Applying System Dynamics to Military Operations

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Abstract. This paper addresses the application of computer-based tools to aid senior decision makers in a modern military environment. It is organized in three sections. First, the key features of successful computer-based solutions are presented. Past database centric efforts are reviewed and found insufficient. Second, simulation generally and System Dynamics (SD) specifically are discussed, developed, and contrasted with more database centric solutions. Third, an example SD model is developed that addresses a classic COIN problem—counterintuitive insurgent subtraction—which explains why insurgent numbers can actually increase after military forces engage them. This paper concludes by discussing several ways in which computational models can be made more relevant to military operations.

Keywords: Counterinsurgency, COIN, decision support, system dynamics, simulation, operational modeling, insurgent subtraction, scenario analysis.

1 Introduction

***"The commander must work in a medium which his eyes cannot see, which his best deductive powers cannot always fathom, and with which, because of constant changes, he can rarely become familiar."* —Carl von Clausewitz**

Warfare has always presented a challenging decision environment. Modern warfare in the form of counterinsurgency (COIN) has proven especially challenging as it blends both governance and development with more traditional security concerns. High levels of complexity result from the number of moving parts because these security, governance, and development lines of effort do not fall into separate, well defined lanes. Instead they combine and blend in ways that confound decision makers. Senior military decision makers and commanders are increasingly confronted with complex decisions that encompass a range of interconnected and dynamic social system features. General and flag level officers especially find themselves choreographing and synchronizing the full range of Diplomatic, Information, Military, and Economic (DIME) elements of national power even though they may only be expert in one or two. Recognizing that the modern military decision-making context is "complex" however is insufficient—some way must be found to analyze and make sense of this complexity. It is natural to use computers and computer-based tools to supplement the

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commander's cognition. The tool should provide clarity and grant the commander a sense of familiarity with this difficult and demanding operational environment.

Using computer-based tools to provide decision-support to senior decision makers remains an ongoing opportunity because getting such tools to fit and contribute within an operational environment is a hard problem. This paper addresses the application of computer-based tools to the problem of aiding senior decision makers in a modern military environment, and it does so in three sections. First, the key features of a successful computer-based solution are presented. Initial database centric efforts are reviewed and found lacking. Second, simulation generally and System Dynamics (SD) specifically are discussed, developed, and contrasted with more database centric solutions. Third, an example SD model is developed that addresses a classic COIN problem—counterintuitive insurgent subtraction—which explains why when military forces engage insurgents they can end up with more of them. The conclusion discusses several ways in which computational models can be made more relevant to military operations.

2 Complexity, Computers, and Decision Support

The insurgencies that modern military forces seek to counter can be thought of as a complex social system [1], which provides several strategic and operational benefits. First, in a long war—and counter insurgencies do tend to be extended with operations often lasting more than a decade—success requires campaign continuity. Treating an insurgency as a complex social system helps to support, achieve, and maintain the long-term perspective necessary for COIN success. Second, treating an insurgency like a complex social system requires developing metrics that are tracked over time to help provide that long-term perspective and measure progress against key objectives. The metrics need to be specified by identifying clearly what is being measured and why. Metrics also need to be quantified by giving values, units, and expected ranges. Third, metrics need to be related to each other and connected to form a system. In this manner, the interactions among security, governance, and development lines of effort can be better identified, monitored, and understood.

Modern computers provide a natural way to try to handle system complexity given their prodigious memory and speed. While much experimentation has been undertaken to address military and COIN complexity with computation, successfully applying the resulting intuitions and insights in an actual operational theatre remains an open problem. Part of the problem is due to the computer technologies employed, a combination of databases, computers, and networks. For example, the Palantir system connects multiple databases together and allows analysts to search and display the extracted information [2]. While the tool provides greater access to data, it does not help to select what data is most critical to a particular problem. Furthermore, Palantir does not "boil down" data into products that are more understandable and thus usable by senior decision makers. While the analyst can decide what data is most pertinent and can condense information for senior decision makers, it is the analyst rather than the computer that is doing the hard work. The computer and database are instead providing easier access to ever more data.

The DARPA Nexus 7 project suffers from similar shortcomings in that considerable effort was put into gaining access to and connecting multiple databases, but the work did not result in the envisioned analytic insights [3]. Much of the problem was due to the team's inability to establish insightful connections among the data. This situation has been encountered frequently when policy makers reach out to engineers and have them develop computer-based products to deal with the complexity that confounds their decision-making. However, reaching out to engineers for help with decision support problems places them into the position of analysts, and while engineers know much about building and programming computers, they know comparatively little about analysis. The gap usually comes in having the appropriate mental models that allow them to weigh, fit, and prioritize the data in their computers for products that inform decision making. The Nexus 7 engineers were trained in the latest pattern matching technology, but it was not clear to them what patterns needed to be matched. Models help construct and identify such patterns and their absence can limit success. So computers play an important role, but by themselves they cannot support decision making.

The military's experience with Effects Based Operations (EBO) tells a similar story. Early works articulated the reasons why a new generation of tools was necessary to help decision makers [4,5]. Proponents argued that a new breed of tool was necessary to understand direct, indirect, and cascading effects. But while the need was clear, the way forward to address that need was less so. Once again the military reached out to engineers to help them build tools for decision makers, and the engineers again provided systems built around computers, databases, and networks. The systems were operated by System of System Analysts (SoSA) who filled the databases with data that they thought would be useful to senior decision makers. However, senior decision makers did not find the data helpful. Moreover, the databases did not address the fundamental problem of EBO, to provide insight into direct, indirect, and cascading effects of complex social systems. Databases store data. They do not "go" or progress; they do not generate scenarios or address causality, which is necessary to address the effects questions. EBO's overreliance on databases caused much frustration, and eventually the effort was discontinued [6].

These examples reveal that while the need to address complex military problems to support senior decision makers is clear, the way to provide that support is less so. Moreover, reaching out to engineers for computer-based tools to support decision making has been shown to result in database-centric solutions that senior decision makers, their intended beneficiaries, have found inadequate. Political scientist and Presidential Special Advisor Richard Beal studied these problems and reached the following conclusions [7]: 1) too much time and effort is spent on data collection, 2) not enough attention is given to synthesis at the macro level for senior level decision making, and 3) there is not enough systems thinking by virtue of education and training. So Beal specifically addresses data collection and finds it insufficient. Instead, those building tools to support senior decision makers need to focus on, "synthesis at the macro level." Information synthesis is a hard computer science problem, which explains why workable solutions have yet to be found. Information synthesis will be addressed in more detail in the following section.

3 Modeling, Simulation, and System Dynamics

One of the key gaps identified in the previous section concerned models—constellations of ideas, variables, and relationship—that help people understand a complex world. Models help order and narrow possible variables and relationships, thereby making variable selection and testing more intentional. Physicist Richard Feynman, in a 1964 lecture at Cornell, describes science as a combination of the following three activities [8]: 1) make a guess, 2) create an experiment to test the guess, and 3) if the guess does not agree with the experiment, then it is wrong. Guesses are always based on some model of the way the world works: the better the model, the more accurate the guess. Experimentation and data collection without an accurate model becomes mere trial and error that ultimately becomes unproductive because too much effort is expended for too little benefit.

Theories and models are inherently used to make predictions about the future, what Feynman calls a "guess." Simulations can be used in a complementary fashion to generate and analyze scenarios that tease out over time. In fact simulations are a type of model and can be used to develop theories through a process of specification and quantification [9]. Instead of providing a prose-based description, simulation requires providing a logical or mathematical description. This entails defining a suite of connected metrics that form a system. Traditional mathematical proofs are limited in the scale and scope of variables that can be considered and tend towards closed-form solutions. With simulation supported by powerful modern computers, a much larger set of variables can be combined to generate a much richer set of scenarios.

System Dynamics (SD) is used here as a tangible and mature methodology to create simulations [10, 11], which provides several benefits. First, SD provides a way to develop, fit, filter, and organize metrics. Too often metrics are developed to acquire data that are unconnected to other relevant metrics. The SD methodology provides a well developed way to create systems of causally connected metrics. Second, SD provides a working definition of complexity, a combination of nonlinear, feedback, and stock-flow (i.e., integration) causal relationships. Each of these confuses human cognition, and together they overwhelm it. SD simulation provides a way for analysts and decision makers to handle this complexity, understand it, and become familiar with it. Third, while SD simulation can be used to develop theory [12], it can also be used to synthesize data and show how multiple data sources together impact key output metrics. To the extent that SD can synthesize data, it begins to address the key concerns articulated by Beal. The following section works though an example that clarifies these descriptions.

