

TOWARD AN AGENT-BASED SIMULATION OF THE FACTORS IMPACTING DIVERSITY WITHIN A COLLEGE STUDENT BODY

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ABSTRACT

Colleges worldwide have identified racial diversity as a vital dimension of their educational experience. Institutions might increase their level of diversity by addressing the problem of perceived social estrangement among minorities: studies have shown that this is an important factor in minority retention. One approach is to deliberately construct integrated social groups for students at the beginning of their college experience. These early interactions, aimed at reducing the social segregation of the population, may lead to lasting friendships between students of different races, and then bear further fruit later as different cultures and attitudes interact in positive ways. In this paper we describe an agent-based simulation of a college student body in which students form dyadic and group connections and change their preferences in response to their peers. We describe how the model can be used to study the impact of institutional policies on overall degree of segregation.

1 MOTIVATION

1.1 Factors in Racial Diversity

Achieving diversity, and in particular racial diversity, is one of the most oft-cited goals of institutions in higher education. Not only is a racially balanced student body evidence of fairness in admission practices, but the experiences of all students – white and minority alike – are said to benefit from exposure to and relationships with peers of different ethnicities and cultures. These benefits range from the simple appreciation and respect for people of different races and backgrounds to deeper concerns such as civic responsibility, identity construction, and strong cognitive growth (Gurin, Dey, Hurtado, and Gurin 2002).

The goal is not easy to attain. College enrollment rates for racial minorities (Asian-Americans excepted) are disproportionately low across the United States, and have been for many years (Ryu 2010). One particularly difficult aspect of the problem is attrition (dropout rate), which is consistently higher for minorities than for white students (Zea, Reisen, Beil, and Caplan 1997). If a university cannot retain its minority students once they are admitted, any improvements in recruitment will be futile. An important question thus arises: why *do* minorities drop out with greater frequency? Contrary to what some might think, the problem is not mainly academic. Studies differ, but the proportion of withdrawals due to academic problems seems to range from around 15% (Kalsner 1991) to somewhat less than half (Suen 1983). There are clearly major contributors to attrition other than academic performance.

One oft-cited contributor is the phenomenon of “alienation” (Burbach 1972, Dean 1961), loosely defined as a feeling of exclusion or non-belonging. Minorities at predominantly white institutions have significant psychological barriers to overcome. This has been well-documented at both the high school (Calabrese 1988) and college (Nora and Cabrera 1996) levels. Kalsner notes that integration into a “largely white

environment” can be especially difficult for black college students, and Loo states that “even if minority students show high levels of academic satisfaction, they may feel socially and culturally alienated” (Loo and Rolison 1986). Zea’s study concludes, not surprisingly, that “when students perceived the environment as unwelcoming because of race, ethnicity, or religion, their desire to continue attending college diminished. Ethnic minority students were more likely to report experiencing disrespect.” (Zea, Reisen, Beil, and Caplan 1997)

Looking more carefully at the phenomenon of alienation, Dwight Dean identified at least three dimensions: feelings of “meaninglessness” (lack of direction and purpose in life), “powerlessness” (lack of control over one’s life), and “social estrangement” (or feelings of loneliness) (Dean 1961). One particularly compelling study of black students at a predominantly white university (Suen 1983) found that in order to mitigate feelings of alienation among minority college students, it is this third dimension that is most important. Apparently, the perception of social estrangement – feeling isolated or disconnected from the larger population – is a key contributing factor to the attrition rate for minority college students. Institutions that value racial diversity must find ways to address this widespread problem.

1.2 Social Phenomenon: Propinquity

Playing out against this backdrop of social estrangement are the dynamics of friendship formation and dissolution, which in turn are based largely on two immemorial principles. The first is that of **propinquity**: the physical proximity between two people, or other factors which affect how often they meet each other by chance (Festinger, Back, and Schachter 1950). Simply put, the more often two people encounter one another, the more likely it is they will form a friendship. And for those who have already become friends, maintaining a steady frequency of contact is important for the relationship to be maintained.

