dyad-specific (observable) covariates  $X_{ij}$
- The distance between  $i$  and  $j$  in “Social Space” affects the probability of a tie from  $i \rightarrow j$ .
  - Actors close together in social space are more likely to form ties.

## Agent-Based Models

- Impose a few simple rules on agents, then study the aggregate effects of the resulting interactions.
- Complex social phenomena can be generated by individual agents acting according to the simple rules.
- Sugarscape (Epstein and Axtell 1996) is a classic example.

## Sugarscape Example

- Agents collect sugar according to “vision” rules and burn it at an individual rate called “metabolism”.
  - The Sugarscape has rules for where and how fast sugar regrows.
  - Patterns of migration and skewed distributions of wealth emerge.
- ★ New rules produce new phenomena:

Rules	Implications
Vision, Metabolism, Regrowth rates	Migration, Wealth distribution
Sex, Reproduction	Evolution, Inheritance
Spice	Trade, Price equilibria
Cultural traits	Tribes, War, Migration

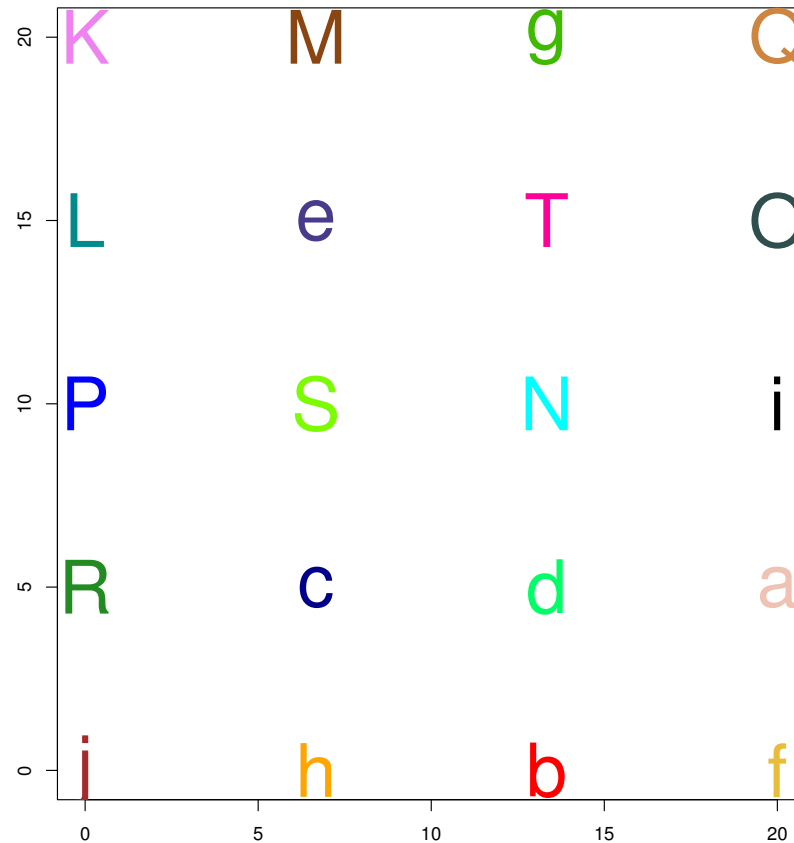
## Our Approach—Background



- Students arrive at a boarding school having no friends and not knowing anyone.
- Each student occupies a position in Social Space.
- Students make friends at each time step according to a specified set of simple rules.

# Student Social Space

Initial Locations in Social Space for Model 1b



- Social Space is a latent variable. It is a useful proxy for that which we cannot measure.
- Perhaps the axes are **IQ** and **Social Status**.
- **Key idea: Students move towards their friends in Social Space.**

## Static Equation Model

The basic p-friendship model:

$$\log\left(\frac{p_{ij}}{1 - p_{ij}}\right) = \beta_0 + \beta_s s_i + \beta_r r_j + \delta X_{ij} - |z_i - z_j|$$

★ **p-Model:**

$$\text{logit}(p_{ij}) = \beta_0 + \delta_1 \left( \mathbf{I}(\text{Sex}_i = \text{Sex}_j) - \overline{\mathbf{I}(\text{Sex}_i = \text{Sex}_j)} \right) + \beta_s (s_i + s_j) - |z_i - z_j|$$

- $\text{logit}(p_{ij})$  is the *degree* of friendship between agents  $i$  and  $j$ .  $p_{ii}$  is undefined.
- $\beta_0$  is the baseline degree of friendship between any two agents.
- $\mathbf{I}(\text{Sex}_i = \text{Sex}_j)$  is an indicator whether agents  $i$  and  $j$  are of the same **Sex**. This dyadic covariate is centered about its mean to retain the interpretation of the baseline degree of friendship  $\beta_0$ .
- $\delta_1$  is the sensitivity of friendships to same **Sex**.
- **Charisma**  $s_i \sim N(0, 1)$ . Both the sender and the receiver have **Charisma** and both are equally weighted when making friendships.
- $\beta_s$  is the sensitivity of friendships to **Charisma**.

## Agent Model

### ★ Rules for Agent Model:

- Rule 0. Twenty agents start randomly at time=1 on a  $(20 \times 20)$  grid in 2-dimensional Social Space.
- Rule 1. At every time step each agent  $i$  proffers a friendship to all agents  $j \neq i$ , and these proffers are accepted with probability  $p_{ij}$ .
- Rule 2. After new friendships are created, agents move a “**move.fraction**” towards the average of their friends’ locations in Social Space.
- Rule 3. Agents are split evenly between the sexes.  $\delta_1$  is the sensitivity of friendships to same **Sex**.
- Rule 4. The **Charisma** (sociality  $s_i$ ) of each agent is added to the model.  $s_i \sim N(0, 1)$ .  $\beta_s$  is the sensitivity of friendships to **Charisma**.

## Evaluation of Rules

How do changes in the set of rules change the results?

- Compare statistics of the network generated by different sets of rules
  - Average number of friends
  - Time until “perfect” clustering
  - Number of clusters
  - Number of completed triads
  - Number of opposite sex friends
  - Net distance moved by all agents in Social Space

## Evaluation of Rules: Model 1

### ★ p-Model 1:

$$\text{logit}(p_{ij}) = \beta_0 - |z_i - z_j|$$

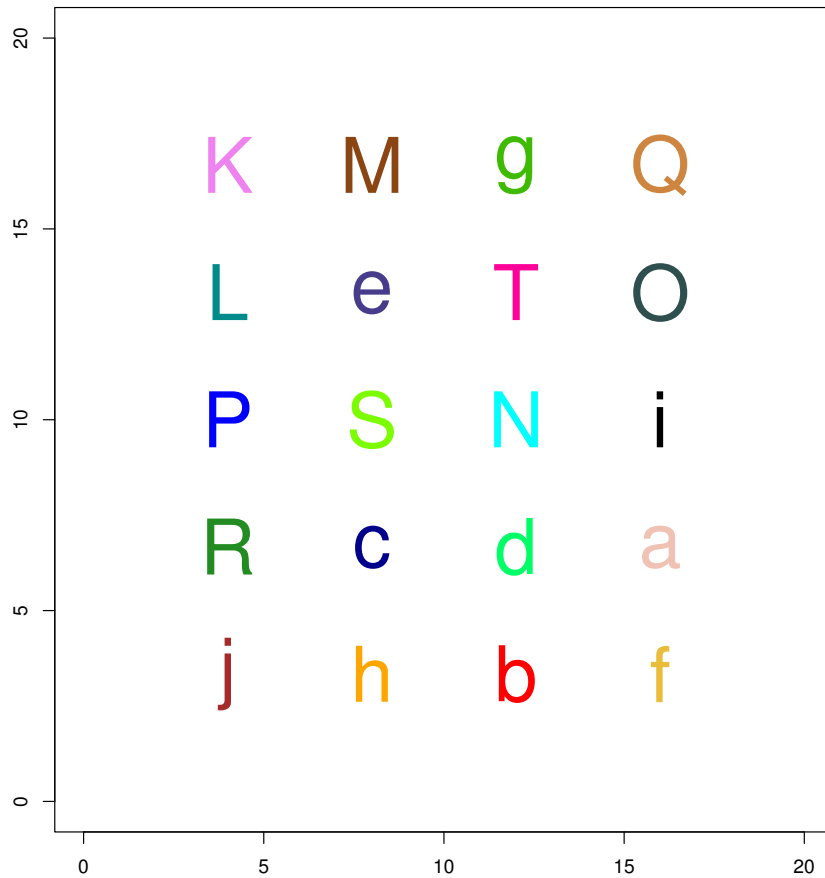
- $\text{logit}(p_{ij})$  is the *degree* of friendship between agents  $i$  and  $j$ .
- $\beta_0$  is the baseline degree of friendship between any two agents.
- $i = 1, \dots, 20$ .  $j = 1, \dots, 20$ . The degree of friendship between an agent and itself,  $\text{logit}(p_{ii})$ , is undefined.
- $z_i$  is the position of agent  $i$  in two-dimensional Social Space.  $|z_i - z_j|$  is the distance between agents  $i$  and  $j$ .

