

A “BLACK BOX-TINKERING” PEDAGOGY: USING LEARNING OBJECTS IN TEACHING MATHEMATICAL MODELS IN ANTHROPOLOGY/SOCIAL SCIENCES

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The paper introduces the basics of the multilevel selection theory of David Sloan Wilson from the perspective of pedagogy. It endorses a simple approach in teaching mathematical models to anthropology students, which is through the “black box-tinkering” approach using an interactive learning material (ILM) that we have developed for the topic. The core of the theory of multilevel selection, used in both anthropology and evolutionary biology, involves the use of algebraic equations in formalizing a simplified population model of two types of behaviors/phenotypes (labeled “altruists” and “selfish”), predicting their generational frequencies when selectional forces operate, and, more importantly, investigating possible pattern differences of selectional forces operating at the individual and group levels. Teaching-wise, the repeated computations needed to illustrate the numerical results are time-consuming, tedious, and divert class-time from directly going into the core of the theory’s arguments. Using a simple *Microsoft Excel*-based ILM, we illustrate the principle of learning by tinkering in the use of ILMs. Only after student-users have seen patterns from input-output tinkering will the model’s transformation rules (the equations) be conceptually unpacked for the explication of its assumptions, limits and logic. The pedagogical challenge, addressed here by the presented ILM, is in maximizing the use of the key equations while bypassing the tedious crunching of numbers by manual computations. While quite simple, we believe that this pedagogical approach in teaching mathematical models to anthropology students highlight the challenge of designing ILMs that widen the user’s tinkering and programming latitude. The challenge to ILM-developers and anthropology teachers is how to translate into ILMs (with expanded tinker-features) the growing number of anthropological theories using complex mathematical models.

Keywords

Multilevel selection, mathematical models, Interactive Learning Material, pedagogy, anthropology/social sciences

In the most fundamental sense, we, as learners, are all *bricoleurs*.
[Seymour Papert]

What is the best approach in teaching mathematical models to anthropology/social science students? Why even teach such at all? Why make formal mathematical models in anthropological theorizing? The last two questions deserve a separate paper for itself. But assuming the importance of formal modeling in anthropology/social sciences, we present here one possible approach in handling such kind of models. We will focus on one specific topic, the multilevel selection theory (Wilson, 1989, 1998; see also Gould, 2002), as an example of a simple mathematical model illustrating our “black-box tinkering” approach. In the process, we hope (1) to illustrate the pedagogical style that could guide other ILM-construction concepts, and (2) to introduce the basics of the multilevel selection model using the ILM we have constructed.

What is the theory about?

The theory is situated in the long argument within evolutionary biology as to the “unit/s” of which the forces of natural selection are acting upon: more specific, on whether or not it is meaningful to talk of “group adaptation” as a result of “group selection,” and not only of individual selections. Assuming that a population of existing variants, with mechanisms for reproduction, would logically result in differing reproductive successes (the core concept of “natural selection”), how does one know whether a certain observed adaptive feature is a result of individual- or group-level selectional processes? The multilevel model presents a method to deal with the question: It partitions the analytical steps into within-group and between-group selectional dynamics so as to know when to say that group-selection is going on.

The core of the theory of multilevel selection involves the use of algebraic equations in modeling selectional forces acting on two posited phenotypic-genotypic types, labeled the “altruists” and the “selfish” types. (Wilson [1998] presented a more elaborate extension of the model to handle situations wherein phenotypic types are not assumed to directly connect with genotypic variations.) What will happen to the proportion of these types after repeated selections? Are the patterns the same at all levels: that is to say, are the forces acting at the level of individual-to-individual interactions the same as the forces acting at the group-level interactions? The set of equations are fed varying combinations of values to get some illustrative results.