As far as mixed-race relations are concerned, it was demonstrated decades ago (Nahemow and Powell 1975) that people of different races tend not to form friendships unless they live in very close proximity to each other. Thus it is crucial that if racial segregation is to be overcome in a campus environment, students of different races simply encounter one another often. In college residence halls in particular, closeness of physical location has been shown to be a good predictor of attraction (Priest and Sawyer 1967), lending weight to this argument.

1.3 Social Phenomenon: Homophily

Even more basically, human beings generally prefer to form friendships with “other people like me,” at least on some dimensions. This is the **homophily** principle: “likes attract”. Sociologists have long noted that people with similar traits (whether physical, cultural, or attitudinal) interact with one another more often than with dissimilar. (Centola, Gonzalez-Avella, Eguluz, and Miguel 2007).

This is the racial diversity problem in its most basic form: students want to be friends with other students like them, and when a white encounters a minority, race is obviously a very visible *non*-likeness immediately evident to both parties. Indeed, although homophily is a general feature that applies to many attributes, it is race and ethnicity that more strongly divide our social environments than any other (McPherson, Smith-Lovin, and Cook 2001). Such an effect must be overcome by other factors if friendship is to occur. To make matters worse, since students of different races tend to segregate themselves by race, they have relatively fewer chances to meet and have that possibility.

As with propinquity, this concept affects not only the likelihood of people becoming friends, but the chances of their maintaining that friendship; McPherson *et al.* note that “ties between nonsimilar individuals...dissolve at a higher rate.” (McPherson, Smith-Lovin, and Cook 2001, p.415) Also, homophily can “flow” in the opposite direction: in addition to “choice homophily,” in which people choose to interact with those who are perceived to be already similar to them, “induced homophily” emerges from influence dynamics that make friends more similar over time (McPherson and Smith-Lovin 1987). Clearly, then, homophily can become self-perpetuating, as people choose friends based on perceived similarity and then

are further influenced by them. In the case of racial segregation, this makes it all the more important for mixed-race encounters to happen early in a student's college career.

1.4 Simulating Campus Racial Diversity

The network of friendships that exists on a college campus is the result of, among other things, the innumerable chance encounters, introductions, impressions, and choices to form relationships that have occurred over many years. It is the product of many generations of different students, the social groups and cliques they have formed and disbanded, the ways they perceived each other when they met, and the ways they have jointly influenced each other afterwards. The formation of a single mixed-race friendship early in a student's career may influence him or her in ways that make it likely to form others, and thus propagate to affect multiple peers and groups. Clearly, no matter how we might choose to measure "segregation," we cannot predict it analytically.

In this paper, we describe an agent-based simulation to model these interrelationships and influences. Software objects, each representing an individual student, possess a set of malleable attributes and also a "race" trait. They encounter each other randomly, decide whether or not to form friendships (using homophily as a key but not decisive factor), influence the attributes of their friends, and dissolve the friendships which are not "refreshed" often enough by additional future encounters. Our goals are to create a useful abstraction for the domain of peer influence on a college campus, to experiment and establish the quantitative effects and boundaries of key parameters, to validate the model against real-world empirical data, and to ascertain the possible effects of certain policies that institutions might choose to enact to encourage racial integration. Our work is still at a preliminary stage, and these goals are only partially realized in this paper.

2 RELATED WORK

The first and most famous agent-based model of racial segregation is of course Thomas Schelling's pioneering work (Schelling 1969), implemented even before computing power was commonly available. Agents living in a grid of housing plots (similar to a cellular automaton, and simulated with coins on paper by Schelling) periodically examine the racial makeup of their neighbors, and decide to move (randomly to a new location in the grid) if the fraction of same-race neighbors falls below a certain threshold. His landmark finding was that even when agents have only very mild preferences to live near "like" neighbors, total segregation of a residential community is likely to result. Schelling's original work has inspired extensions of this general theme that continue to the present day (Laurie and Jaggi 2003, Chen, Irwin, Jayaprakash, and Warren 2005, Collard, Mesmoudi, Ghetiu, and Polack 2013, Pate 2010, Yin 2009, Fossett and Warren 2005, Abbas and Ali 2013, Bischi and Merlone 2011, to name just a few).