### ★ Rules for Agent Model 1:

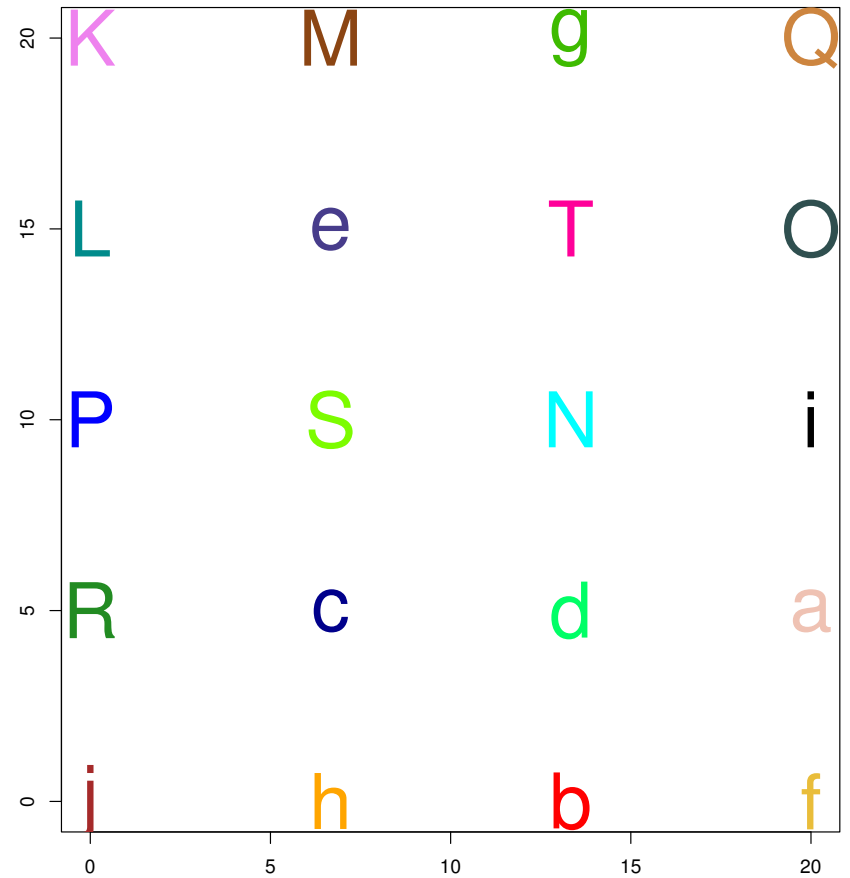
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- Rule 2. After new friendships are created, agents move a “**move.fraction**” towards the average of their friends’ locations in Social Space.