Here are the five key equations used by Wilson (1989):

$$W_A = X - c + b \frac{Np - 1}{N - 1} \quad [1]$$

[2]

$$N' = N[pW_A + (1 - p)W_S] \quad [3]$$

$$p' = \frac{NpW_A}{N'} \quad [4]$$

$$P' = \frac{N_1' p_1' + N_2' p_2'}{N_1' + N_2'} \quad [5]$$

Where:

N	initial population
p	proportion of A-type individuals
1-p	proportion of S-type individuals
X	number of offspring in the absence of altruistic behavior
b	additional number of offspring due to altruism
c	loss due to altruism
W_A	fitness of A-individual (average number of offspring per A-individual)
W_S	fitness of S-individual (average number of offspring per S-individual)
N'	total population at the second generation
p'	the proportion of A-type individuals at the second generation
P'	the global proportion of A-type individuals at the second generation

And below are our modifications of above equations to handle multiple groups and multiple generations:

$$W_{A,i}^{(t)} = X - c + b \frac{N_i^{(t)} p_i^{(t)} - 1}{N_i^{(t)} - 1} \quad [6]$$

[7]

$$N_i^{(t+1)} = N_i^{(t)} (p_i^{(t)} W_{A,i}^{(t)} + (1 - p_i^{(t)}) W_{S,i}^{(t)}) \quad [8]$$

$$p_i^{(t+1)} = \frac{N_i^{(t)} p_i^{(t)} W_{A,i}^{(t)}}{N_i^{(t+1)}} \quad [9]$$

$$P^{(t+1)} = \frac{N_1^{(t+1)} p_1^{(t+1)} + N_2^{(t+1)} p_2^{(t+1)} + \dots + N_k^{(t+1)} p_k^{(t+1)}}{N_1^{(t+1)} + N_2^{(t+1)} + \dots + N_k^{(t+1)}} \quad [10]$$

for $i = 1, 2, \dots, k$ and $t = 1, 2, \dots$

Where:

X number of offspring in the absence of altruistic behavior

B additional number of offspring due to altruism

c loss due to altruism

$N_i^{(t)}$ population of group i at generation t

$p_i^{(t)}$ proportion of A-type individuals in group i at generation t

$1 - p_i^{(t)}$ proportion of S-type individuals in group i at generation t

$W_{A,i}^{(t)}$ fitness of A-individual in group i at generation t
(average number of offspring per A-individual in group i at generation t)

$W_{S,i}^{(t)}$ fitness of S-individual in group i at generation t
(average number of offspring per S-individual in group i at generation t)

$N_i^{(t+1)}$ population of group i at generation $t+1$

$P_i^{(t+1)}$ the global proportion of A-type individuals at generation $t+1$

Where ILMs are crucial

Teaching-wise, these repeated computations, done by either chalkboard works or paper seatwork for students, are time-consuming, tedious, and diverts class-time from directly going into the core of the theory's arguments. Performing twice or thrice the numerical computations give the students a needed "feel for the equations," but repeatedly doing it to look for illustrative patterns does not anymore add 1-bit of understanding, aside from punishing students by doing boring computations. Such task must be assigned to automatic processes of ILMs.

The pedagogical challenge, therefore, is to maximize the use of the key equations but to escape the tedious crunching of numbers by manual computations. This is where the use of ILM is crucial, if not a necessity. Using a simple *Microsoft Excel*-based Multilevel Selection-ILM (MS-ILM),¹ which programs iteratively the Wilson equations, both the instructor and the students could maximize time in deriving important principles from the model’s equations. The Screen Shots Section at the end of this paper (Screen Shot [7]) provides the assumptions and notations of the above equations [1]-[5].

As given in equations [6] to [10], the MS-ILM expands the number of groups (from the two groups of Wilson’s article to four) and levels (from two to three) and allows iteration into the 5th generation/selectional time (only 1st and 2nd generation in Wilson’s). In this way, students observe more patterns (e.g., downward frequency of altruists in the 1st selection recovers on the succeeding cycles, showing the importance of observing long-term trends) than given in the article of Wilson’s.

Tinker with the “black box”

The educational theorist Seymour Papert (1980), who pioneered the interactive use of computers in educational context, emphasizes the importance of tinkering and programming in computer-assisted instructional tools. Working within the limits of the specific learning objectives we set here (that is, to explicate the key ideas of multilevel selection), we believe we are working within the same principles advocated by Papert.