Junfu Zhang (2002) strengthened this claim and discovered that even in a model where all agents *desire* to have mixed-race neighbors (rather than simply being willing to tolerate them), total segregation will still occur. This underscores just how inherent the segregation of agents is to complex systems, and suggests that any measures taken to correct it must be drastic. Indeed, as Clark and Fossett state (2008), "mere tolerance and the absence of virulent housing discrimination will not produce integration under the prevailing patterns of ethnic preference, at least not in the short run."

Gretchen Koehler (2001) critiqued the Schelling model's applicability to the university housing problem, observing that empirically, dissatisfied college students do not usually request housing reassignment as the Schelling model would require (Koehler and Skvoretz 2010). Our model accordingly does not involve students transferring from their initially assigned (mixed-race) residential assignment, as described in the next section. Interestingly, Koehler also found through surveys that both white and minority students express a preference for integrated residence halls, although this preference is much stronger for the minorities.

Kathleen Carley's "Construct" system (Carley 1991, Schreiber, Singh, and Carley 2004) was an early, powerful agent-based simulation framework for modeling complex social and behavioral dynamics. It has

been used, among other things, for investigating the effects of homophily on relationship formation and whether or not homophily alone is sufficient to produce the kind of tiered social network seen in practice (Hirshman, St Charles, and Carley 2011). It isn't.

Regarding the social influence of friends upon one another, one important work is Robert Axelrod's agent-based model of cultural diffusion (Axelrod 1997), which incorporates interaction effects between agents' attributes. "... the likelihood that a given cultural feature will spread from one individual (or group) to another depends on how many other features they may already have in common." (p.205) Axelrod's work does not address segregation with respect to a fixed attribute (race), but instead examines the number and nature of stable cultural regions, with some surprising results (for instance, that moderately-sized territories have more distinct stable regions than either larger or smaller ones do). One key difference between this model and ours is that in Axelrod's model, agents only interact with their immediate geographic neighbors, which limits the number of paths through which influence can propagate. In our model, students are not restricted to interacting only on a fixed grid, but instead can form any number of overlapping groups, and indeed meet each other completely randomly with a certain probability. Our aim is to explore how the "messy" structure of social networks plays out in a setting of multiple races and mutual influence.

A more recent model of mutual social influence (Schuhmacher, Ballato, and van Geert 2014) focused on risky vs. conventional behaviors in adolescents, and the ways in which behavioral choices propagated in a social network with both dyadic and group interactions. The authors had great success reproducing stylized facts from the adolescent development literature, confirming that an agent-based approach can indeed capture the key dynamics here. They did not, however, study racial factors or effects.

Ghasem-Aghaee and Oren (2007) give a detailed and principled model of personality attributes and the ways in which they develop over time. Unlike our scheme and those of Axelrod and others (Epstein and Axtell 1996), which assign to agents generic "attributes" as placeholders for unspecified real-world qualities, Ghasem-Aghaee's model is based on contemporary psychology research and simulates specific personality traits such as openness, conscientiousness, and extraversion. Adopting such an approach in future work may help us refine our model to more closely imitate specific personality effects. Ghasem-Aghaee's simulation, however, does not explicitly model the relationships in an evolving social network, as ours does.

We are unaware of attempts to simulate institutional policies regarding race in higher education. Feitosa *et al.* (2011) pursued a similar aim in the domain of urban segregation, and express cautious optimism about their simulator's utility in determining the range of impact of anti-segregation policies.

