Brains Vs. Brawn – Comparative Strategies For The Calibration Of A Cellular Automata – Based Urban Growth Model

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Biography

PhD candidate, UCSB Department of Geography, 2001-Present; MA in Geography, UCSB Dept. Of Geography, 2000; Research interests in GIS, temporal urban mapping, and evolutionary computing, published in journals including Computers, Environment and Urban Systems, and Conservation Biology.

Introduction

The use of evolutionary computation has been increasingly incorporated into computational spatial modeling, and urban modeling is no exception (Openshaw and Openshaw 1997). Evolutionary computing has been mostly visible with the use of Cellular Automata (CA) and Neural Networks that simulate patterns of urban growth on a landscape. The SLEUTH urban growth model is a CA-based urban change model that simulates urban growth according to a calibrated set of parameters (Clarke et al, 1997). The following work compares two methods of calibration. The first, "Brute Force" (BF) method uses a predetermined order of stepping through the "calibration space". The second method, to be fully introduced here, uses a Genetic Algorithm (GA) to search thought the coefficient space in an adaptive manner. This work compares the computational speed and modeled accuracy of the two methods, using the city of Sioux Falls, South Dakota (US) as a testbed. Our results show that the GA method of calibration is superior to the BF method, because of improved model fits, as well as superior computational needs.

Background On Sleuth

The SLEUTH urban growth model is a CA-based model of urban and land use change. To date, it has been successfully applied to a variety of international urban regions including San Francisco, Porto and Lisbon, Portugal, and Porto Alegre City, Brazil and many others (Clarke et al, 1997, Silva and Clarke, 2002, Leao et al, 2001, Gigalopolis 2003). SLEUTH models urban change with four forms of growth: Spontaneous Growth, New Spreading Centers Establishment, Edge Growth, and Road-Influenced Growth. Five coefficients are used to parameterize the four growth forms. In the calibration process, historical urban data is used to determine the best coefficient set that captures the “flavor” of that cities’ growth. The five coefficients, called Dispersion, Breed, Spread, Slope, and Road Gravity, can vary between 1 and 100, allowing for 100^5 or 10^{10} possible unique coefficient set. An example for one coefficient set is {Dispersion = 10, Breed = 22, Spread = 75, Slope = 45, and Road Gravity = 3}, or {10-22-75-45-3}.

To date, the recommended method of coefficient calibration is the “Brute Force” method, which steps through the calibration space in large, and then increasingly smaller steps. The first step, Coarse Calibration, takes steps of 25 through the calibration space, for all coefficients. The second, Medium Calibration, takes steps of 5 and the third, Fine Calibration, takes steps of 1 through the calibration space. For an example of a BF calibration run, see the box below. It should be noted that the BF method tests all combinations of the coefficients at that resolution. The BF method is efficient in searching through the coefficient space in a complete, regular, and reproducible manner. However, it has two major shortcomings. The first is that it is computationally expensive. It takes 9,375 (3125 x 3) runs of SLEUTH in calibration mode for just one dataset. While this now can happen on parallel computing platforms, it is still a time and computationally expensive process. The second shortcoming is that due to non-linearity in the model for coefficient combinations, the BF method may get trapped in a local maximum, missing the optimal coefficient set at a global maximum. As seen in the example below in the Coarse calibration, one of the three best calibration sets {75 - 75 - 75 - 75 - 75} is very different from the other two. This set, though potentially closer to the global optima, will be in essence discarded in favor of the more popular {25 - 25 - 25 - 25 - *} sets.

Example of Brute Force Calibration

Coarse steps of 25 over all the coefficient space [0 to 100]

15 Sample chromosomes of 3125 (5^5):		
{0 - 0 - 0 - 0 - 0}	{25 - 25 - 25 - 25 - 0}	{0 - 0 - 75 - 0 - 0}
{25 - 0 - 0 - 0 - 0}	{25 - 25 - 25 - 25 - 25}*	{25 - 25 - 75 - 25 - 25}
{50 - 0 - 0 - 0 - 0}	{25 - 25 - 25 - 25 - 50}	{50 - 50 - 75 - 50 - 50}
{75 - 0 - 0 - 0 - 0}	{25 - 25 - 25 - 25 - 75}*	{75 - 75 - 75 - 75 - 75}*
{100 - 0 - 0 - 0 - 0}	{25 - 25 - 25 - 25 - 100}	{100 - 100 - 75 - 100 - 100}