The MS-ILM has two kinds of input boxes (see Screen Shot [1] and [3]) that the user can interact with by putting different values and observing the resulting output in tables and plots. By taking a “black box” approach in teaching the model, student-users are given an ILM tool to tinker with and to observe the transformative powers of equations when fed with differing values: letting them observe input patterns shape output results. Only later, as a result of the observed patterns (is simple presence of variations driving

¹The interactive learning material (ILM) presented in the paper is part of the working models for the UP-funded *Game Theory Learning Objects* that Dr. Norberto R. Navarrete (Department of Mathematics and Computer Sciences, CSM) and the present author are working on. We are also in the process of improving our model for Extended Hawk-Dove Games ILM and in the preliminary conceptualization-design of other game models (e.g., Coordination Game ILM used by the anthropologist J. Stephen Lansing [2005] in the Balinese agricultural system context). As draft materials, they can readily be requested for copying; each worksheet in the materials, however, is password-protected to shield the embedded functions. Comments for these materials, philosophical/pedagogical-wise, are welcome.

some values or is it the degree of variations?; how will variations of group characteristics interact with population size in shaping outcomes?, etc.), are students made to “open the black box” and made to understand the equations: how they are constructed (algebra as both a descriptive and analytical language), the underlying assumptions, and the limits/potentials of formalized models.

Feeling the math

In my [MJP] own experience of teaching the model, through an assigned reading of Wilson’s article (1989), I found out that anthropology students think it more “fun” if they are just made to see differing results through their own tinkering with varied values for each of the given parameters in the MS-ILM. There seems to be “magic” in the hidden mathematical equations and the way it generates non-intuitive results (the second level values “went up” while those of the first level groups “went down” (Screen Shots [1] and [4]). Then, once they “get used to” the outcome predicted by the model or they discover some patterns (e.g., variance between groups is a major factor in driving up the p at the group level) they could then move on to inquire about the equations underlying the ILM, and the class can then proceed to making sense of the model in real-world terms. This is where the instructor enters with the traditional discursive explication of the model’s logic. I also gave assignments, before letting them use the MS-ILM, for students to do the manual solving for some givens (two, three groups; varied values for each students for [N], [X], [b], [c]) to have them a feel for the mathematics of the model. As a by-product, the MS-ILM, like a calculator, is also handy in checking their papers.

The point of “doing math,” by minimal traditional manual computation steps and by maximal use of mediating ILMs, is to “feel the game” of mathematical modeling and to have the cognitive experience of the transformative process acted by the equations. One then does not simply discuss the resulting conceptual results of the theory’s math, which can be done by verbal ways, but discuss the meaning of the equations lying at the theory’s core. This elementary exercise is important in view of the long-term goal of this style of analytic method: to learn the skill of constructing the equations themselves as a modeling language.

While quite simple and very elementary, we believe that the presented concept in teaching mathematical model to anthropology students highlight the pedagogical challenge of constructing ILMs that widen the user’s tinkering and programming latitude. By taking advantage of programmable softwares, the challenge to ILM-developers and anthropology teachers is how to translate into Papert-inspired ILMs (one with expanded tinker-

features) the growing number of anthropological and behavioral theories and models using formal mathematical approaches (aside from DS Wilson's, see the works of, and relevant references in, Boyd and Richerson, 1985; also, Dugatkin and Reeve, 1998, and cited references therein; and Lansing, 2005, and cited references).

Pidgin for interdisciplinary transactions

Whether or not the anthropology teacher's philosophy is appreciative of formal mathematical modeling directions, it is imperative for the instructor to expose our students to a sample of this kind in the field. Learning mathematical modeling is a language that we, and our students, could use as one pathway in interdisciplinary transactions with the diverse evolutionary and biological sciences. In this mode of knowing, our theoretical, methodological and analytical toolkit would be greatly expanded.

References

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Screen shots

[1]

Microsoft Excel - Multifactorial selection - Version 4.0

File Edit View Insert Format Tools Data Window Help

And - 10 -

AI Group 1

Scenario		Percentage		Direction
Levels [L3[L2[L1]]]		p	p'	p-p'
3	L3 [L2a+L2b]	50.00%	50.17%	↑ Increasing p
2	L2a [L1a+L1b]	40.00%	37.29%	↓
	L2b [L1a+L1b]	60.00%	68.83%	↑ Increasing p
1	L1a	10.00%	8.28%	↓
	L1b	70.00%	67.25%	↓
	L1c	40.00%	34.05%	↓
	L1d	80.00%	77.22%	↓

Input Box

(Rule: N>1; X=0, b>0, c=0, 0<=p<1)

