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## P2\_1 Cultural Segregation on the Sugarscape

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### Abstract

This article investigates a cultural segregation rule in the Sugarscape environment introduced by JM Epstein and R Aktell in “*Growing Artificial Societies*”. Methods for producing segregation, and quantitatively measuring the degree of segregation are discussed, and it is found that these simple rules are effective at producing segregation between 2 or many cultures.

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## P2\_1 Complex Systems

### Introduction

Schelling’s segregation model [1] is a well studied model for the organisation of individuals from a random distribution, to large cultural groups. This article presents an extension on the Sugarscape model presented by JM Epstein and R Aktell [2] to model a similar form of cultural segregation with 2, or many cultures. They begin by describing the Sugarscape as a 50x50 grid of patches. Each patch on the grid is assigned a maximum capacity for sugar. Patches begin following a single rule (G) to grow back sugar to this capacity. The Sugarscape is populated by agents who begin with a single rule (M) to move and eat the sugar. A “tick” is a single time-period on the Sugarscape. Each tick, all agents and patches carry out their rules in a random order and by adding additional simple behavioural rules, the Sugarscape becomes home to a colourful variety of emergent structure and behaviour.

### Model

For this model, the Sugarscape presented by JM Epstein and R Aktell has been constructed in NetLogo. Agents typically obey movement rule M and patches follow grow back rule G.

The next step is to describe the agents’ culture. A simple approach to this is to assign each agent a random integer between 1 and *numCultures* to represent their individual culture. This parameter can be altered to change the number of possible cultures. They are also given the ability to store a short list of agents they consider friends. Agents initially have no knowledge of the culture of other agents. Each tick, agents follow an additional rule, friendship rule F. For each agent in a patch adjacent to the active agent:

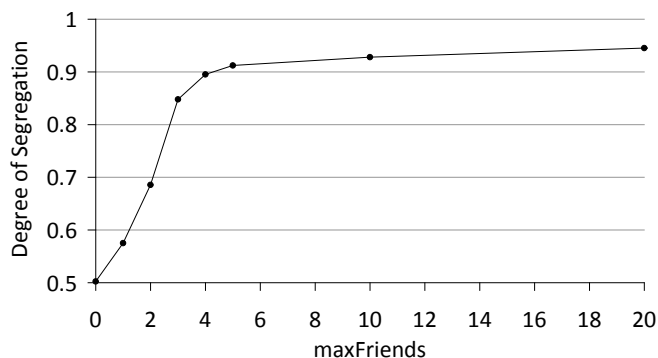
1. Calculate the difference between my culture and the neighbours culture
2. If this result is greater than *tolerance*, stop
3. If the neighbour is not already there, add him to my list of friends
4. If the length of my friends list is greater than *maxFriends*, remove 1 friend at random

Agents create individual lists of culturally similar friends up to a length *maxFriends*. The effect of this is to slightly modify the existing movement rule M. Rather than identifying the richest patches, and moving to the closest one as they would normally, agents identify the richest patches, and move to the patch with the lowest mean distance to the members of their friends list. Although they prioritise gathering sugar over their friends, they show preference for patches closer to their friends.

This article focuses on applying this model on a “flat” landscape, where patches are all uniform (as opposed to the “hills” in the traditional Sugarscape) in the simple case of  $numCultures = 2$  (only 2 possible cultures, as with Schelling’s model) and  $tolerance = 0$  (agents will only befriend culturally identical agents).  $maxFriends$  is varied, and its effect on the overall degree of segregation is measured. The method used to quantitatively define degree of segregation,  $S$ , at each time-step is to take each agent in turn, find the fraction of neighbours with the same culture as the agent and average across the whole population.

$$S = \frac{1}{n} \sum_A \frac{C_a}{N_a}$$

where  $a$  is a member of  $A$ , the set of all agents,  $C_a$  is the number of adjacent agents with the same culture as the agent,  $N_a$  is the total number of neighbouring agents and  $n$  is the total number of agents.



Plot (1) shows how the degree of segregation achieved varies with  $maxFriends$ . Data points are taken by using the mean segregation between 1000 and 2000 ticks. Errors are taken as the variance of segregation during this time period.

As can be seen in (1) by  $maxFriends = 5$ , we have almost reached saturation with a degree of segregation of  $0.91 \pm 0.0001$ , increasing slightly to  $0.95 \pm 0.00002$  with a list length of 80. The character of this graph is interesting, and illustrates a phase transition from generally unorganised agents, to an organised structure around  $maxFriends$  values of 2 and 3, where the increase in segregation achieved increases most rapidly.

This model transfers equally well to a non-uniform landscape producing several different modes of segregation. Additionally, by increasing  $numCultures$ , segregation between many cultures can be seen. The effect of increasing  $tolerance$  is for much more mixing to occur, although agents still tend to cluster with other culturally identical agents to some degree.

### Discussion

The result of this model is interesting, as with each agent only remembering 3 or 4 friends, a large degree of segregation can be seen with clusters of hundreds of agents. The length of the friends list acts as a binding force. Smaller lists produce a more dynamic population with more mixing between cultures. Clusters move, divide and join constantly, while longer lists produce a more static population distribution.

### Conclusion

This method of segregation has been successful in creating a form of cultural segregation *from the bottom up*. From a short list of personal friends, agents cluster into large and often spatially distinct groups. This has potential to create some interesting effects on the Sugarscape. For example, we would expect a culture occupying rich sugar regions to have a *comparative advantage* over other cultures due to the low mixing.

### References

- [1] T Schelling, *Micromotives and Macrobehavior* (W. W. Norton, 1978)
- [2] JM Epstein and R Aktell, *Growing Artificial Societies* (MIT Press, 1996)