# Evaluation of Rules: Model 1 and 1b

Initial Locations in Social Space for Model 1



Initial Locations in Social Space for Model 1b

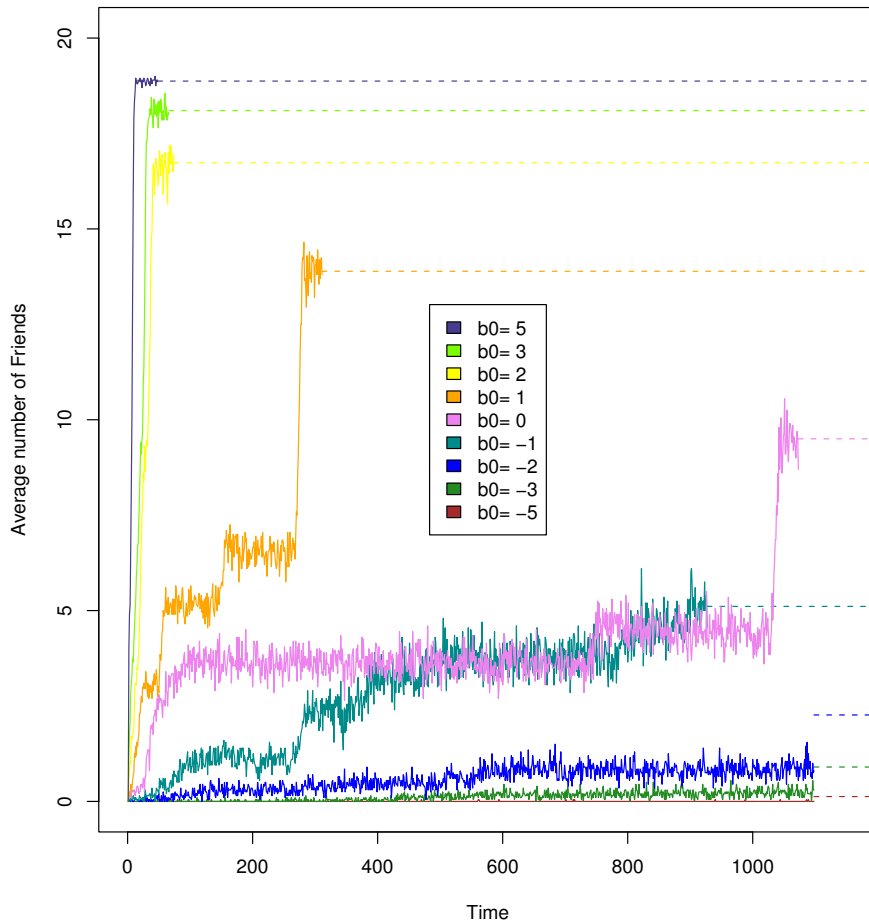


$$\text{logit}(p_{ij}) = \beta_0 - |z_i - z_j|$$

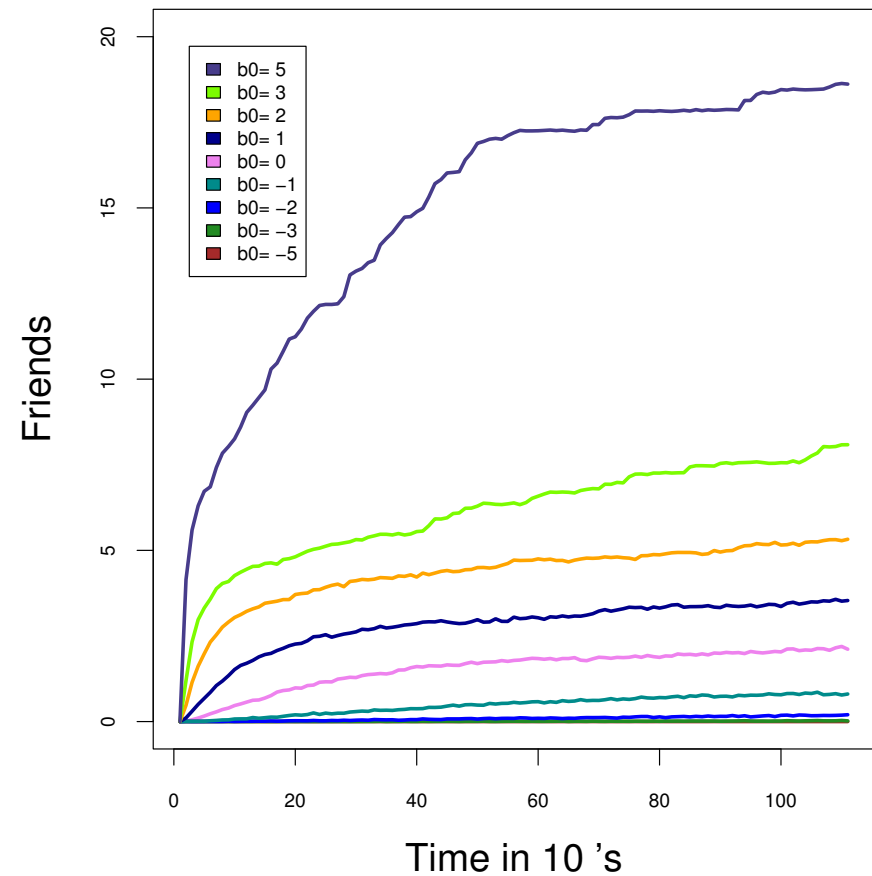
Rule 0. Size of Social Space

# Evaluation of Rules: Model 1 and 1b

Average number of Friends Model 1



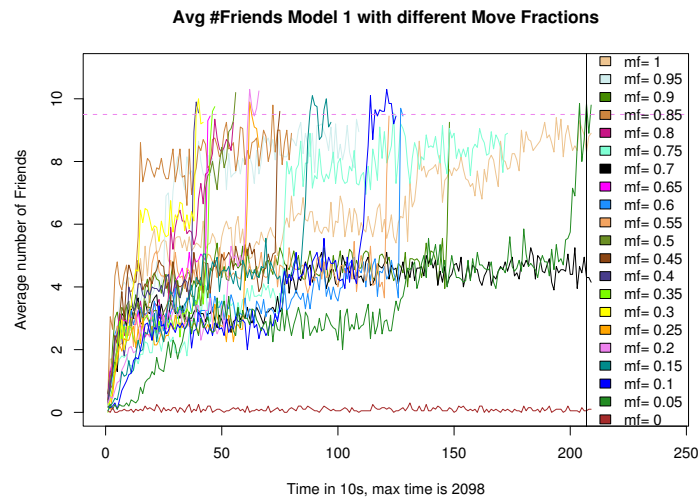
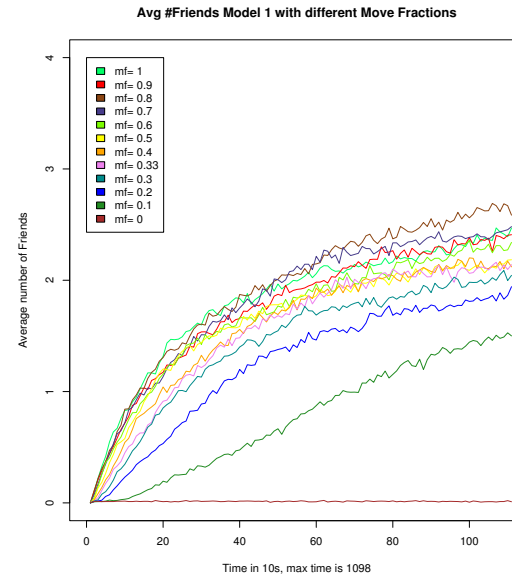
Average number of Friends Model 1b