*Indicates the top three coefficient sets

Medium steps of 5 “around” top performers [range of 20 for each coefficient]

15 Sample chromosomes of 3125 (5^5):		
{15 - 15 - 15 - 15 - 75}	{25 - 25 - 25 - 25 - 65}	{25 - 15 - 15 - 25 – 75}*
{20 – 15 - 15 - 15 - 75}	{25 - 25 - 25 - 25 – 70}*	{25 - 20 – 20 – 25 – 75}
{25 –15 - 15 - 15 - 75}	{25 - 25 - 25 - 25 - 75}	{25 – 20 - 15 – 25 – 75}
{30 -15 - 15 - 15 - 75}*	{25 - 25 - 25 - 25 – 80}	{25 - 15 – 20 – 25 – 75}
{35 - 15 - 15 - 15 - 75}	{25 - 25 - 25 - 25 - 85}	{25 - 15 - 25 – 25 – 75}

*Indicates the top three coefficient sets

Fine steps of 1 “around” top performers [range of 5 for each coefficient]

15 Sample chromosomes of 3125 (5^5):		
{30 –13 - 15 - 15 - 75}	{30 –13 - 15 - 15 - 75}	{28 -15 - 15 – 13 – 73}

{30 –14 - 15 - 15 - 75}	{30 –14 - 15 - 15 - 75}	{29 -15 - 15 – 14 – 74}
{30 –15 - 15 - 15 - 75}	{31 –15 - 15 - 15 - 75}	{30 -15 – 14 – 14 – 75}
{30 –16 - 15 - 15 - 75}	{30 –16 - 15 - 15 - 75}	{31 -15 - 14 – 14 – 76}
{30 –17 - 15 - 15 - 75}	{30 –17 - 15 - 15 - 75}	{32 -15 - 14 – 15 - 77}

As an alternative, the GA method of SLEUTH calibration provides some benefits and improvements on the BF method. The GA method uses the standard routines of genetic programming, namely: Choosing Population 1, Evaluation of Population 1, Selection of members of Population 1 with best fitness, Breeding of chosen Population 1 members using crossover and mutation, thereby creating Population 2. In SLEUTH calibration, this means allowing well-performing coefficients sets to be used as the progenitors of new coefficient sets, searching the coefficient space in a very different manner from BF calibration. For an example of 2 generations of coefficient sets using the GA method of calibration, see the table below.

Genetic Algorithm Example:

2 Generations, Population of 8

Generation 1 – Seed

ID	Coefficient description	Coefficients	Score (out of 100)
P1-1	Predetermined	1-1-1-1-1	8
P1-2	Predetermined	25-25-25-25-25	7
P1-3	Predetermined	75-75-75-75-75	30 * 2nd Best
P1-4	Predetermined	100-100-100-100-100	21
P1-5	Random	35-42-21-9-0	33 ** Best
P1-6	Random	6-48-2-52-55	17
P1-7	Random	38-89-62-48-3	8
P1-8	Random	83-34-43-90-5	22

Generation 2 -

ID	Coefficient description	Coefficients	Score (out of 100)
P2-1	Cross of P1-3 & P1-5	35-42-75-75-75	5
P2-2	Cross of P1-3 & P1-5	75-75-75-75-0	30
P2-3	Cross of P1-3 & P1-5	75-75-21-9-0	18
P2-4	Cross of P1-3 & P1-5	35-42-21-75-75	36 ** Best
P2-5	Mutation of P2-1	35-42-**5**-75-75	8
P2-6	Mutation of P2-2	75-**33**-75-75-0	17
P2-7	Mutation of P2-3	75-75-21-9-**55**	31 * 2nd Best
P2-8	Mutation of P2-4	**34**-42-21-75-75	22

Bold coefficients indicate point mutations

Results

The GA method of SLEUTH calibration is much less computationally expensive, as 20 generations of 20 coefficients is only 400 runs and obtains a better fit that an entire BF calibration run. In this paper we describe further the metric of fit, which is comprised of the product of three spatial metrics; number of urban pixels, number of urban clusters, and the Lee-Sallee index (Lee and Sallee, 1970). We find that calibrating SLEUTH using the

GA method provides a better fitting urban model for urban growth prediction. In addition, we provide a discussion on the use of evolutionary computation in urban modeling, specifically its pitfalls and potential benefits. In spatial urban modeling there has been little attention paid to the calibration of model parameters and their import. We speculate on why this is, noting the challenges of urban modelers and audiences for their models.

References

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