Other simulations have focused on inter-school segregation, rather than intra-school. Researchers (Stoica and Flache 2014, Millington, Butler, and Hamnett 2014, for instance) have adapted Schelling's model to scenarios in which parents choose the school they will send their children to, in part based on its proximity to their residence, its reputation, and its racial composition. This is very different from our work, which analyzes the social relationships between students of different races within a single institution.

3 THE MODEL

We present the model for the CollegeSim simulation using an abbreviated version of the ODD protocol (Polhill, Parker, Brown, and Grimm 2008, Grimm *et al.* 2008).

3.1 Purpose

CollegeSim is an agent-based model designed to simulate an evolving social network among college students. In addition to their other attributes, Student agents are assigned one of two "races" (white or minority) which factors into their perceived similarity to other agents they encounter, and accordingly to their likelihood of forming friendships with them. The ultimate goal of the model is to investigate how racial segregation – defined as the average proportion of friendships students have with others of the same race – is affected by the strength (importance) of the race trait, the speed with which students adapt their preferences, and the presence or absence of certain institutional policies designed to influence segregation.

3.2 Entities, State Variables and Scales

The model has two kinds of entities: Students and Groups.

Each **Student** agent has the following attributes:

ID A unique ID number.

Race Either “white” or “minority.”

Year An integer from 1 to 4 indicating the Student’s current year in school (freshman, sophomore, junior, and senior). For simplicity the model does not allow larger numbers (“fifth-year seniors”); any Student reaching the end of their 4th year automatically graduates.

Preferences An array (of configurable size) of real numbers (between 0 and 1) representing the student’s abstract preferences. None have fixed interpretations, but as a conceptual example one might consider preference #9 to represent “political persuasion, on a scale from extremely liberal (0) to extremely conservative (1).” Preferences are strictly independent of each other in the sense that a high value for one does not imply a high or low value for any other.

A Student’s preferences (and hobbies; see below) will change throughout the simulation in response to their friends. This is in line with Axelrod’s definition of an agent’s “culture” as “a set of individual attributes that are subject to social influence” (1997).

Hobbies An array (of configurable size) of real numbers (between 0 and 1) representing how much of the student’s time is dedicated to a particular activity. Again, none have fixed interpretations (hobby #17 might be thought of as “the proportion of time the Student spends playing Pokémon”), but they are *not* independent of each other since a greater value for one implies a lesser value for the others. Every time a Student’s hobby value changes, all of that Student’s hobby values are recalibrated proportionately so that they sum to 1.

Friends An array of references to other Student objects with whom it has active relationships. This array will grow and shrink over time as new friendships are formed and “non-refreshed” friendships expire.

Note that Students do not have spatial coordinates; their “position” in the simulation is defined solely by their friendships with each other and their membership in Groups.

Group entities represent the abstract social groups (corresponding to anything from common residential hallways to student clubs to simple informal cliques) that Students form with each other. Groups impact the simulation in two ways: (1) a Group’s members will jointly influence each other’s preference and hobby attributes, and (2) Students interact with those in their groups more often than with the population at large.

Each Group agent has the following attributes:

ID A unique ID number.

IsFixed A logical (boolean) value indicating whether or not the group’s membership is permanently fixed, or whether it can fluctuate over time. This is used to implement certain policies (see below).

RecruitmentFactor A real number (from 0 to 1) indicating how aggressive the group is in attracting new members. (See below for interpretation.)

Members An array of references to the Students who comprise its membership.

There are also two Policies in the model, **OrientationGroups** and **InitialMixedRaceDyads**, which can be separately enabled (see below).

3.3 Process Overview and Scheduling

The simulation progresses according to an idealized academic calendar. Each academic year is comprised of nine academic months (August through April) and three summer months. Student agents and Group agents carry out their actions in each academic month: all students, followed by all groups. Additionally, a high-level controller called “Sim” carries out activities at the start of every academic year (immediately before all Students run in August) and at its end (immediately after all Groups run in April). See the “Submodels” section, below, for details about each step.