$$\text{logit}(p_{ij}) = \beta_0 - |z_i - z_j|$$

Rule 0. Size of Social Space

# Evaluation of Rules: Model 1 and 1b

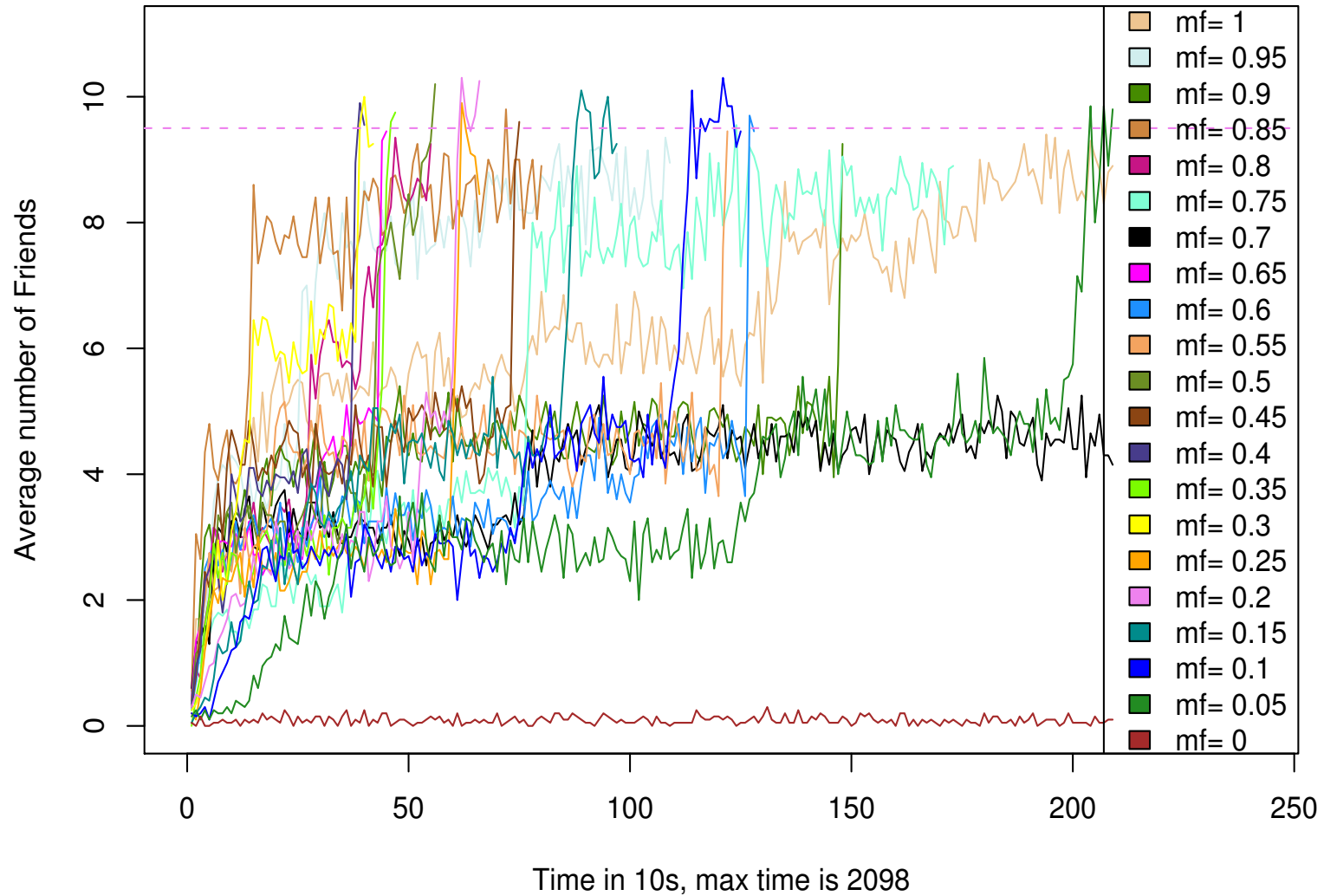


$$\text{logit}(p_{ij}) = \beta_0 - |z_i - z_j|$$

Rule 2. Students “**move.fraction**” towards friends in Social Space

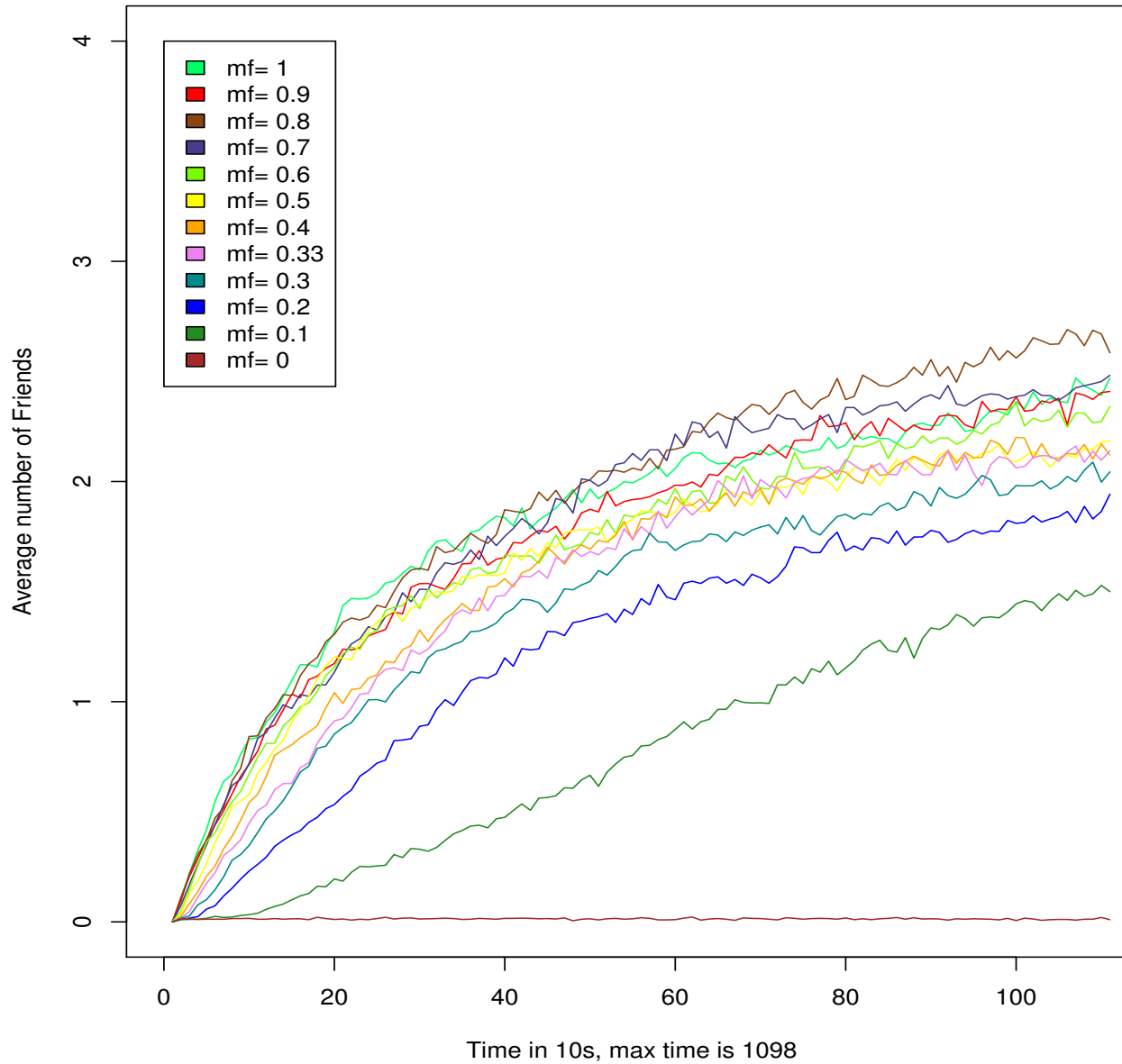
# Evaluation of Rules: Model 1 and 1b

## Avg #Friends Model 1 with different Move Fractions



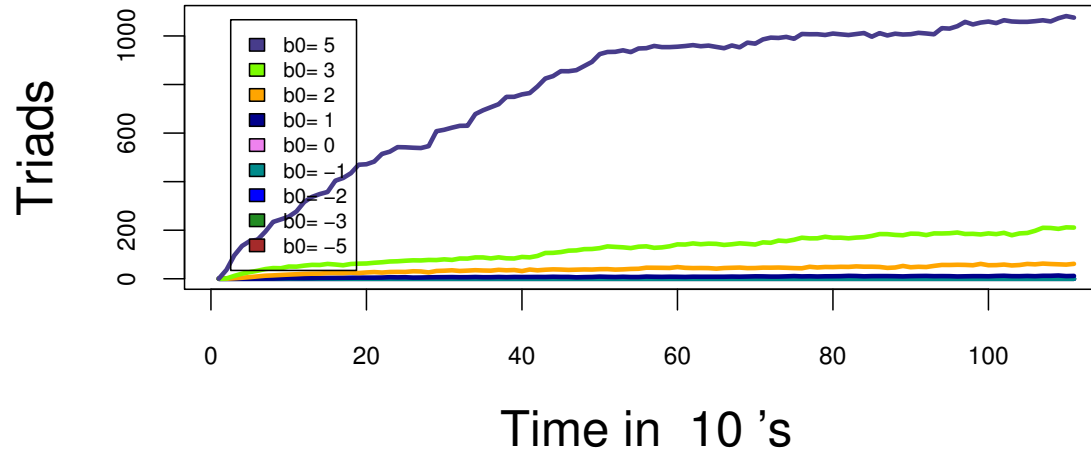
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Avg #Friends Model 1 with different Move Fractions

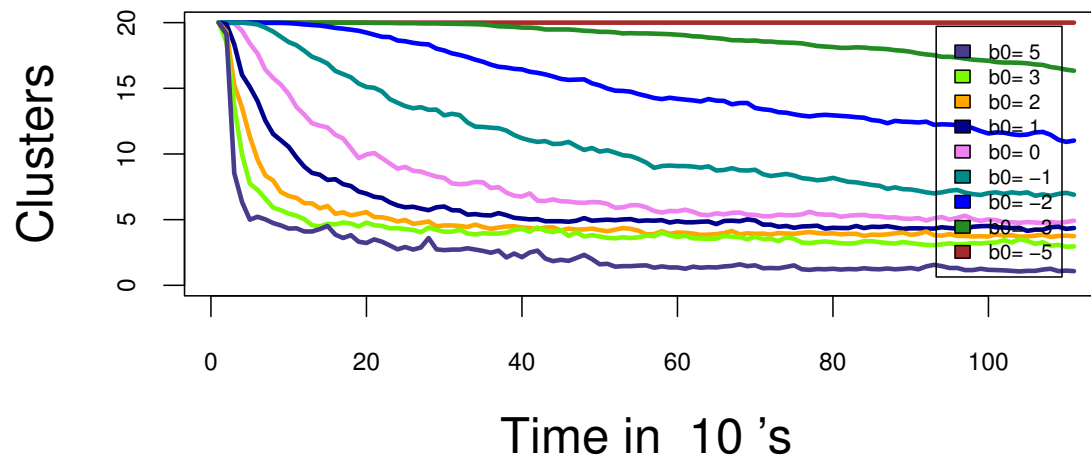


# Evaluation of Rules: Model 1b

## Average number of Triads Model 1b



## Average number of Clusters Model 1b



## Gender is Added to Agent Model 2

### ★ p-Model 2:

$$\text{logit}(p_{ij}) = \beta_0 + \delta_1 \left( \mathbf{I}(\text{Sex}_i = \text{Sex}_j) - \overline{\mathbf{I}(\text{Sex}_i = \text{Sex}_j)} \right) - |z_i - z_j|$$