4 A Complex Social Systems Example

This paper has discussed both social systems and complexity. A complex social system example is developed in this section to provide specificity. The example is taken from MG Michael Flynn who talked about the calculus of counter insurgency, in which direct action against insurgents can counter-intuitively result in even more insurgents [13]. This example provides an example of how the complexity of social systems can result in counterintuitive behavior. The crux of the problem is this: if you have one hundred terrorists and neutralize ten of them, then how can you end up with even more?

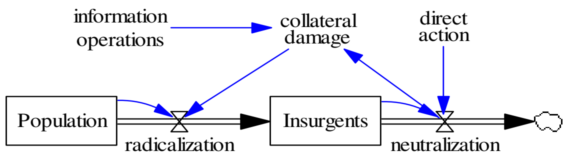

Fig. 1. Insurgent Subtraction Model

Figure 1 shows the "Insurgent Subtraction Model," which consists of seven variables. Starting at the beginning, military units undertake "`direct_action`," which results in "`neutralization`" of "`Insurgents`." This reduces the square stock of Insurgents, which starts at 100. However there is a secondary consequence to direct action, "`collateral_damage`." The application of military force can result in noncombatants getting hurt. When direct action events occur, collateral damage—whether real or imagined—can be exploited through "`information_operations`." These operations can take the form of television, radio, internet, leaflets, or even word-of-mouth, but they can achieve "`radicalization`" of a certain percentage of the "`Population`," who in turn become "`Insurgents`."

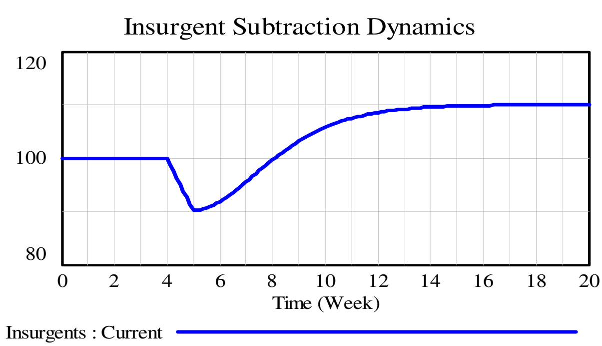

Fig. 2. Insurgent Subtraction Dynamics

Figure 2 provides an Insurgent Subtraction Dynamics scenario that demonstrates several simulation features. First, the scenario takes place over time, here 20 weeks. Second, it charts the dynamics for a single variable in the simulation, "`Insurgents`." The graph shows the number of insurgents over those 20 weeks, which starts at 100, dips to 90 as a result of direct action, and then grows back to 110 as a result of collateral damage, information operations, and radicalization. Each of the seven variables have values that can be measured and displayed, which means that simulated social system can be changed, observed, and measured much more easily than real social systems. Finally, the variables are causally connected, which allows for the system's direct, indirect, and cascading consequences to be analyzed.

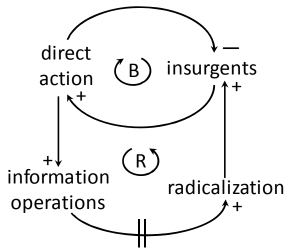

Fig. 3. Insurgent Subtraction Causal Loop Diagram

Figure 3 shows a Causal Loop Diagram of the Fig 1 model. The arrows indicate causality and begin with the cause and point to the effect, so cause and effect are defined. The arrows each have polarity, with a positive sign indicating change in the same direction. So the greater the cause, the greater the effect. Arrows with a negative sign indicate change in the opposite direction. So the greater the cause, the smaller the effect. These causal arrows combine to form systems of circular causality or *feedback*, which also takes two forms. Feedbacks with an odd number of negative connections result in a *Balancing* loop, which tends to maintain system equilibrium. Feedbacks with zero or an even number negative connections result in a *Reinforcing* loop, which causes growth until a balancing loop intervenes to re-establish system equilibrium. Figure 3 features two feedbacks: a balancing loop between `direct_action` and `insurgents`. The causal arrows represent that the more direct action there is, then the fewer insurgents. The positive arrow in that loop indicates the greater the number of insurgents, the more direct action is required to neutralize them. The positive loop explains the counterintuitive behavior of this simple social system. Direct action indeed decreases insurgents, but it also provides the subject matter for `information_operations` that leads to `radicalization` and more insurgents. Figure 3 also features two parallel lines on the positive connection between `information_operations` and `radicalization`, which indicates a time delay. The delay represents the real-world process of a person hearing a media message, becoming radicalized, and then taking the steps to become an insurgent.

It is not enough to simply articulate the problem with a simulation. Some policy recommendations should result. For this model, scenario analysis shows that if information operations are reduced, then so are the number of generated insurgents. Conversely, if information operations are more effective, then more insurgents are generated. Thus, Figure 4 shows that information engagement is as important as the security, governance, and development lines of effort. Looking to Figure 1, information operations works in conjunction with the reality of collateral damage, so reducing collateral damage also provides a way to reduce insurgent creation. Finally,

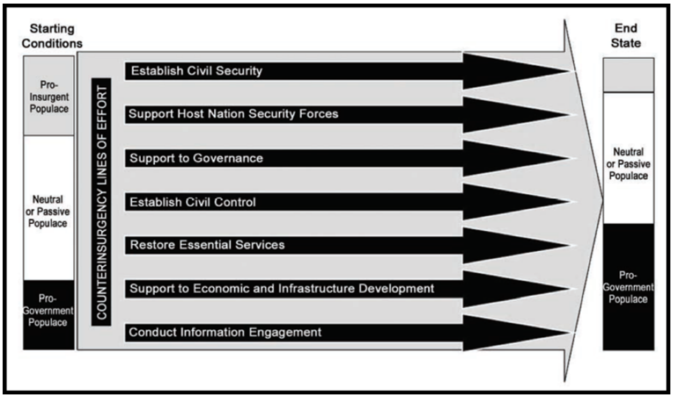

Fig. 4. COIN Lines of Effort [14]

the model can be extended because insurgent activities are subject to the same information operations. Too much collateral damage from insurgent operations can result in reduced popular support, which diminishes the insurgents' capabilities.

5 Conclusion

This paper draws from the complex social system and COIN literatures and discusses ways that computer technology aids senior decision makers. Systems focused on database technology have not helped decision makers because they push information rather than synthesize it. Moreover, they don't tease out scenarios over time in a way that addresses the direct, indirect, and cascading consequences of complex social systems. Simulation generally and SD specifically is offered as an analytic alternative because SD naturally synthesizes information, represents complex causal connections, and calculates their behavior over time. These claims are developed in a simple simulation that depicts the calculus of insurgent subtraction, which shows how neutralizing insurgents can counter-intuitively result in more insurgents.

SD is not offered as a panacea, but as a way to operationalize certain characteristics of computer-based tools that must be present to support decision making in an operational rather than a research environment. In so doing, gaps can be identified that then become requirements for the next generation of tools. Three are discussed here. First, better visualizations are needed for senior military decision makers. The system depictions of Figures 1, 2, and 3 are comfortable and meaningful for an engineer but they are opaque and off-putting to a flag or general officer. The behavior over time graphs can yield good results, though senior decision makers would rather see real rather than simulated data. Second, decision makers want to see disaggregated analyses that depict regions. The insurgent subtraction model is aggregated in that only a single region is addressed. However, multiple variables can be defined to represent different regions. This data can be used to drive a map-based display, which would be more comfortable for a senior decision maker. Third, decision support systems in operational commands must be able to support non-expert users as opposed to research communities that feature a small group of skilled developers and users. Making complex social systems models and simulations more modifiable, maintainable, and interpretable by non-expert users continues to present a significant research challenge [15].

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Lessons Learned in Using Social Media for Disaster Relief - ASU Crisis Response Game

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Abstract. In disasters such as the earthquake in Haiti and the tsunami in Japan, people used social media to ask for help or report injuries. The popularity, efficiency, and ease of use of social media has led to its pervasive use during the disaster. This creates a pool of timely reports about the disaster, injuries, and help requests. This offers an alternative opportunity for first responders and disaster relief organizations to collect information about the disaster, victims, and their needs. It also presents a challenge for these organizations to aggregate and process the requests from different social media. Given the sheer volume of requests, it is necessary to filter reports and select those of high priority for decision making. Little is known about how the two phases should be smoothly integrated. In this paper we report the use of social media during a simulated crisis and crisis response process, the *ASU Crisis Response Game*. Its main objective is to creat a training capability to understand how to use social media in crisis. We report lessons learned from this exercise that may benefit first responders and NGOs who use social media to manage relief efforts during the disaster.