	Groups			
	1a	1b	1c	1d
N	300	200	100	300
p	0.1	0.7	0.4	0.6
X	5	7	3	5
b	4	2	4	2
c	1	1	1	1

See a Simple World Example

Assumptions Equations Tinker Tinker and Iterate p vs 1-p (Local) Iterated Gabriel p vs 1-p (Go)

Draw AutoShapes

Ready

[2]

Microsoft Excel - Multilevel Selection, Version 3.0

File Edit View Insert Format Tools Data Window Help

Type a question for help

Arial 10

Table 1a

	D	E	F	G	H	I	J	K	L	M	N
82											
83											
84											
85											
86											
87											
88											
89											
90											
91											
92											
93											
94											
95											
96											
97											
98											
99											
100											
101											
102											
103											
104											

To Tinker

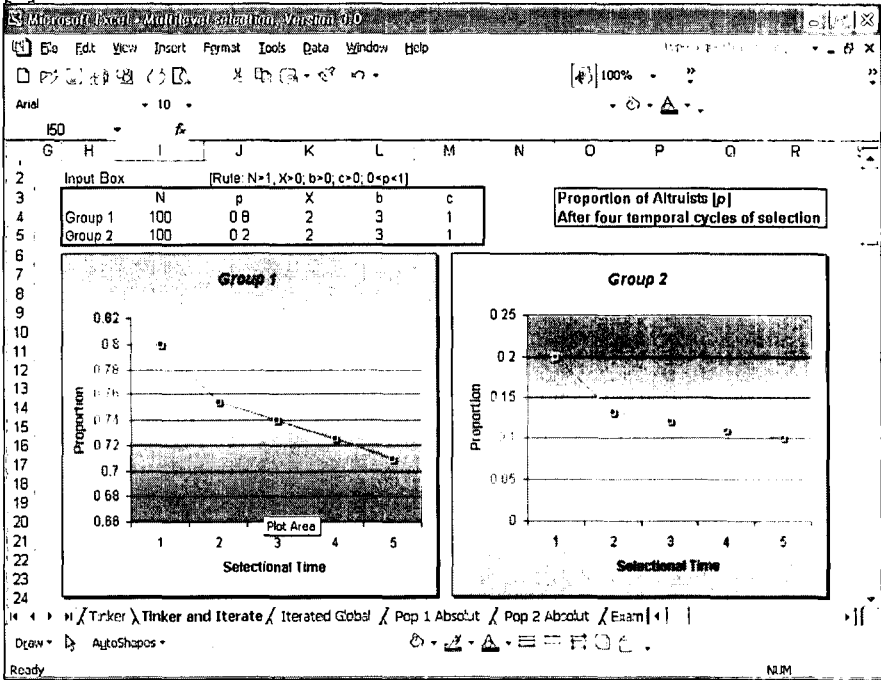
Hypothetical Scenario		Bansa				Initial N	
Check inputs for this scenario		Banwa I		Banwa II		(Individuals)	
		Lumad 1	Lumad 2	Lumad 3	Lumad 4	Total	
Level 1	Ethnic/kin formations (Within Ethnos)	4	300	200	250	500	1250
Level 2	Bioregional/multi-ethnic formations	2		500		750	1250
Level 3	Supra-bioreg (Across Bioregions)	1			1250		1250

Percentage of p [representing A-types]	From		To		p → p'
	Bansa	50.00%	Bansa	57.03%	
At the upper-level dynamics, A-types are favored in Banwa II but not in Banwa I.	Banwa I	39.50%	Banwa I	36.75%	↓
	Banwa II	60.50%	Banwa II	63.56%	↑ Increasing p
Even as, at the lower-level dynamics, A-types are always dis-favored.	Lumad 1	10.00%	Lumad 1	8.28%	↓
	Lumad 2	69.00%	Lumad 2	66.19%	↓
	Lumad 3	45.00%	Lumad 3	41.09%	↓
	Lumad 4	76.00%	Lumad 4	74.59%	↓