1. At the start of each academic year (pre-August):
 - (a) **Sim** – *IncrementYears, AddNewStudents, AddNewGroups*.
2. In each academic month (August through April, inclusive):
 - (a) Each **Student** – *EncounterOthers, AdjustAttributes, DecayFriendships*.
 - (b) Each **Group** – *InfluenceMembers, RecruitStudents, LoseStudents*.
3. At the end of each academic year (post-April):
 - (a) **Sim** – *GraduateStudents*.

3.4 Initialization

When the simulation begins, n_{s_0} Student agents are created with unique **IDs**, with **Year** $\sim [U(1,4)]$ and $\mathbb{P}(\mathbf{Race} = \textit{white}) = p_w$. Each of n_p **Preferences** and n_h **Hobbies** are generated i.i.d. $\sim U(0,1)$, and then the hobbies are normalized so that they sum to 1.

If policy **InitialMixedRaceDyads** is enabled, each Student is also initially provided with n_{d_0} friendships of randomly selected other students of the opposite race.

Also at simulation start (regardless of policy), n_{g_0} Groups are created exactly as described in the *AddNewGroups* submodel, below.

If policy **OrientationGroups** is enabled, n_{f_0} Groups are created with unique **IDs** and with **isFixed** equal to TRUE. Each of these groups \mathcal{G}_k , like those above, is assigned an initial number of students $n_{sg_k} \sim [U(\min_{sg}, \max_{sg})]$. These students are deliberately chosen so that the proportion of minorities is $[n_{sg_k} \cdot f_{minority}]$. The default value of $f_{minority} = 0.5$, considerably higher than $(1 - p_w) = 0.2$, since the purpose of the policy is to expose white students to greater numbers of minorities than they otherwise would encounter.

(All these numerical parameters are configurable. The simulation’s default values for them are $n_{s_0} = 4000$, $p_w = 0.8$, $n_p = 20$, $n_h = 20$, $n_{d_0} = 10$, $n_{g_0} = 200$, $n_{f_0} = 5$, and $f_{minority} = 0.5$.)

3.5 Submodels

IncrementYears Add 1 to the **Year** attribute of every Student still in the simulation.

AddNewStudents Add n_s (default 1000) new Student agents to the simulation with unique **IDs**, with **Year** = 1, and $\mathbb{P}(\mathbf{Race} = \textit{white}) = p_w$. Each of n_p **Preferences** and n_h **Hobbies** are generated i.i.d. $\sim U(0,1)$, and then the hobbies are normalized so that they sum to 1.

AddNewGroups n_g (default 10) Groups are created with unique **IDs** and with **isFixed** equal to FALSE. Each Group \mathcal{G}_k is randomly assigned n_{sg_k} initial students, where $\forall k, 1 \leq k \leq n_g, n_{sg_k} \sim [U(\min_{sg}, \max_{sg})]$. Each Group’s **RecruitmentFactor** is generated $\sim U(0,1)$.

ComputeSimilarity Given two Student agents, compute their perceived similarity as:

$$w_r [|r_1 - r_2|] + w_p \sum_i |p_{1i} - p_{2i}| + w_h \sum_i |h_{1i} - h_{2i}|$$

where w_r , w_p , w_h are weights given to race (default 20), preferences (default 1.5), and hobbies (default 2.5), $[[r_1 = r_2]]$ is 1 if the students have the same race and 0 otherwise, and p_{ki} and h_{ki} are the values of the i th preference and i th hobby, respectively, of student k .

ComputeAffinity Given a Student and a Group, compute the mean similarity between the Student and all individual members of the Group (using submodel *ComputeSimilarity*).