1 Introduction

Social Media is a term ascribed to the current generation of Internet-based social information sharing and social interaction platforms. Some popular examples of social media are Facebook, Twitter, Youtube, and Flickr. Advances in mobile devices, have allowed social media to become available and accessible to anyone who is connected to the Internet. Social media such as Twitter has even let users share microblogging messages via SMS.

In August, 2010, Red Cross published a report[1] that for the first time surveyed 1,054 respondents from the United States population and reported on the expectations from and usage of social media during disasters. The study discovered that Facebook was the most popular social media website with more than 58% of users maintaining a Facebook account and it was also the most preferred channel for posting eyewitness information or sending information about one's safety. The study also discovered that population between 18-35 was more

[1] http://www.redcross.org/www-files/Documents/pdf/SocialMediainDisasters.pdf

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likely to use social media to send and receive information during emergencies. The number of users on social media sites has been constantly increasing. Now Facebook has more than 800 million users and over 75% of these users are from outside the United States[2]. Twitter, a popular microblogging site has more than 200 million users. Several million messages are posted on these two sites everyday and it is clear that they can play a key role as an information source during disasters. In the light of these facts, the results from the ASU Crisis Response Game show that people do have expectations from social media that must be addressed by agencies responding to a disaster. Moreover, it shows that social media can be a valuable means to reach out to people and offer assistance.

In the past, social media has been used to publish eyewitness accounts after a disaster. Twitter was one of the first sources of eyewitness information during the Mumbai terror attacks in 2008[3]. After the earthquake in Japan in early 2011, a Japanese Twitter user reached out to the American Ambassador in Japan, John Roos, who was heading the American rescue operations after the earthquake. With the following tweet: "Kameda hospital in Chiba needs to transfer 80 patients from Kyoritsu hospital in Iwaki city, just outside of 30km(sic) range"[4].Social media can be a valuable source of information to obtain situational awareness during and after a disaster. More recently, the disaster relief agencies have recognized the potential of social media as an information outlet. Hurricane Irene was the first natural disaster where the official agencies used social media to spread information about disaster awareness and preparation[5].A recent Congressional research report [6] on social media outlines how social media was used by agencies during disasters. The focus of agencies is now shifting from passively observing on social media to actively communicating with people. Social media has been used previously for disseminating disaster preparation information and at times for community outreach. Obtaining situational awareness through monitoring of information flow is another utility of social media sources as outlined above. The report also suggests several ways in which an agency like FEMA can use social media in disaster recovery efforts.

Existing HA/DR systems that aid agencies need to adapt to the changing focus of the agencies. For this change to occur, we think it is essential to understand how information from a disaster can be effectively harnessed. A suitable way to start this process is by testing the systems in a real environment. However, due to the nature of the domain this is not advisable. Therefore, we need a simulated controlled environment where we can conduct these tests. Hence, we create a disaster simulation game that can be played with real people to simulate a disaster and test the systems for crisis and disaster response.

[2] http://www.facebook.com/press/info.php?statistics

[3] http://www.guardian.co.uk/technology/2008/nov/27/mumbai-terror-attacks-twitter-flickr

[4] http://www.usatoday.com/tech/news/2011-04-12-1Ajapansocialmedia12_CV_N.htm

[5] http://www.huffingtonpost.com/2011/08/28/hurricane-irene-fema-response_n_939545.html

2 Related Work

Disaster simulation games have been played prior to our game. Exercise 24 was one of the first humanitarian assistance and disaster relief exercise to test the usage of social media and communication tools in response to a simulated disaster. First conducted in September 24, 2010, an earthquake and a tsunami were simulated off the coast of California. People were encouraged to create social media accounts and participate in the testing of social media sources. In the second installment of this event conducted on March 28, 2011[6], the USEUCOM and the San Diego State University's Viz Lab, simulated an earthquake in the Adriatic Sea off the coast of Montenegro. Volunteers on site participated using social media and programmed messages were posted at each of the three stages of the disaster. Several volunteers assisted in mapping and geolocating responses which were collected and visualized using a Ushahidi[7] based crowdmap.

Another disaster simulation, the Great California Shake Out[8], was conducted in October 20,2011. Nearly 9 million people participated in this exercise where people were encouraged to imagine that an earthquake had hit California and to perform the "Drop, Cover, and Hold On" procedure. Although users were not required to publish any information on social media in this simulation, the size of the population that participated is of interest.

The exercises mentioned above focus on testing the ability to collect information from social media and preparing people for a disaster. In order to effectively use social media for disaster response, we need to be able to collect reports from the various social media sources and act upon the ones that require a response. Trustworthiness of such data has been of some concern lately as social media is a free medium. This issue was investigated in the study performed by Mendoza et.al. [7] on tweets generated during the 2010 Chilean earthquake. The authors discovered that immediately after the earthquake several rumors were posted on Twitter which increased the already existing chaos after the disaster. In a subsequent study [1] they propose a model based on features constructed using the qualities of the user, tweet, topic, and propagation that can be used to predict the credibility of a message. A system to detect rumors and misuses of Twitter has also been built by researchers at the University of Indiana, called Truthy[9].

Crowdsourcing is one of the approaches that demonstrate the power of social media. Crisis maps are one type of social media based system which are being used more prominently for disaster response during crises. Authors Gao et.al. discuss some existing systems using examples from crisis maps deployed for real disasters [2]. One such platform is Ushahidi which can collect, organize, and visualize SMS reports on a map. Challenges in using this system include a manual verification and preprocessing step necessary to ensure that the received information is accurate and actionable. At NSCWDD[10], the Quicknets team has built

6 `https://sites.google.com/a/inrelief.org/24/media-report`
7 `http://www.ushahidi.com/`
8 `http://www.shakeout.org/`
9 `http://truthy.edu`
10 `http://www.navsea.navy.mil/nswc/dahlgren/default.aspx`

a plugin for the Ushahidi system which facilitates identification of actionable information by trained volunteers from organizations, such as Humanity Road Inc. It is also capable of replying back to a user via SMS to request additional information or to send an update on the response. Quicknets focuses on SMS but can be potentially used with other social media for disaster relief. In [4], the author outlines some of the problems with existing crisis map platforms and suggests guidelines that will help in the future development of such systems. Recently, Twitter has attracted a lot of attention for its role in various disasters. It represents one popular way to produce timely and instant data. At ASU, we have built a Twitter monitoring and analysis system - TweetTracker [5] that can be easily customized for tracking and retrieving disaster-related information to assist first responders to make critical decision and effective response. These systems concentrate on using the information from social media to respond to a disaster. Such a response has not been tested previously.

3 ASU Crisis Response Game

The game is a live-action role-playing exercise in which volunteers take part as either victims or first-responders involved in a disaster. In this game, there is intensive use of Twitter and SMS. In the game victims use social media to ask for help. These requests are collected and processed by a relief system (TweetTracker or QuickNets). Based on these reports, missions will be generated upon which the first-responders can act. Figure 1, shows the architecture of the game.

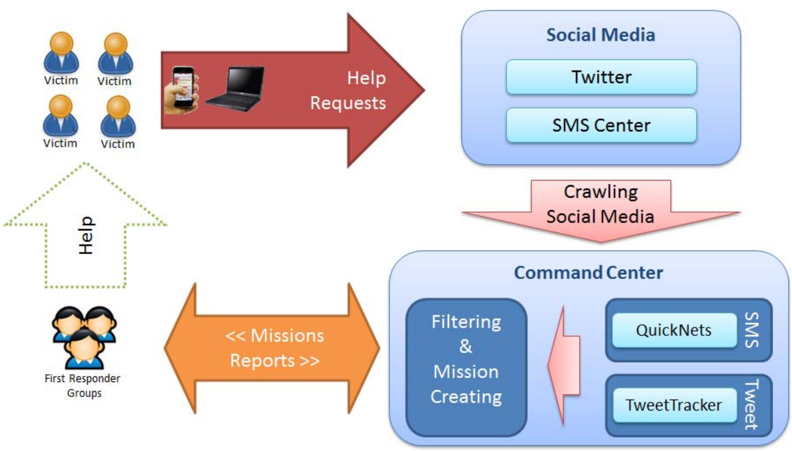


Fig. 1. ASU Crisis Response Game, Architecture

3.1 Game Components

There are three main components, Victims, First-responders, and Filtering team.

Teams Victim (TV). These teams perform the role of victims in a disaster scenario. They use social media (Twitter in this case) or send SMS to ask for help or report injuries. In each message they should include their location, a specific game related hashtag, and their request. They can report any kind of problem, such as fire, rioting, injuries, among others. Individuals or a group of two or more people make a team. Each team should have a device for communication (e.g., smart phone, laptop, or tablet) with ability of connecting to the Internet to send tweets or use their phones to send SMS. At the beginning of the game Victims scatter themselves around the pre-defined game locations. They only can send requests when they are settled in the game locations. Then they should stay till first-responders arrive to resolve their problem. Using social media or sending SMS to a center is the only way that victims can communicate with relief organizations. Teams should activate geo-location related features on their device when they use it to ask for help. This feature helps first-responder teams to locate them easily.