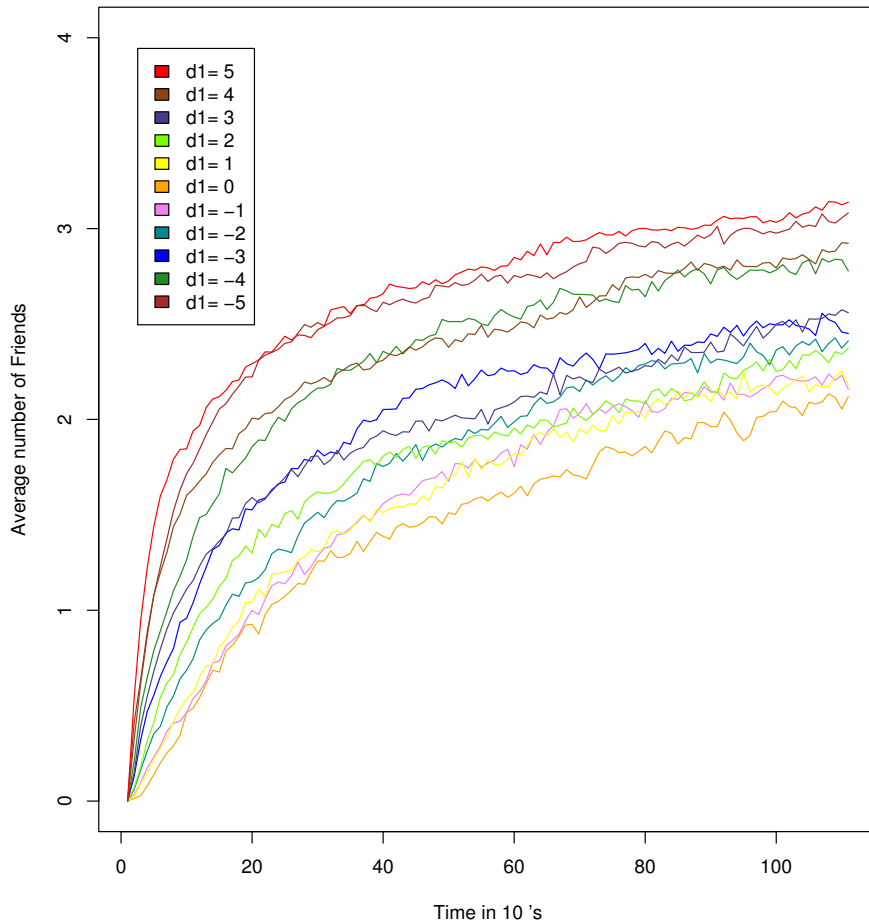
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### ★ Rules for Agent Model 2:

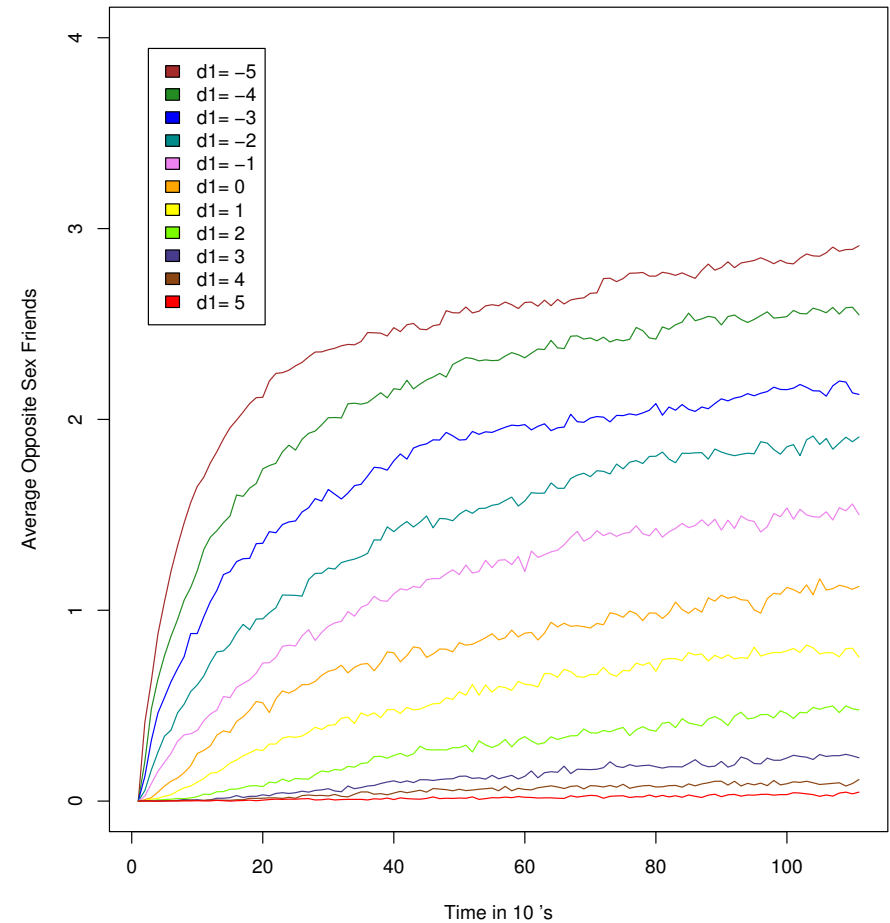
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- Rule 2. After new friendships are created, agents move a “**move.fraction**” towards the average of their friends’ locations in Social Space.
- Rule 3. Agents are split evenly between the sexes.  $\delta_1$  is the sensitivity of friendships to same **Sex**.

# Evaluation of Rules: Model 2

Average number of Friends Model 2



Average number of Opposite Sex Friends Model 2

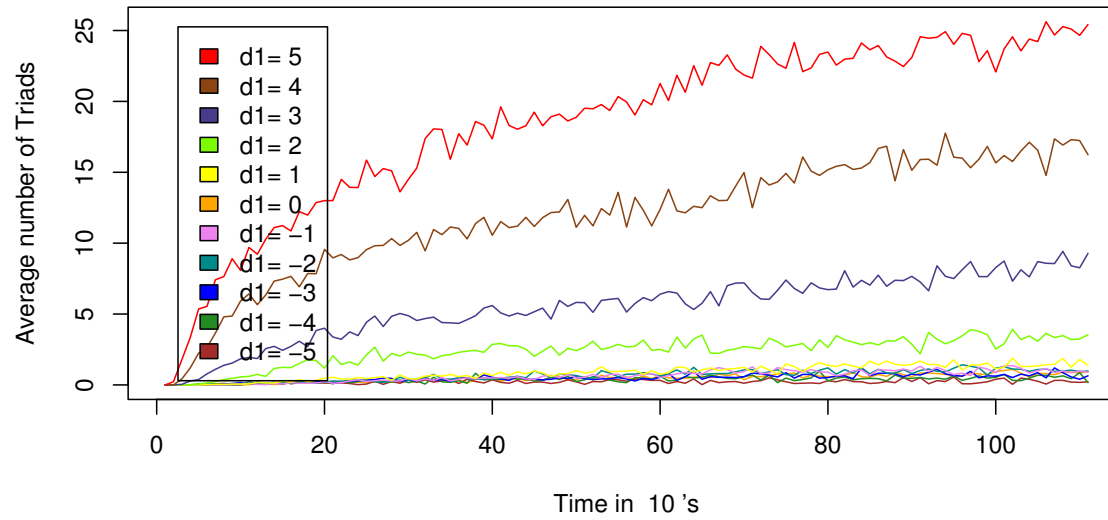


$$\text{logit}(p_{ij}) = 0 + \delta_1 \left( \mathbf{I}(\text{Sex}_i = \text{Sex}_j) - \overline{\mathbf{I}(\text{Sex}_i = \text{Sex}_j)} \right) - |z_i - z_j|$$