EncounterOthers Choose n_{eg} (default 10) other students at random from the Student’s current Groups, and n_{ep} (default 5) from the population at large. For each one, if the two Students are already friends, “refresh” their friendship. (See *DecayFriendships*, below.) If not, determine the Students’ similarity via the *ComputeSimilarity* submodel, and compute $\mathbb{P}(\text{become friends}) = f_c \cdot \text{similarity} + f_i$, where the default “friendship coefficient” $f_c = 0.22$ and “friendship intercept” $f_i = 0.05$. (The rationale for this transformation is to establish a separate baseline probability range for friendship rather than simply equating the raw 0-1 similarity measure with a probability. Using the similarity directly as a probability would make friendship likelihood unreasonably high for similar Students and unreasonably low for dissimilar.) With this probability, make the two Students friends.

AdjustAttributes For each of a Student’s preferences and hobbies, compute the average value of that preference/hobby for all friends of that Student. Then, with probability p_a (default 0.1), adjust the Student’s attribute towards the mean by d_a (default 0.2) multiplied by the difference between its current value and the mean. (With probability $1 - p_a$, make no such adjustment to that attribute.)

InfluenceMembers Adjust the attribute values for each Student in the Group, using the exact same algorithm as the *AdjustAttributes* submodel except that instead of using the Students’ friends’ mean, use the Group members’ mean.

DecayFriendships Remove the friendship with each of the Student’s friends who has not been “refreshed” (encountered while already friends) in the most recent t_d (default 2) academic months. This “decay threshold” models the maximum time two friends can be apart from one another and still remain friends.

RecruitStudents Choose n_r (default 10) Students from the general population, and compute their *affinity* to this Group via *ComputeAffinity*. For each of the Students who are not already a member of the Group, compute $\mathbb{P}(\text{join group}) = \text{affinity} + \text{RecruitmentFactor} - t_r$, where the “recruitment threshold” is t_r (default 0.6). With this probability have the Student join the Group.

GraduateStudents Remove every Student with **Year**=4 from the simulation.

The simulation proceeds for a fixed number of years n_y (default 20), after which it terminates. Throughout the simulation, text files are produced to capture relevant data each academic month and year.

4 RESULTS

We obtained data for each parameter of interest by running the simulation for ten trials, and capturing the value for each student for every year of the simulation. Often, this was the proportion of that individual’s friends who are minorities, but on occasion we were interested in other variables. We considered only the value corresponding to each student’s senior year. Also, when considering friendship proportions, we omitted the data for students who had zero total friends.

For analysis, we formed two vectors (arrays) of the values of interest, one for white students and one for minority students, concatenating all students of that race from across all trials. The resultant vectors were around 160,000 in length for the white data and around 40,000 in length for the minority data.

To compare the populations, we chose to use the Wilcoxon rank test (as opposed to the more common Student’s t-test) because much of our data is decidedly non-normal. Figure 1 illustrates this fact by using the proportion of minority friendships data as an example. A histogram of all values for one set of ten trials (both white and minority data included) is most closely modeled by the beta distribution instead of a normal distribution. (A Q-Q plot, not shown, gave evidence of non-normality). We use the standard $\alpha = 0.05$ rejection value for p .

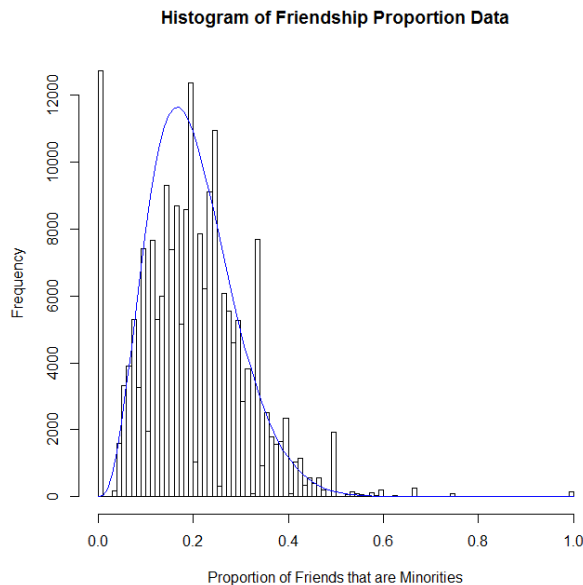


Figure 1: The minority friendship proportion data compared to an ideal Beta($\alpha = 4, \beta = 16$) distribution.