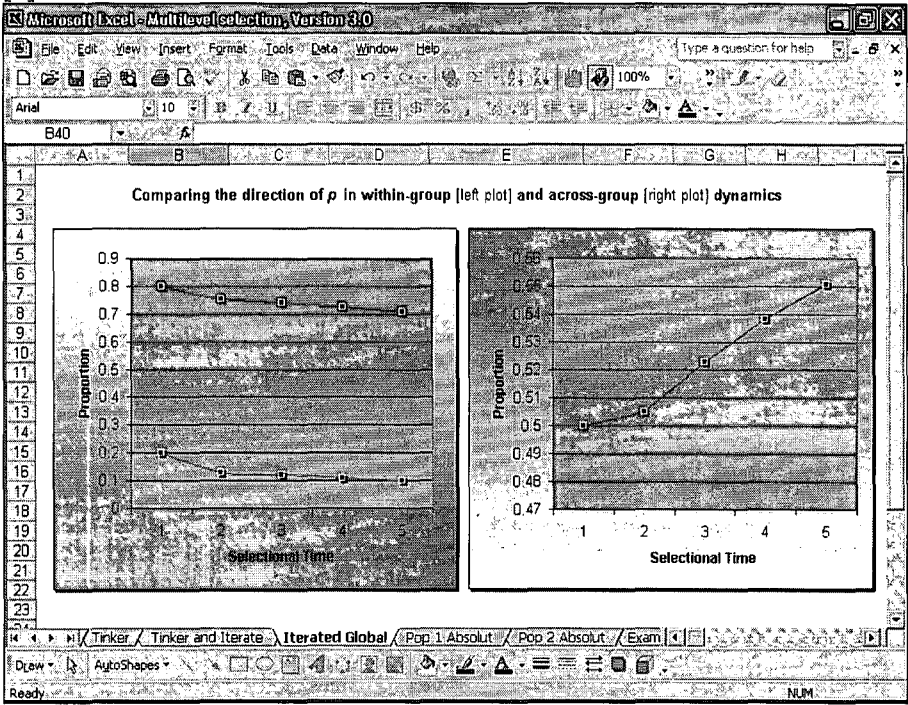
p vs 1-p (Local) /
 Iterated Global /
 p vs 1-p (Global) /
 Pop 1 Absolut /
 Pop 2 Absolut /
 Example /
 Banwa I