First-Responder Teams (FR). These teams perform the role of NGOs, government agencies, and any other organization able to help. They use a relief coordination system (QuickNets, ACT or TweetTracker in the ASU Game) to find requests for which they can take responsibility. Each team is composed of two or more volunteers. Each team member has one or more capabilities such as Security, Fire and Rescue, Medical, and Wildcard. Teams can perform missions according to their capabilities. In addition some teams can have Wildcard which enables teams to perform all kind of missions. At the beginning of the game, first-responders are at their designated homebase. After Victims send requests for help, FRs select missions based on team members' capabilities and go to the TV's location. Team-Victim members have to stay in place until first-responders arrive and fulfill their request. If the FR team does not have all of the necessary capabilities they should collaborate with other FR teams to accomplish the mission. When a problem has been solved they report back the new situation to the center. When they run out of resource cards to spend, they must go back to their head quarter and get resources renewed.

Filtering Team. During a disaster people send many tweets about the disaster. The filtering team is responsible for reviewing the tweets and selecting ones that are related to the mission of first responders. After the selection process they generate missions. These missions includes details about the problem and the location. Each mission can be generated by analyzing one or more tweets. It is possible that they generate more than one mission from a single tweet. This team is using specific software that is able to collect data from social media or receive SMS from victims. Then they use their own system to publish missions that will be used by FR. This team is responsible for generating missions. To do this task they need to perform the following sub-tasks:

- Selection (Deciding whether a message is actionable)
- Categorization (for the game, what capabilities are necessary to do the task)
- Geolocation (Finding the exact locating of the victims)

These tasks can be done manually or by using software systems. After this step, first-responders will be able to see and select the missions.

4 Game Exercise and Lessons Learned

We ran our game during the last week of the August 2011, at ASU main campus. Over 75 volunteer students participated in the real game and played for more than 4 hours. We assigned them to 25 teams of victims, and 8 teams of First-Responders. In addition around 20 more people participated in the game as the Filtering team and Line-Judges[11] Victims had the opportunity to scatter into 7 different buildings in the campus as shown in Figure 2. Finally, 17 (68%) Victim teams and 4 (50%) First-Responder teams visited at least 1 out of 7 game location which is labeled on the ASU map. All of the seven buildings were visited by both teams. We collected 212 Short Messages (SMS) and 230 tweets from 13 distinct tweeters. Victims used #ASUGAME as part of their tweets to make it possible to be found by the First-Responder's twitter crawler software.

4.1 Social Media Data Collection

TweetTracker was used to collect tweets from Twitter. In addition, we used ACT and QuickNets to collect SMS. *TweetTracker* is a tool for collecting and analyzing tweets to obtain situational awareness. *ACT (ASU Coordination Tracker)* is a tool for crisis event visualization, communication, monitoring, and coordination [3]. *QuickNets* is a plugin of Ushahidi for NGOs to collect and respond to SMS and email requests that have been validated by domain experts.

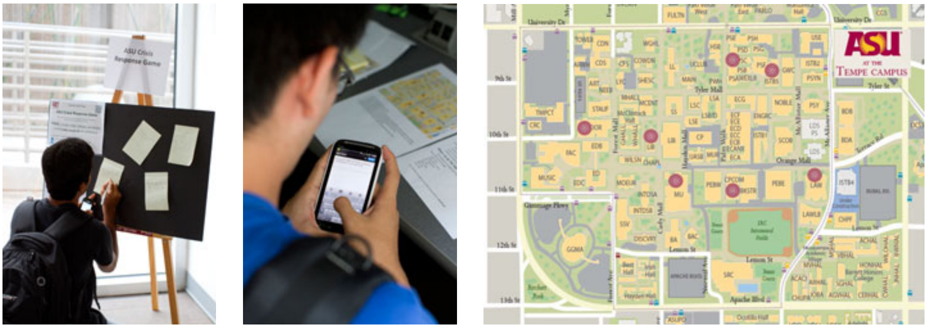
4.2 Lessons Learned

Many valuable lessons are learned. We summarize the major ones below.

Collecting Tweets. Each day people use Twitter to send more than 200 million tweets. Employing a proper method to find related tweets is very important. In this game, we used two different systems to collect tweets. One uses Twitter streaming API to collect and the other uses the jTwitter API to increase coverage. Twitter steaming API does not have limitation but jTwitter has the limitation of 150 or 20,000 requests per hour for regular and white-list users, respectively. In both methods we searched for tweets that mentioned the hashtag #ASUGAME. The most reliable way to find tweets related to a crisis is by searching for hashtags that people create and use during the crisis.

Creating FR missions. The filtering team was responsible for reviewing all of the tweets and generating missions based on the tweets. Even during the ASU-Game in which we only had 220 tweets our filtering team was overloaded. In a

[11] Line-Judges act as moderators, with free will to decide if a particular capability can be applied to a particular mission or not. They also help volunteers with any doubts.



(a) (b) (c)

Fig. 2. (a) and (b) show victims that tweeting and posting a help request during the game. (c) Shows the game map. We used 7 locations (which are highlighted by a circle) in ASU main campus to simulate the real disaster relief.

real crisis, the number of tweets and SMSs would be significantly higher, thus we must use automated systems. Finding related and actionable tweets is the most complicated task in this process. During the disaster a small fraction of tweets are related and can be used to create missions. To find that tiny percent, all of the tweets should be processed. In addition, there are many conversational tweets about the crisis that using the same hashtags and keywords used by victims. Spammers are another problem that generate lots of tweets that should be found and ignored. A practical way to handle this process is using a system that rank tweets according to their importance for a specific crisis. One practical way to help first responders is asking victims to include as much information as they can in their tweets. For example, we asked each team to include location and team identification. This task consumed resources and quickly became a bottleneck. Two solutions for this problem are (1) to develop an intelligent analytic system that can prioritize the tweets or (2) to recruit a sufficient number of experienced people to work for the Filtering team.

GeoLocation. People are able to attach their location information to new Tweets through the web and mobile clients. The knowledge of the exact location of victims and areas that require assistance is invaluable during disasters. In the past, we have observed that less than 5% of users provide location information with their tweets due to privacy concerns and lack of awareness about this feature. In the game, even after being given explicit instruction to add location information to their tweets only few of the tweets had geotag.

NOT REAL THIS IS A GAME!. During the gameplay we were concerned that our tweets might be observed by a real agency and they might be mistaken to have been generated in response to a real disaster in ASU. We coordinated with the campus police department and instructed the participants to begin their messages with "NOT REAL THIS IS A GAME!"

Languages. In crises such as Haiti's earthquake people used different languages to tweet. The crawler should be able to search among tweets with popular languages in the area that disaster happens. In the game, we encouraged victims to use languages other than English, and tried to have one non-English speaker in each team if possible. Translation is critical for information gathering and integration and could be time-consuming and error-prone.

5 Conclusions

ASU Crisis Response Game simulates a disaster scenario (e.g., earthquakes) and tests how social media based disaster relief systems would work in a crisis simulation on ASU campus. Around 75 students voluntarily played different roles (victims and first responders) in this disaster scenario. In the simulation, victims had sent out their requests using Twitter or SMS. First-responders used different software to collect the requests from victims and manage actions, and responses. The process helped us evaluate how these systems work on real situations. The experience of using social media during a controlled disaster relief process had valuable lessons for our team.

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Intergroup Prisoner's Dilemma with Intragroup Power Dynamics and Individual Power Drive

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Abstract. This paper introduces a game paradigm to be used in behavioral experiments studying learning and evolution of cooperation. The goals for such a paradigm are both practical and theoretical. The design of the game emphasizes features that are advantageous for experimental purposes (e.g., binary choice, matrix format, and tractability) and also features that increase the ecological validity of the game (e.g., multiple players, social structure, asymmetry, conflicting motives, and stochastic behavior). A simulation of the game based on human data from a previous study is used to predict the impact of different levels of power drive on payoff and power, to be corroborated in future studies.

Keywords: Prisoner's Dilemma, Nested repeated games, Power, Cooperation.

1 Introduction

The US President Barak Obama and the House Speaker John Boehner played four hours of golf before returning to the negotiation table. It was everyone's hope that playing golf would help the two leaders to build a relationship and a sense of camaraderie that would transfer to their negotiation situation and ultimately would increase the chances of bipartisan cooperation in Congress.