4.1 Simulation Verification

We first consider the average number of friends held by minorities and whites across all years in the simulation to verify that segregation occurs. We see that for any $w_r \neq 0$, minorities had fewer friends on average than whites, regardless of other parameter settings. The following table shows the average number of friends held by each of the two races, with the associated p -value used to determine if the difference is significant.

Table 1: For varying race weights, the average number of friends that white students and minority students have during senior year.

w_r	White students: mean # of friends	Minority students: mean # of friends	p -value
0	15.66	15.73	0.0784
10	15.54	14.15	$< 2.2 \times 10^{-16}$
20	15.49	12.97	$< 2.2 \times 10^{-16}$
100	15.43	7.90	$< 2.2 \times 10^{-16}$

That is, if race matters even slightly to the students in the simulation, then minorities will form fewer relationships. When race is not a factor in friendship formation, the races have an approximately equal average number of friends, as expected. Additionally, the number of friends held by whites does not vary

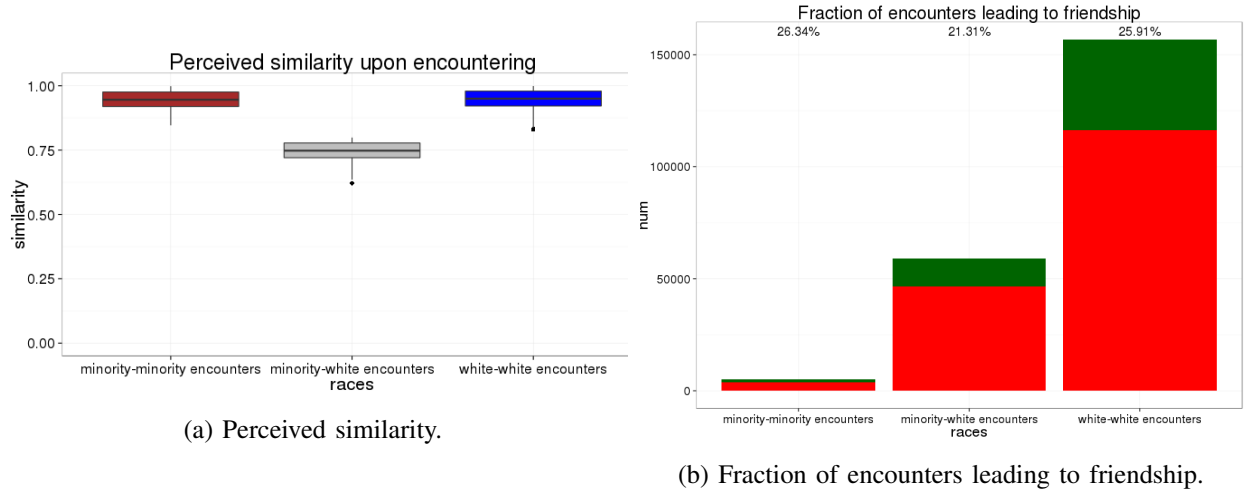


Figure 2: Perceived similarity and encounters for $w_r = 20$.

for varying w_r , indicating that w_r does not directly impact their ability to form and maintain relationships, at least for $p_w = .85$.

For $w_r = 0$, students participating in interracial encounters perceived the same average similarity levels as students involved in same-race encounters, as expected. For higher values of w_r , the homogeneous race interactions had similarity values that remained at approximately the same level. Meanwhile, the perceived similarity of heterogeneous race interactions crept lower.

Because of this, homogeneous encounters resulted in friendship slightly more often (with respect to a percentage) than heterogeneous encounters with $w_r > 0$. As the importance of race increased, the proportion of heterogeneous encounters which resulted in friendship decreased as expected, while the proportion of homogeneous encounters which resulted in friendship stayed approximately the same.

