Virtual Experiments

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Overview

- Virtual Experiments Overview
- Variables and Methods
- Examples

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Virtual Experiments

- Virtual Experiments
  - Test a model, not reality
  - Model should be as close to reality as possible
  - "All models are wrong, but some are useful" - George EP Box
  - Good for testing assumptions
  - Good for what-if analysis
  - Good for generating hypotheses

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Why Virtual Experiments?

- Real Experiments
  - Expensive - (Spaceship launches)
  - Unethical - (What if spray poison gas on Pittsburgh?)
  - Infeasible - (Bridge hold up if 500 concrete trucks on it?)

- Don't use Virtual Experiments:
  - When you're looking for 'truths' and not 'trends'
  - When you can get what you want from a survey

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Cost of Virtual Experiments

- Virtual Experiments can be expensive!
  - Buy data
  - Buy software
  - Buy computing power
  - Cost of coding the model, maintaining the code
  - Human Resources

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Virtual Experiment Design

Many of the same problems and challenges of real experiments!

- Dependent Variables
- Independent Variables
- Method of experiment
- Control Conditions
- Generality
- Power

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Independent Variables

- What am I changing run to run?
- How many different independent variables?
- **BE CAREFUL!**
  - **Too many combinations can be difficult to interpret**
  - **Too many combinations could take time, ie - years, to complete the simulation**

Dependent Variables

- What am I measuring?
- What does this imply in the real world?
- Is the independent variable manipulation *believable*, as it relates to the dependent variable?
- Usually best narrow down the dependent variables to just a few

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Method

- Most of the "method" is - explaining the control variables, and how the independent variables are manipulated
- Strategies for manipulation of independent variables
  - Set them to create a baseline
  - Set them to show when there is no impact
  - Set them to show best/worst case
  - Set them randomly across an appropriate distribution
- **Has anyone done virtual experiments?**

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Control Conditions

- Control Conditions, often, are independent variables that are not changing, or changing in a controlled manner
- EG - In network topologies, ER Random networks are often used as control conditions
- EG - Holding a temperature constant in climate models
- EG - Holding Windows server vulnerability growth rate within a distribution between 1 - 3% in cyber security models

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Generality

- Defining model parameters can become very specific
  - Best to draw from literature when possible!
- EG - Examining network information flow after actor removal
  - Bad example
    - Case 1: Remove Gordon
    - Case 2: Remove Jill
    - Case 3: Remove Pat
  - Good example
    - Case 1: Remove Actor with highest degree centrality
    - Case 2: Remove Actor with highest betweenness centrality
    - Case 3: Remove Actor with highest eigenvector centrality

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Power

- Given enough repetitions, even trivial differences between simulation conditions will produce statistically significant results.
- It's important to focus on trends, rather than specific values.
  - Wrong: Because of the manipulation condition, Y increases by 5%.
  - Better: Y tends to increase under the manipulation condition.
- A reasonable heuristic is 25 repetitions per combination

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Example 1

How does varying the degree of ethnocentrism in an artificial society affects the formation of social relationships across social groups under different models of the underlying cultural structure?

Joseph, K., Morgan, G. P., Martin, M. K., & Carley, K. M. (2013). On the Coevolution of Stereotype, Culture, and Social Relationships: An Agent-Based Model. *Social Science Computer Review*.

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Virtual Experiment

Parameters	Values Taken
Parameters of Interest	
Initial knowledge distribution	random, group based, all same
Initial Bias Parameter (IBP)	0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1
Other Parameters Varied	
Group Activation Threshold (GAT)	-5, -1
Group Learning parameter (GLP)	5, 25, 50
Individual Activation Threshold (IAT)	-1, 0
Constants	
Number of Simulation Turns	150
Number of Agents	1000
Number of Knowledge Bits	500
Number of Interactions	2
Number of Knowledge bits passed per interaction	1
Density of knowledge (percent of bits set to 1)	0.4
Decategorization Parameter (DP)	6
Groups Per Agent	1
Total number of groups	4
Repetitions	
Number of repetitions	10
Total Runs	3*11*2*3*2*10 = 3960

Analyzing the results

- Run the simulation
- Construct a network of who talked to who more than N (N=2 here) times
- Look at the *log-odds* of a tie to a member of the outgroup

$$log_2\left(\frac{\#relations\ connecting\ two\ agents\ in\ different\ groups + 1}{\#relations\ connecting\ two\ agents\ in\ the\ same\ group + 1}\right)$$

Results from VE

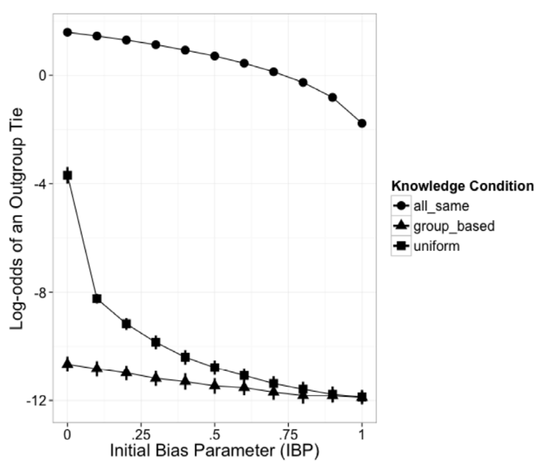

Figure 4- The x-axis represents the ten different IBP conditions and the three different shapes of points represent knowledge conditions. The y-axis gives the log-odds of an out-group tie, and lines connect the mean outcomes across the different conditions. Ninety-five percent (95%) bootstrapped confidence intervals are drawn at each IBP condition.