Learning from games and transfer of learning across games have been vastly documented. For example, Haruvy and Stahl [1] showed that players were able to learn sophisticated beliefs about others and use those beliefs in subsequent games. In a related project, we have observed that players' ability to learn to cooperate in a game increases their chance to cooperate in a subsequent unrelated game. More generally, human studies show ensemble effects, that is, spillovers of strategies and/or beliefs across games suggesting that games are not treated as independent of each other [2].

Real-world cooperation and negotiation situations are rarely (if ever) independent of each other. For example, domestic and international politics are usually entangled:

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international pressure leads to domestic policy shifts and domestic politics impact the success of international negotiations [3]. The paradigm of nested repeated games has been suggested to represent real-world situations better than specific games. For instance, a two-level conflict game extensively studied is the Intergroup Prisoner's Dilemma [4]. In this game, two levels of conflict (intragroup and intergroup) are considered simultaneously. The intragroup level consists of an n-person Prisoner's Dilemma (PD) game while the intergroup level is a regular PD game.

Previous research in our labs shows that players' awareness of interdependence influences their chances to establish mutual cooperation. Awareness of interdependence was manipulated by gradually displaying information about the existence of another player, the other's choices, and their payoffs. The condition hypothesized to afford the maximum level of awareness of interdependence was that in which the game matrix was presented at each round, because the game matrix shows all conceivable combinations of strategies and their associated payoffs. The last condition was indeed the one that increased mutual cooperation the most.

In this paper we introduce a three-level nested game called Intergroup Prisoner's Dilemma with Intragroup Power Dynamics and Individual Power Drive (IPD^3, pronounced IPD-cube). We intend to use this game in a series of behavioral studies to investigate the role of power in interpersonal and intergroup conflicts. We also intend to use it as a learning tool to develop strategic interaction skills. For these reasons, we developed a game interface and a learning protocol that are intended to allow human participants to: (1) learn to play the game, (2) play it in an engaging fashion, and (3) ultimately develop skills of strategic interaction that can be transferred to real-world settings.

1.1 Background

IPD^3 is a direct descendent of Intergroup Prisoner's Dilemma with Intragroup Power Dynamics (IPD^2, pronounced IPD-square). IPD^2 was extensively described elsewhere [5] and it is only briefly summarized here.

IPD^2 introduces the concept of power which is relevant for many real-world situations involving cooperation and conflict. For example, power imbalances are known to be involved in radicalization and escalation of political conflicts. In IPD^2, two groups play a Repeated Prisoner's Dilemma game. Each group is composed of two players. Within a group, each player chooses individually whether to cooperate or defect, but only the choice of the player with the greatest power within the group counts as the group's choice. This is equivalent to saying that the two players simultaneously vote for the choice of the group and the vote of the powerful player bears a heavier weight. On a given round, individual power and payoff increases or decreases depending on the group payoff, the power status, and whether or not there is consensus of choice between the two players on a group. The key feature is that in the absence of consensus, positive group payoffs will result in an increase in power for the powerful player while negative group payoffs will result in an increase in power for the powerless player. The players make simultaneous decisions and they receive feedback after each round.

The main results from the previous study were as follow. The level of mutual cooperation gradually increased as the game unfolded. The intragroup power dynamics prevented the groups from settling in the mutual defection equilibrium: prolonged mutual defection would cause power shifts which would effectively reset the interaction and give cooperation a chance to start anew. The human participants were perfect reciprocators, that is, on average, their level of cooperation or defection at each trial matched that of their opponents. The human participants played a strategy that was most similar to a combination of the Tit-for-tat and Pavlov strategies (this result will be demonstrated in Section 3.2). The same study also revealed a number of limitations of IPD^2: The game was administered in a tabular format with brief instructions. Some participants reported that they did not fully understand the rules and the dynamics of the game. The intragroup power game did not include an important component of power – prestige. The motivation to acquire power was partly confounded with that of acquiring payoff. Only in a few cases, when the player's behavior was extreme, it was possible to disentangle the drive for power from the drive for payoff. Sometimes players found themselves in a situation where they wanted to increase their power but they did not know the right combination of moves to do so. In these cases their power drive did not materialize in their behavior.

2 Conceptual Design of IPD^3

IPD^3 adds a third level to IPD^2. Thus, IPD^3 has three levels: (1) intergroup, (2) group, and (3) individual.

2.1 The Intergroup Game

The intergroup game is Repeated Prisoner's Dilemma. In this game, two players, "Player1" and "Player2," each decide between two actions that can be referred to as "cooperate" (C) and "defect" (D). The players choose their actions simultaneously and repeatedly. The two players receive their payoffs after each round, which are calculated according to a payoff matrix setting up a conflict between short-term and long-term payoffs. If both players cooperate, they each get one point. If both defect, they each lose one point. If one defects while the other cooperates, the player who defects gets four points and the player who cooperates loses four points. Note that the Repeated Prisoner's Dilemma is a non-zero-sum game: one player's gain does not necessarily equal the other player's loss. In our case, each "player" is a group of two players that have to produce a group choice. This choice is the result of the intragroup game presented next.

2.2 The Intragroup Game

The intragroup game is an interpersonal power game. As in IPD^2, the power game is a zero-sum game because only one of the two players in a group can be in power at a given time. The choice of the powerful player gets counted as the group's choice.

The rules that govern changes in power correspond to important characteristics of the power concept. We included in IPD^3 three of the most relevant aspects of power: outcome power, dominance, and prestige. The outcome power or "power to" is a measure of a player's ability to bring about positive outcomes. Dominance or "power-over" is the ability of a player to impose its decisions over another player whether the latter accepts it or not. Prestige or "power-from" is the empowerment a player gets from other players willingly supporting or agreeing with the player's decisions.

Outcome power is implemented in IPD^3 by a rule that makes power updating dependent on the group payoff. Thus, if the powerful player makes a choice that results in positive (or negative) payoff for the group and the powerless player opposes that choice, the power of the powerful player increases (or decreases) with an amount that is proportional with the group payoff.

Dominance is reflected by the rule that makes the choice of the powerful player count as the group decision. The powerful player not only makes the decisions for the group but also takes a larger share of the group payoff, because individual payoff is a function of group payoff and individual power. The powerless (dominated) player cannot influence the outcome of the intergroup game. The choice of the powerless player is only consequential for the intragroup power game. Thus, the power of the powerless player increases (or decreases) when he or she opposes a bad (or good) choice (negative and positive outcome, respectively) of the powerful player.

Prestige conferral occurs when the powerless player supports (i.e., makes the same choice as) the powerful player. In such cases, the power of the powerful player increases (and consequently the power of the powerless player decreases because the power game is a zero-sum game).

2.3 The Intraindividual Game

Up to this level, players could only influence their intragroup power through their choices in the intergroup game (cooperate or defect) and in the intragroup game (support or oppose the other player's choices). Players' drive for power could not be expressed independently of their ability to make good decisions for themselves and for the group. Presumably, players could have a range of preferences related to power and payoff. Some players may be unable to make good (i.e., lucrative) decisions but could have as high (or higher) drive for power as all other players (see, for example, the case of some dictators). Other players might want to secure power because they are confident in their ability to make positive payoffs for the group. Also, some players might prefer to remain powerless as long as the powerful player makes lucrative decisions for the group.

At each round in the game, each player has the option to raise their payoff or their power with one unit. When a player raises his power, he forfeits the opportunity to raise payoff. It is as if the payer pays a cost for raising power (or buys power). If both players in a group raise their power, the actions cancel out and the power standings remain the same. The choice to raise power or payoff indicates players' preferences and motives. This choice also affects the dynamics of the intragroup and intergroup games. Thus, for example, if a powerless player A decides to raise her power and her group mate B decides to raise his payoff, the power standings might change: A might become the powerful and B the powerless. This, in turn, might change the dynamics of the intergroup game, as A (the new leader) might decide to change the group's strategy.

3 Design of IPD^3 as an Experimental Paradigm

We developed an interface and a learning protocol that allows human participants to learn to play the game and play it in an engaging way.

3.1 The IPD^3 Interface

Previous research in our labs [6] shows that displaying the available choice and payoff in the game matrix at each round increases the chances of mutual cooperation. We decided to use the game matrix not only to display all the options and payoffs but also as a game interface. The cells of the game matrix showing the players' available options are also used as buttons that can be used to select those options. The payoffs resulting from the selected options are displayed and highlighted on the same matrix. We extended the classical matrix format to show interdependencies between the nested games, running totals for payoff and power, and visualization of the players power standings (Figure 1).