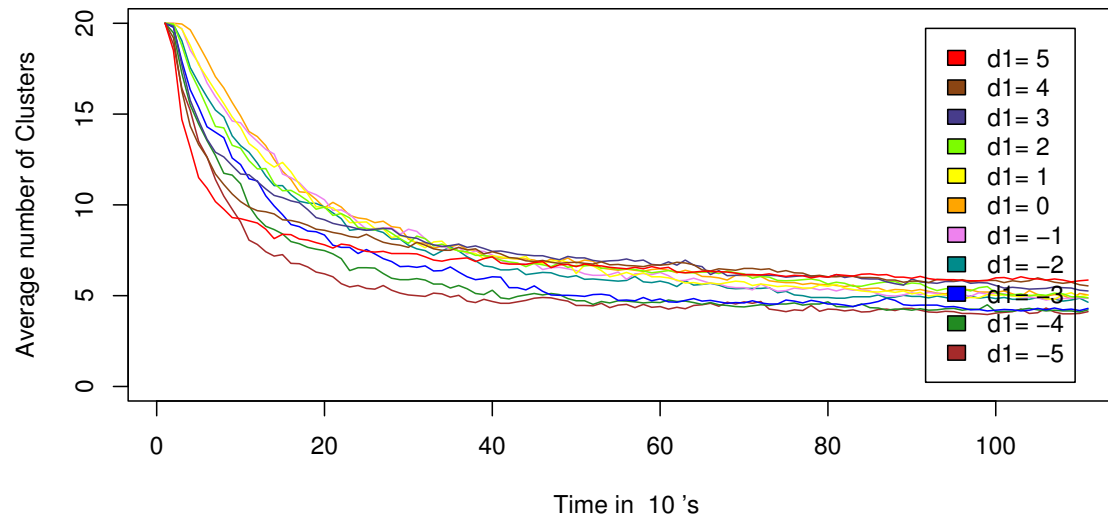
**Rule 3.**  $\delta_1$  is the sensitivity of friendships to same Sex.

# Evaluation of Rules: Model 2

## Average number of Triads Model 2



## Average number of Clusters Model 2

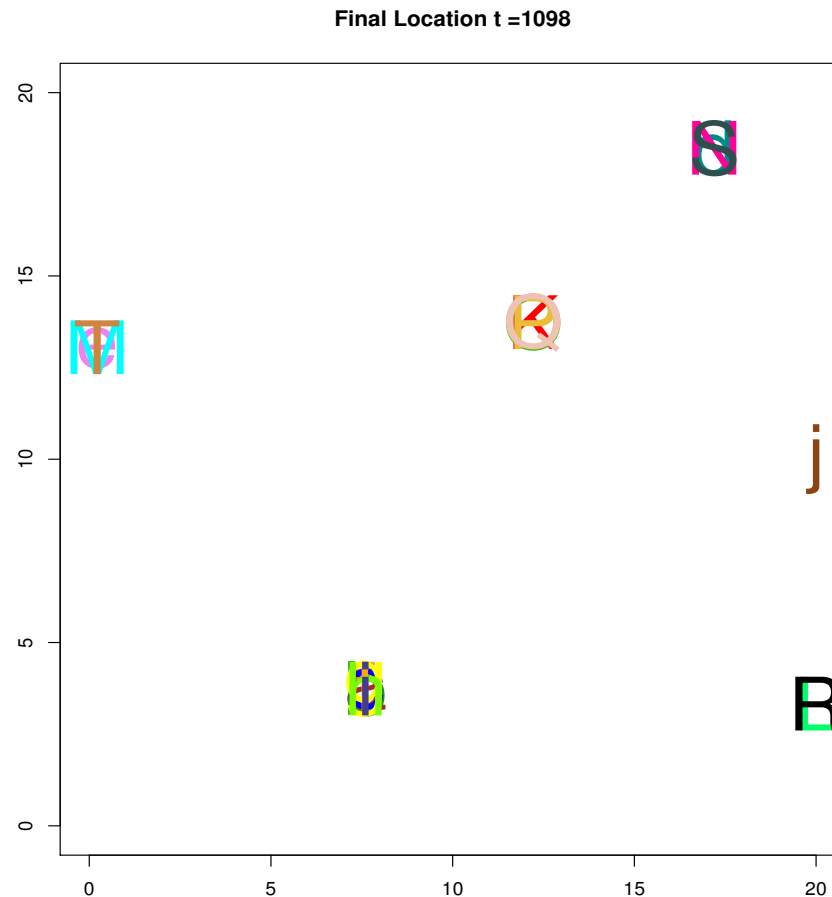


## Evaluation of Rules: Model 2

- As long as **move.fraction**  $> 0$ , all the agents will eventually move together to form one perfect cluster. But it could be practically impossible based on  $\beta_0$ ,  $\delta_1$ , and the size of Social Space.
- Often one agent (starting in a corner of Social Space) will fail to make friends early and become isolated (nearly forever).
- Even when  $\delta_1$  was large, clusters of opposite sexes emerged in Social Space.
- Students in the same location in Social Space are not necessarily friends.
- In general, the larger  $\delta_1$  in absolute value, the higher the average number of friends.
- Adding sex into the equation drastically changes the dynamic behavior of the system. No longer do we observe one perfect cluster of agents at the end of the run. Sub-clusters in Social Space form and persist.

## Agent Model 2 Example

- Social Space after 1098 iterations  $\delta_1 = 2$  (preference for same sex):



- Six clusters of students emerge: A big cluster of 7 males, a cluster of 4 females, a smaller cluster of 2 females, two mixed clusters of 1 male and 2 females, and one lone male who never made any friends.

## Charisma is Added to Agent Model 3

### ★ p-Model 3:

$$\text{logit}(p_{ij}) = \beta_0 + \delta_1 \text{Sex}_{ij} + \beta_s (s_i + s_j) - |z_i - z_j|$$

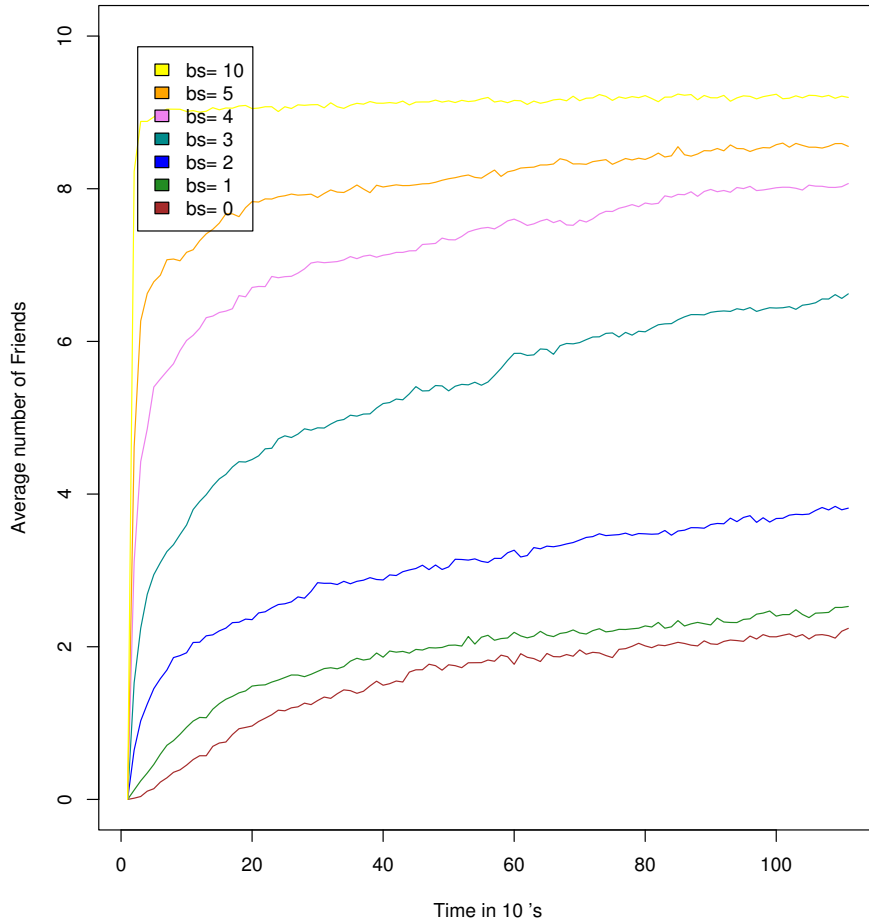
- $\beta_s$  is the sensitivity of friendships to **Charisma**.
- **Charisma**  $s_i \sim N(0, 1)$ . Both the sender and the receiver have **Charisma** and both are equally weighted when making friendships.