<Your Name>

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Results from VE

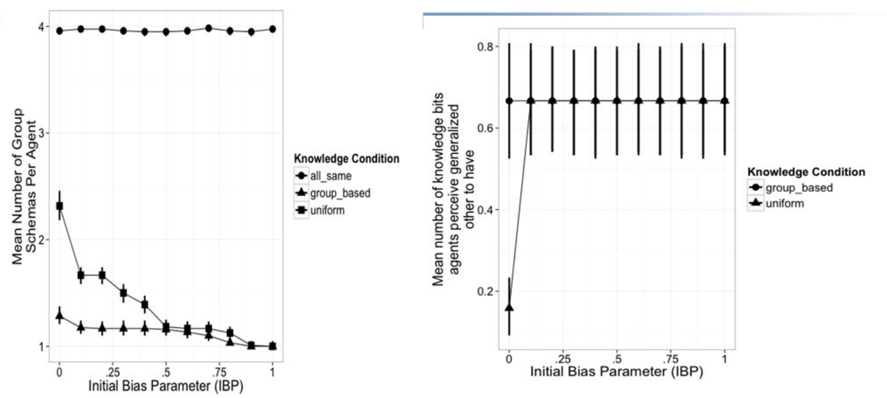

Figure 5a) The mean number of group schemas that agents held across all conditions. 5b) The mean number of knowledge bits that the generalized other schema had set to 1 across all agents in the group based and uniform knowledge conditions only. Error bars are 95% bootstrapped confidence intervals

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Results from VE

Our findings suggest two broad claims of sociological interest in the context of interventions promoting intergroup relations. First, we show that when cultural structure aligns with group structure, interventions aimed at altering social stereotypes alone will fail; rather, it is necessary to take aim at the dynamic, cultural forms within the society. In contrast, when a unifying cultural form (such as nationalism) already exists but is muted by ethnocentrism (e.g., via race), simply increasing the spread of cultural forms between groups is not always enough to mitigate ethnocentric stereotypes. Instead, intergroup relationships can only be built via the breakdown of ethnocentric stereotypes. Future work hopes to solidify these findings and to provide a stronger connection to similar empirical threads of research in the social psychology literature, most notably those stemming from contact theory (Allport, 1979).

Conclusions from VE

- Results suggested that neither stereotypes nor the form of underlying cultural structures alone are sufficient to explain the extent of social relationships across social groups
- Rather, we provide evidence that shared culture, social relations and group stereotypes all intermingle to produce macro-social structure.

Example 2

How many cyber forces should we deploy to minimize the effect of a routing protocol attack (RPA)?

Dobson, G. B., & Carley, K. M. (2017, July). Cyber-FIT: An Agent-Based Modelling Approach to Simulating Cyber Warfare. In International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction and Behavior Representation in Modeling and Simulation (pp. 139-148). Springer, Cham.

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Example 2

Independent Variables		
IV	Variants	Specific Values
DCO Forces	12	1, 2, 3, 4, …12
Control Variables		
CV	Variants	Specific Values
Exploit Success Rate	1	4
Attack Type	1	RPA
Vulnerability Growth Rate	1	5
Dependent Variables		
DV	Variable Type	
Vulnerability Rate	Continuous	
Compromise Rate	Continuous	
Repetitions		
Number of Repetitions	30	
Total Runs	12*1*1*1*30 = 360	

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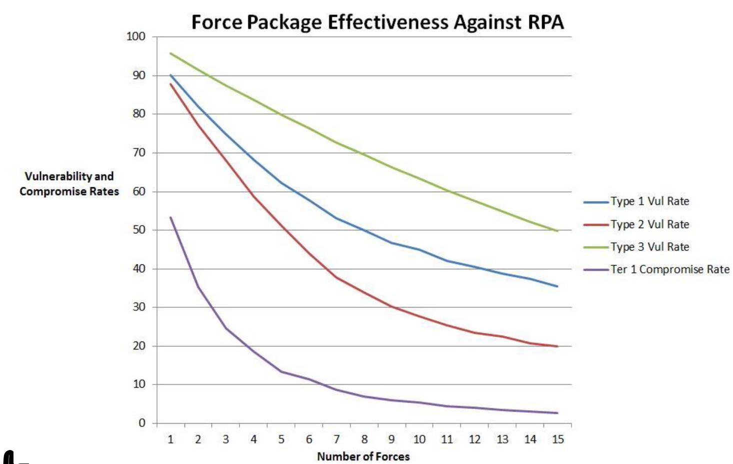
Example 2



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