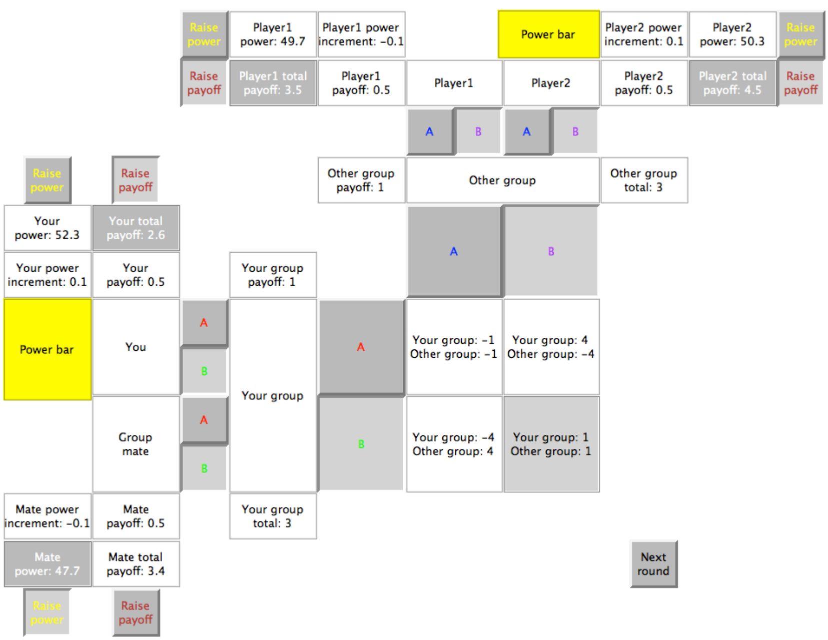

Fig. 1. The IPD^3 interface. The sunken buttons show individual and group selections. The power bars indicate the powerful players and their power levels.

3.2 The Other Player's Strategies

Although the game can be played between four human players, it is useful sometimes for experimental and learning purposes to have a set of preprogrammed strategies. This makes the game more tractable and allows for implementing various manipulations. We designed a set of three strategies to be used as players together with a human player. Tit-for-tat and Pavlov are two strategies that are frequently used in behavioral experiments in which human participants are paired with computer strategies. Tit-for-tat repeats the last move of the opponent while Pavlov repeats its winning move and switches its losing move (win-stay-lose-switch). We added a stochastic component (5%) to make them less predictable and more human-like. We also added a simple strategy to use when they lack power. This strategy was "stochastic always cooperate" because it was determined to be the most effective strategy to gain power when the game settles in the mutual defection equilibrium.

However, neither Tit-for-tat nor Pavlov matches the human data on repetition propensities from our previous study [5]. Repetition propensities refer to players' probabilities to repeat their last choice contingent upon the outcome of that choice. Rapoport, Guyer and Gordon [7] defined four repetition propensities: alpha (D after DD), beta (C after CD), gamma (D after DC), and delta (C after CC). The correlation of the human repetition propensity data with Tit-for-tat is 0.85 and with Pavlov is 0.51. We noticed that a combination of Pavlov and Tit-for-tat that simply averages their repetition propensities is better at matching the human data (correlation 0.96). We called this strategy Pavlov-tit-for-tat and used it as another preprogrammed strategy in our simulations. Although Pavlov-tit-for-tat is the best at matching the human data among the preprogrammed strategies, there are important differences (see Figure 2): humans are more retaliating (higher alpha), more forgiving (higher beta) and more exploiting (higher gamma) than Pavlov-tit-for-tat.

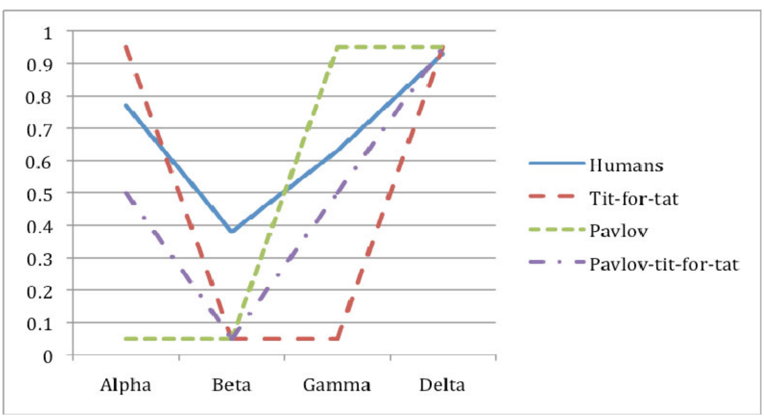

Fig. 2. Comparison between humans and preprogrammed strategies with regard to repetition propensities

3.3 The Learning Protocol

We learned from the previous study on IPD^2 that the game is fairly complex and thus challenging for the human participants. For this reason we designed a protocol to facilitate learning and improve players' experience with the game. The participants are invited to play a sequence of progressively more complex games: IPD (Iterated Prisoner's Dilemma), IPD^2, and IPD^3. Detailed instructions and quizzes are administered before each level. At each level, the human participants play three games of 100 rounds where the human is paired with each of the three preprogrammed strategies described above. We are in the process of collecting pilot data with this paradigm, and the preliminary results are encouraging: the pilot human participants report not only complete learning of the game but also a pleasant experience.

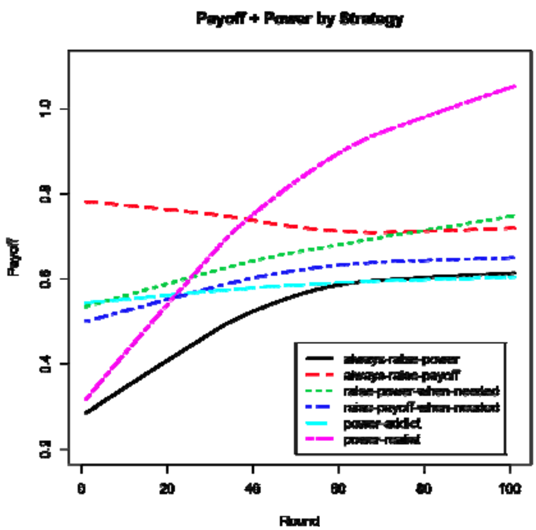

Fig. 3. Predicted time course of the sum of payoff and power for different strategies

4 Simulation and Prediction

In preparation for running a human study with IPD^3, we ran a number of simulations aiming to predict the human behavior in this game. We simulated a human player based on the data from our previous study on IPD^2, that is, we set the probabilities to cooperate or defect in various conditions according to the average frequencies observed in the previous study. In addition, the simulated human was given six different strategies to play the intraindividual game (raise power vs. payoff). These strategies were as follow: (1) Always-raise-power, (2) Always-raise-payoff, (3) Raise-power-when-needed (the probability to raise power is inversely proportional to the value of power), (4) Raise-payoff-when-needed (raise payoff when payoff is negative), (5) Power-addict (the probability to raise power is directly proportional to the value of power), and (6) Power-realist (the probability to raise power is inversely proportional to the difference in power between the two players in a group). The preprogrammed strategies (stochastically and dynamically) matched the simulated human with regard to these strategies. Under the assumption that humans are motivated by both power and payoff, IPD^3 predicts that they will adopt the power-realist strategy because this strategy maximizes both power and payoff on a long run (see Figure 3). However, we expect to find significant individual differences in the drive for power. Based on our previous study we hypothesize that extreme drive for power will be associated with extreme aggressive behavior.

5 Conclusion

This paper introduced IPD^3 – a game paradigm to be used in behavioral experiments and learning of strategic interaction skills. We have designed the game so that it is solidly grounded in state-of-the-art game theoretic and socio-cognitive research. This design keeps features that are advantageous for experimental purposes (e.g., binary choice, matrix format, computational tractability) while adding features that increase ecological validity (e.g., multiple players, social structure, asymmetries, conflicting motives, and stochastic behavior). We will run a series of experiments with IPD^3 to test its conceptual and ecological validity.

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Modeling South African Service Protests Using the National Operational Environment Model

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Abstract. The Air Force Research Laboratory's National Operational Environment Model (NOEM) is a strategic analysis/assessment tool that provides insight into the complex state space that depicts today's modern nation-state environment. A key component of the NOEM is its Populace Behavior Module, an agent-based model that describes activist behavior in terms of populace agents' perceptions of hardship and government legitimacy. Although based on Epstein's grievance vs. net risk model [1], enhancements have been made that make the model more practically applicable. We applied the model to an actual scenario, namely service protests in Gauteng Province, South Africa from 2004-2010. When model parameters were fit based on the data, the model successfully duplicated both qualitative and quantitative characteristics of the historical data.

Keywords: Agent-based modeling, behavior modeling, population simulation.