### ★ Rules for Agent Model 3:

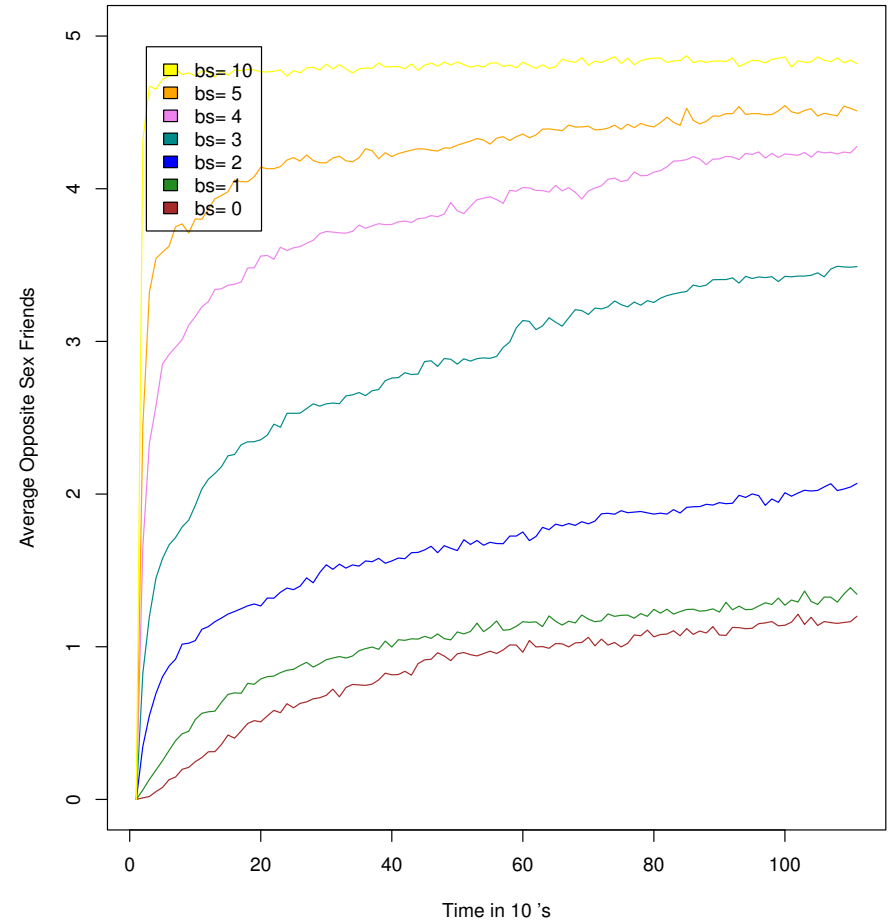
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- Rule 3. Agents are split evenly between the sexes.  $\delta_1$  is the sensitivity of friendships to same **Sex**.
- Rule 4. The **Charisma**  $s_i \sim N(0, 1)$  of each agent is added to the model.

# Evaluation of Rules: Model 3

Average number of Friends Model 3



Average number of Opposite Sex Friends Model 3

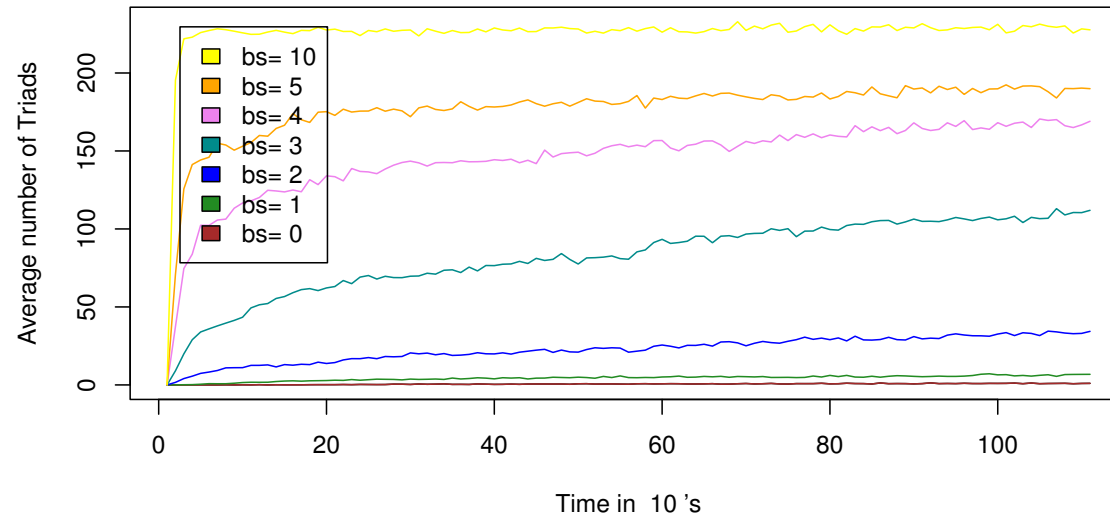


$$\text{logit}(p_{ij}) = 0 + \delta_1 \text{Sex}_{ij} + \beta_s (s_i + s_j) - |z_i - z_j|$$

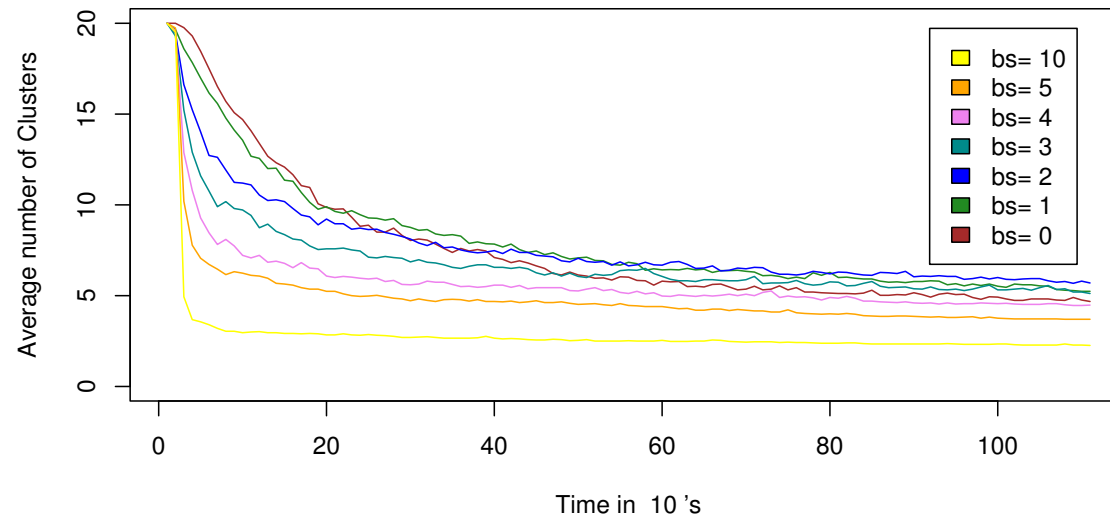
Rule 4.  $\beta_s$  is the sensitivity of friendships to Charisma.