Ready NUM

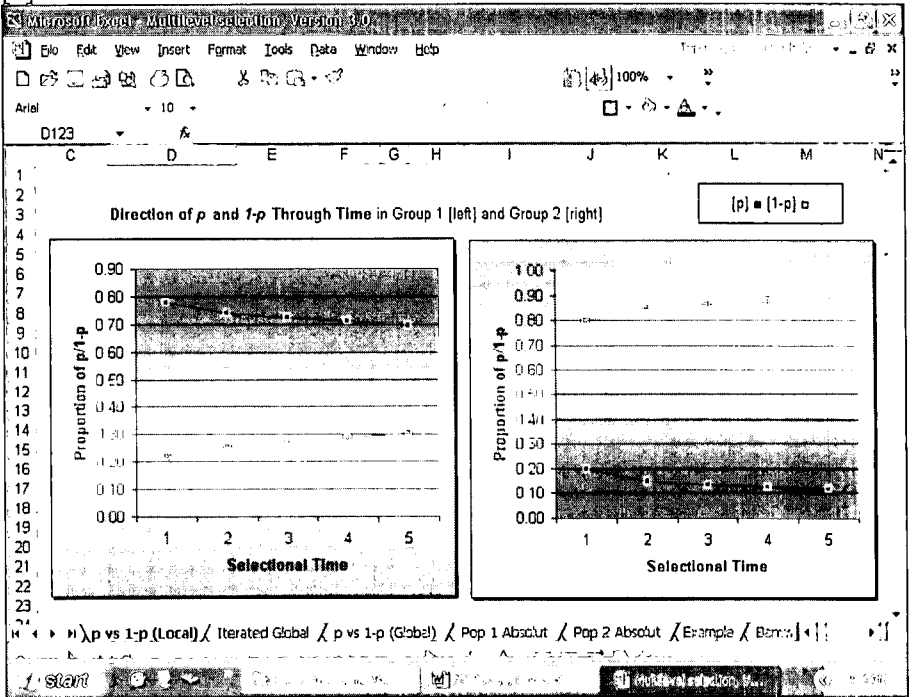
3



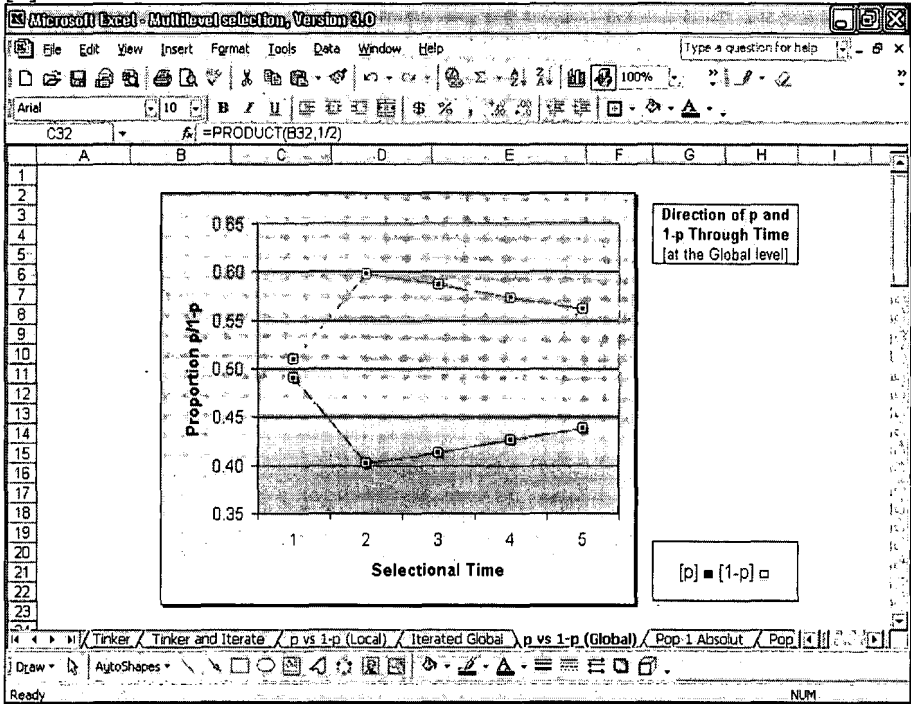
[4]



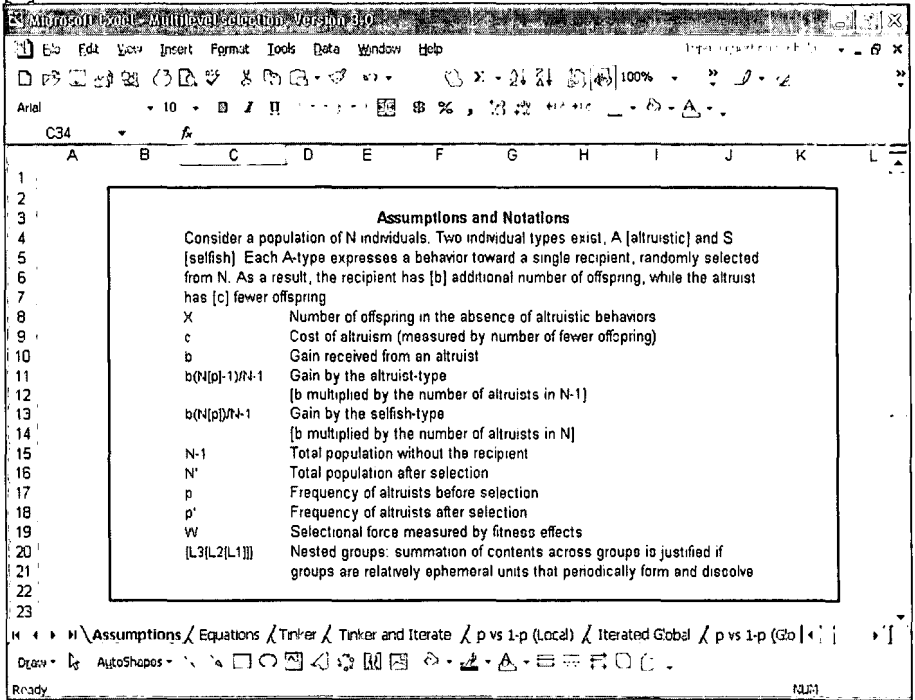
5



6



[7]



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