1 Introduction

The Air Force Research Laboratory's National Operational Environment Model (NOEM) is a large-scale stochastic model representing the environment of a nation-state or region, with a focus on population behavior. The NOEM enables the user to identify potential problem regions within the environment, test a wide variety of policy options on a national or regional basis, determine suitable courses of action given a specified set of initial conditions, and investigate resource allocation levels that will best improve overall country or regional stability. The different policy options or actions can be simulated, revealing potential unforeseen effects and general trends. An overview of the NOEM may be found in [2].

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At the heart of the NOEM is the Populace Behavior Module, which receives inputs from other modules and generates alternative possibilities for the population's response to regional conditions. Unlike other modules it relies on an agent-based model, where each agent represents a certain fraction of the population (this fraction is called the scale factor). As is typical with such models, randomness plays an important part – the same set of inputs can yield considerably different outcomes.

A key difficulty in using the Behavior Module for practical scenarios is furnishing suitable input parameters. We were able to develop a methodology for estimating model parameters from historical data from a particular scenario (Gauteng Province, South Africa from 2004-2010). Furthermore, we obtained model outputs that were consistent with observed levels of activism.

2 Background

2.1 Model Specification

The NOEM behavior model is based on Epstein's agent-based model [1], in which a region's population is modeled as a set of agents located on a two-dimensional grid. Each agent corresponds to a subset of individuals in the population, and the agent's status represents in some sense the cumulative effect of those individuals' behavior. At each time step, each populace agent is either active, inactive, or in "jail". Each agent that is not in jail makes an individual decision every time step whether or not to be active at that time step. This decision is based on the agent's perceived "grievance" (G) and "net risk" (N) according to the criterion: $G–N > T$, where T is a threshold that is the same for all agents for all time steps.

The quantities G and N may be further broken down. The grievance G depends on "hardship" (H) and "legitimacy" (L) according to the relation: $G = H(1–L)$, where both H and L are assumed to take values from 0 to 1. On the other hand, net risk N depends on the agent's estimated arrest probability P and risk aversion R according to the formula $N = P{\cdot}R$

Besides populace agents, the model also includes "cop" agents that represent the government's efforts at law enforcement. These patrol the grid and "arrest" active agents they come across. The location of cop agents is a major determining factor in each populace agent's estimated arrest probability P: specifically, the more cops that are "nearby" a given agent, the higher that agent's estimated arrest probability. On the other hand, the more active agents that are "nearby" a given agent, the lower that agent's arrest probability. For more specific details on the mathematical specification of P and the dynamics of arrest and imprisonment, see reference [1]. Further details of the specific NOEM implementation may be found in [3].

2.2 Service Protests in Gauteng Province, South Africa 2004-2010

In order to evaluate the behavior model's applicability to real data, we chose to look at service delivery protests in Gauteng Province, South Africa from 2004-2010: one major reason for this choice was the availability of fairly complete data over an extended period of time.

Since 2004, an increasing number of protests and outbreaks of violence have occurred in South Africa due to the government's inability to provide basic services (such as electricity, running water, housing and sanitation). These protests are normally restricted to the country's townships, the squatter camps/shanty-towns often located within the boundaries of larger cities. Townships, occupied by rural poor or migrant workers who moved to urban areas in hopes of finding employment, are rife with poverty and crime and are generally in squalid condition. Many demonstrations turn violent, with looting, destruction of property, stone-throwing, the burning of tires, and arson not uncommon. South African police are often on-site, and at times have had to enact crowd-control measures such as tear gas to quell protests.

Gauteng, the province with the highest number of protests, is South Africa's most urbanized and heavily populated province. It is the location of Johannesburg, the largest city and home to several townships. The province was formerly divided into six districts, including Johannesburg: two of these districts merged in May 2011.

Table 1 shows the increasing frequency of service protests in Gauteng Province over the period from 2004 to 2010.

Table 1. Protests in Gauteng Province by year

Year	2004-06	2007	2008	2009	2010
Number of Protests	10	9	9	25	44

Ironically, data obtained from the Gauteng provincial government[4][5] indicates that over this seven-year period basic services were considerably improved, which would seem to indicate that the populace's hardship was significantly decreased. In terms of our mathematical model, this can be explained as the result of a decrease in legitimacy that more than offset any decreases in hardship.

Data from Municipal IQ, (a South African intelligence service which tracks service delivery protests) indicates that 97 service protests took place from 2004 to 2010[6]. From South African media archives we found dates and locations for 67 of these protests. Figure 2 shows a cumulative plot of protest occurrence times by district.

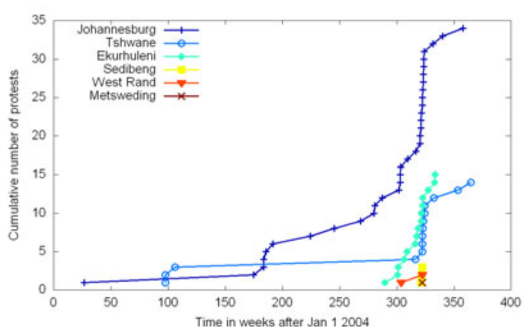

Fig. 1. Cumulative plot of protest occurrence times in Gauteng Province districts

The curves in Figure 1 exhibit a large number of "humps," where each hump indicates multiple protests occurring in a relatively short period of time. Apparently protests tended to occur in bursts, with one "superburst" occurring around week 320.

Not surprisingly, the more populous districts had the most protests. But we also found that the most densely populated districts had more protests per population than those more sparsely populated: a weighted least-squares regression of number of protests per million population versus population density (in thousands per square km) gave a regression coefficient of 0.37±0.1. Surprisingly, service levels actually tended to be higher in more urbanized districts. Some observers[6] suggest that this counterintuitive situation is due to the urban poor's greater "relative deprivation" resulting from their exposure to nearby wealth which they themselves cannot attain.

Interestingly, during the "superburst" of March 2010 protests were spread evenly across all districts without regard to their urbanization. There is no apparent event that touched off the superburst, and there is no evidence of coordination between the protests: rather, this superburst has the characteristics of a completely spontaneous "flash mob"-type phenomenon that caught up the entire province. This sudden increase in activism is inconsistent with Epstein's model: Epstein found that gradual increases in grievance never led to sudden increases in activism[1].

3 Modeling Considerations

3.1 Basic Grid Configuration

In order to model the Gauteng Province data, we had to decide how to map the South African populace onto a grid populated by agents. Since the protests were reported by township, in one sense it seemed appropriate to use townships as the effective agents in the model, and to model each township protest as one incident of agent activism. On the other hand, townships consist of tens of thousands of individuals, and we wanted to include effects due to the statistical behavior of the township populations. We did this by introducing modifications to the model, as described in Section 3.2.

Using data drawn from a World Bank study[7], we determined that there were 37 significantly underserved townships in Johannesburg. For the other districts, for want of detailed data we assumed that the number of underserved townships per population was the same for all districts. Altogether, our model used 100 township-agents: one example model configuration is shown in Figure 2 (configurations were re-randomized for each simulation run).

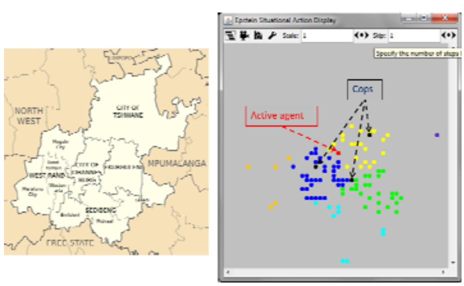

Fig. 2. Gauteng province (left); Example agent configuration (right)

3.2 Modifications to the Model

Due to the characteristics of our model, we found it necessary to make some key modifications to Epstein's model.

First, as mentioned above we addressed the statistical effect of the large populations within each township-agent. For this purpose, we considered each township itself as an agent-based system similar to Epstein's. Such systems can be mathematically described as finite Markov chains, since the system state change from time step to time step via fixed transition probabilities. Protests comprise a subset O of the possible states of the Markov chain. Aldous[8] has shown that if the chain is rapidly-mixing and the set O is rarely-visited, then the hitting time distribution is approximately memoryless, so that the distribution of inter-protest times is roughly geometric. As a result, we assumed that intra-township populations gave rise to a geometric distribution of township protest times. To obtain this, we added a mean-zero normal random variable to the grievance G for each agent for each time step. The standard deviation of this random factor was a fixed parameter input to the simulation. Under constant neighboring conditions, for each township-agent this produces a constant protest probability at each time step: while changing neighbor conditions changes the protest probability by changing the net risk level.