4.2 Discoveries

After preliminary analyses utilizing various graphs, we proceeded to analyze the data in a more concrete manner. For the following observations, we choose to use the proportional friendship data.

First, we consider the impact of the **OrientationGroups** policy. We collected data for several values of w_r , both with the policy enabled and disabled.

We began with n_{f_0} (the number of fixed-membership, intentionally mixed-race orientation groups) set to 5, and $f_{minority}$ (the proportion of minorities in such groups) to 0.5. For $w_r = 0$, **OrientationGroups** did not demonstrate any significant effect on the population (as measured by Wilcoxon rank test), as expected. This policy also did not have an effect at $w_r = 1$ through $w_r = 10$, with the campus still as segregated as before. When w_r was increased to 20, however, the white population did experience a significant change. Finally, for the extreme setting of $w_r = 100$, **OrientationGroups** again had a significant effect on the white data. Interestingly, with double this number of orientation groups ($n_{f_0} = 10$) the policy had a significant effect even for $w_r = 1$.

Note that since the mean is not a sufficient statistic for the beta distribution (the information held in a distribution of this type is not adequately captured by reporting the mean, as it would be for a normal distribution), we do not compare or even report the means here. The alternative hypothesis for the Wilcoxon test is not that the means are equal, as in the Student's t-test, but instead is that the true location shift is not zero. Therefore, two statistically significant vectors may have the same or similar means, but come from two very different beta distributions with differing shape parameters and location shift not equal to zero.

While this may be difficult to interpret within this context, the important conclusion is that the policy has been verified to have a tangible effect on the relationships formed by Students.

For the **InitialMixedRaceDyads** policy we set n_{d_0} (the number of mixed-race friendships each Student begins with) to 10, a value which is relatively high considering the average total number of friendships (see Table 1). At $w_r = 1$, the policy had an effect on both races in the population. When this was repeated for $w_r = 20$, the policy appears to have had no effect. It may be that even at a relatively low value for the importance of race, the policy is already not strong enough to overcome the perceived barrier. We suspect that this in turn may be due to friendship decay: even if students are initialized with mixed-race friendships, those friendships will soon evaporate if not refreshed often enough.

5 CONCLUSION

We have presented a principled model of a college social environment, based on findings from the social psychology literature on friendships, groups, race relations, and campus culture. We have verified the model and demonstrated that the basic effects we hoped to see realized do materialize as expected. We are now in a position to use the simulation to explore the impact of various policies and parameters.

In future analyses, we hope to collect data on more combinations of the parameters. We seek to determine how extreme a policy must be for it to effectively integrate the population for a variety of race weights. Our cursory examination thus far revealed that although both of our policies had a noticeable effect, neither is sufficient to completely overcome segregation. It may be that the parameter settings need to be more extreme, or that we must use the policies in conjunction. It also may be that with a small proportion of minorities in the population the policies are unsatisfactory, but would excel if the number of minorities was marginally increased.

True validation of the model will be challenging, as not all relevant parameters can be ascertained from existing empirical data. For instance, the number of friendships students have with students of the same or different race is largely inaccessible except through surveys. In addition, it will be difficult to find a real-world institution that has implemented policies like **InitialMixedRaceDyads** and **OrientationGroups** and has data for both before and after the implementation. We plan to approach these challenges in creative ways in our future work, to attempt to establish confidence that the model's behavior resembles that of real-world institutions.

[CollegeSim](#) (Davies and Brown 2015a) is open source, and is available for browsing or download. It was written in Java using the MASON agent-based toolkit (Luke, Cioffi-Revilla, Panait, Sullivan, and Balan 2005).

A [web demo](#) (Davies and Brown 2015b) of CollegeSim is available, and we encourage readers to experiment with parameter settings and run the simulation themselves.

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