# Evaluation of Rules: Model 3

## Average number of Triads Model 3



## Average number of Clusters Model 3



## Implications of Rules: Model 3

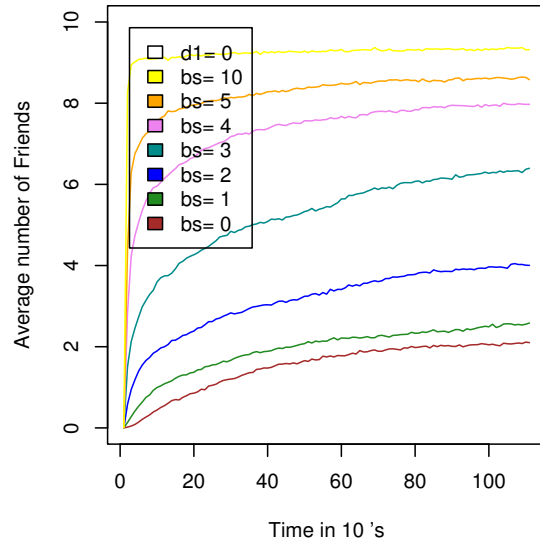
$$\text{logit}(p_{ij}) = \beta_0 + \delta_1 \text{Sex}_{ij} + \beta_s s_i + \beta_r r_j - |z_i - z_j|$$

$$\text{logit}(p_{ij}) = 0 + \delta_1 \text{Sex}_{ij} + \beta_s (s_i + s_j) - |z_i - z_j|$$

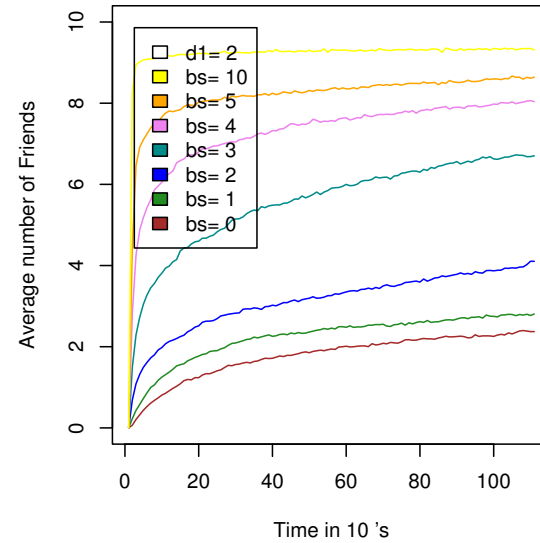
- **Charisma** of the sender  $s_i$  and the receiver  $r_j = s_j$  are equally important in making friendships since the coefficients are equal ( $\beta_s = \beta_r$ ) and the ties are undirected. What if there are differential sender and receiver effects?
- Students with high **Charisma** make lots of friends and live in large clusters. They might even bring everybody together into a perfect cluster.
- The distribution of **Charisma** might make a difference in the behavior of the model.
- What results when **Charisma**  $\beta_s$  and **Sex**  $\delta_1$  both vary?

# Varying Charisma and Sex in Model 3

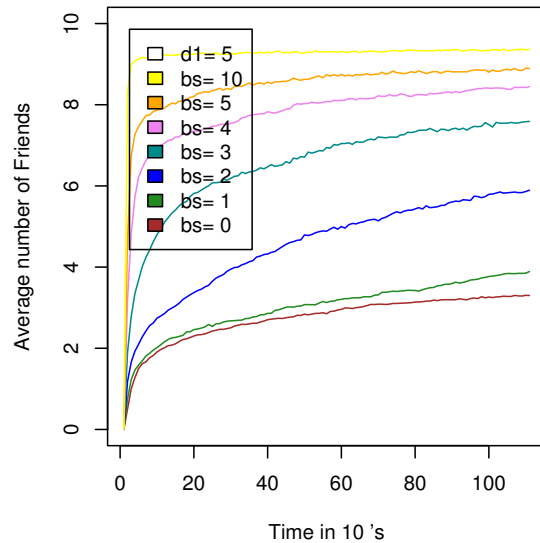
Average # of Friends Model 3b,  $d1=0$



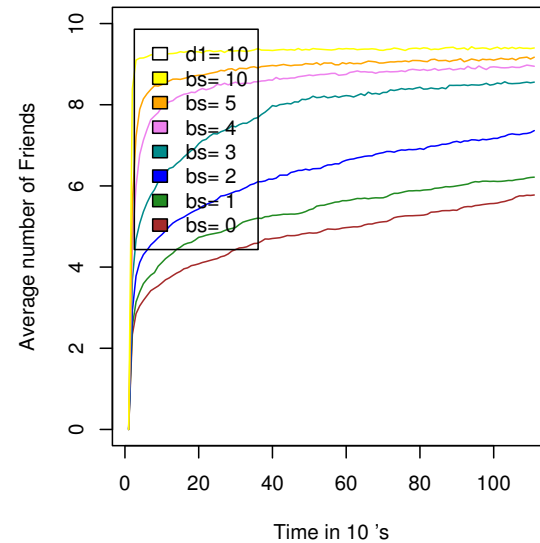
Average # of Friends Model 3b,  $d1=2$



Average # of Friends Model 3b,  $d1=5$



Average # of Friends Model 3b,  $d1=10$



## Varying Charisma and Sex in Model 3

$$\text{logit}(p_{ij}) = 0 + \delta_1 \text{Sex}_{ij} + \beta_s (s_i + s_j) - |z_i - z_j|$$

- 1. Only when  $\delta_1 = 10$  is there a noticeable difference in **Average Number of Friends** for different values of  $\beta_s$ .
- 2. For all values of  $\delta_1$  (sensitivity to **Sex**), Average friends increases with an increase in  $\beta_s$ .
- 3. Average number of **Opposite Sex Friends** seems very high for all values of  $\delta_1$  when  $\beta_s = 10$ . For most values of  $\delta_1$ , opposite sex friends increases with an increase in  $\beta_s$ .
- 4. The average final location is not a perfect cluster for any values of the parameters. Social Space seems to be big enough to get stable sub-clusters. Agents start far enough apart to have a high probability of remaining apart.
- 5. The **Number of Triads** is the same for all values of  $\delta_1$  (except slightly when  $\delta_1 = 10$ ). There is a clear monotonic relationship between number of triads and  $\beta_s$  (for a given  $\delta_1$ ).
- 6. The **Number of Clusters** is also largely unaffected by  $\delta_1$  and the relationship between clusters and  $\beta_s$  is fairly strong.

## New Rules

- New rules could be imposed to add complexity to the model.
  - Introduce enmity or hatred between the students (a repulsive force)
  - Add jealousy to the model
  - Make movement in social space less likely as time goes on
- Model 4 bases movement in social space on all the *probabilities* of friendship  $p_{ij}$  rather than on 0/1 friends.
  - Given the random assignment of genders and charisma, the model becomes deterministic.
- Could change the interpretation of social space from a distance model to Peter Hoff's inner product social space, or could allow students to belong to specific "classes".

## Statistical Challenges

- Sufficient statistics for the social network
- Which summary statistics to use for the network?
- How does one summarize a story?
- Evaluating models and rules without data