An additional modification to Epstein's model was made to reflect the influence of media on legitimacy. Current world events show that episodes of activism within a nation that are reported in the media (either mass media or social media) can stir up additional activism at long distances. One could model this by increasing the township-agents' "vision", that is the distance used in computing an agent's estimated arrest probability. However, enlarging the vision also increases the number of visible cops, which is both unrealistic (long-range cops cannot readily arrest an agent) and effectively counterbalances any increase in visible activism. So we took another approach, and modified the expression for legitimacy L as follows:

$$L = L_{\text{basic model}} - K(\#\text{TotalActivists} \,/\, \#\text{TotalPopulace}), \tag{1}$$

where the positive constant K reflects the long-range effects of activism. Equation (1) expresses the fact that an increase in overall average activism, as reported by the media, should increase agents' inclination to protest regardless of their location.

3.3 Estimation of Model Parameters

For NOEM to be a practical tool for describing the behavior of populations, it is necessary to develop a systematic methodology for estimating model parameters from real data. In the case of service protests in Gauteng Province, we used heuristic methods based on statistical analysis to the data to come up with plausible values for the different model parameters: these are summarized in Table 2.

Table 2. Model parameters used in NOEM simulation

Parameter	***Value***
Number of agents (townships)	100
Number of cop agents	3
Size of grid (in km & cells)	270 & 50
Populace vision & cop vision (in km)	10 & 25
Hardship *H* (all districts)	0.5
Legitimacy *L* (by district)	0.8(Joh),0.83(Tsh),0.85(Ek), 0.87(other)
Legitimacy decrease per time step δ	000037
Activism-determining threshold *T*	0.366
Agent grievance standard deviation σ	0.0
Jail term *J* (in time steps)	25
Long-range activism constant *K*	6.3

Temporal parameters were based on the choice of one week as time step: this choice was made because the time step in the model functions corresponds to agent "memory," and analysis of the experimental data suggested that agents were much more strongly influenced by events less than one week prior. The jail term parameter was chosen so that the median jail term was equal to the median time between protests at the same location. Agent vision was determined by examining protests less than one week prior to a given protest: a disproportionate fraction occurred within 10 km. Cop vision was set as the radius of a typical district. The threshold *T*, legitimacies, and legitimacy decrease were found via a system of equations based on pre-outburst per-province protest frequency data. The long-range activism parameter was chosen so as to account for the discrepancy between protest frequency during the superburst and the expected protest frequency without long-range activism.

4 Results

Figure 3 shows a typical simulation run: details varied from run to run.

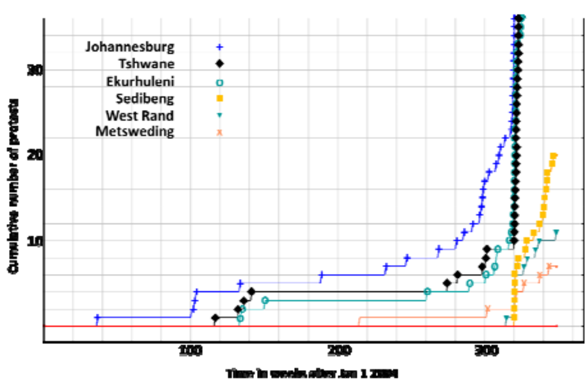

Fig. 3. Example NOEM simulation output for cumulative protest occurrence times, by district (compare Figure 1)

Figure 3 exhibits striking qualitative similarities with Figure 1, showing both isolated protests and small bursts of protests leading up to the superburst, Once the superburst breaks out all districts become involved, even those that have had no previous protests. In the NOEM model, once the superburst occurs the model breaks down and activism overtakes virtually all agents that are not imprisoned. Of course in the real world, widespread violence introduces new dynamics into the picture, such as the government calling in additional police and/or military resources. Hence, the model should not be expected to remain valid.

In order to make quantitative comparisons between simulation and observation, we ran ten simulations while recording the following statistics:

- Number of isolated protests preceding the superburst, where an isolated protest is one for which no other protest occurs during the same, preceding, and subsequent time steps;
- Superburst time, defined as the time step during which the maximum number of protests was observed;
- Precursor interval, defined as the number of time steps prior to the superburst time during which at least one protest occurred per time step;
- Number of pre-superburst protests, defined as the total number of protests up until the beginning of the precursor interval.

Table 3. Comparison of simulation results with Gauteng Province data

	# isolated protests	*Superburst time (weeks)*	*Precursor interval (weeks)*	*#pre-superburst protests*
Simulation	9.4±6.6	269±70	6.2±5	20.7±19
Observed	10	320	5	26

The error bars in Table 3 correspond to two standard deviations. The table shows that there is a wide variation in results from simulation to simulation: this suggests that unpredictable random factors play a large role in determining the space-time distribution of protests. The observed data was within error bars for all values.

We also investigated the sensitivity of the model to parameter changes. Table 4 shows averages of five simulation runs for various parameter changes, together with 2-standard deviation error bars.

Table 4. Effect of parameter changes on simulation averages

Parameter change	*# isolated protests*	*Superburst time (weeks)*	*Precursor interval (weeks)*	*#pre-superburst protests*
Baseline	9.4±2.2	269±23	6.2±1.7	20.7±6.3
J:25→30	8.4±2.2	281±49	4.2±0.8	26.2±13
K: 6.3→7	7.8±2.9	268±36	4.6±1.5	30±16.7
T:0.366→0.4	11.8±0.8	471±47	5.6±3.2	33±15
δ:.00037→.0004	8.4±5.5	272±47	5±0.7	29±13
σ: 0.085→0.09	9±1.9	200±40	4.8±1.3	49±9.9

Table 4 shows that the 10-20% changes for most parameters did not have a large effect on the simulation averages. One exception is the activism threshold *T*: a 10% increase in *T* (from 0.366 to 0.4) led to large increases in superburst time and non-isolated pre-superburst protests. Increasing the agent grievance standard deviation by 5% also had a large effect, reducing the superburst time by roughly 30% while more than doubling the average number of non-isolated pre-superburst protests.

5 Conclusion

We have modified Epstein's seminal model to obtain a model for which parameters can be estimated from actual data, and which produced simulation results that agreed with real data in many qualitative and quantitative respects. Widespread, non-localized outbursts of activism arise naturally from our model, in contrast to Epstein's findings with his model that gradual decreases in legitimacy never lead to bursts in activism. Our model provides a plausible quantitative mechanism to explain how media reporting of protests can lead to widespread outbreaks of activism.

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Modeling and Estimating Individual and Population Obesity Dynamics

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Abstract. The obesity trend in the U.S. and many other countries has increased the need for models that can assess the potential impact of alternative interventions to reverse this trend. In this paper we report on building a generic dynamic model that can be used for obesity policy analysis at multiple levels. We build an individual level model for both childhood and adulthood to capture the energy balance and weight change throughout the life of individuals, and aggregate individual level models to create population level trends of obesity. Simulated method of moments is used to estimate uncertain parameters of this model from NHANES data. The resulting model enables community, state, or national policy analysis building on a calibrated model.

Keywords: Obesity, simulation, simulated method of moments, energy balance, system dynamics.

1 Motivation and Background

The obesity trends in the U.S. and many other countries are alarming. The percentage of Americans who are obese has doubled to near 30% during the past four decades [1, 2]. Multiple levels of factors, from biological to environmental, are involved in creating the obesity problem and thus a systems approach to analyze the problem and assess interventions is called for [3]. Models that can assess the potential impact of alternative interventions are much needed in turning the obesity trend. Such models can facilitate policy analysis by expanding the boundaries of our mental models and enhancing learning from evidence [4]. However due to ethical and practical considerations in data collection available dynamic models for obesity rely on short-term time series data and small sample sizes [5-9] which reduces their direct applicability for policy analysis at the population level. While this literature provides a great starting point for modeling individual level body weight dynamics, none of the current models include both childhood and adulthood dynamics. Moreover, the current models focus on modeling a single "average" individual. Extending them to capture variations across individuals is critical for population health policy analysis. Simulating population level weight gain and loss dynamics, and assessing alternative interventions in a new population group, requires dynamic models that 1) Capture the

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individual-level body weight dynamics realistically, building on biological processes that regulate energy balance in body. 2) Connect individual level and population level dynamics in a robust and generalizable fashion. 3) Express the impact of interventions on energy intake and physical activity for different individuals.

2 Analysis and Results

The purpose of the research is to study the dynamics of obesity in the United States over time to build a generic system dynamics model that can be used for obesity policy analysis at multiple levels. We first introduce the individual level model of body weight dynamics used in this study. The population level model which consists of multiple replicas of individual model and their relationships will then be discussed. Finally we explain the calibration and parameter estimation processes and some of the results of the analysis.

2.1 Modeling Body Weight Dynamics

Several models of body weight dynamics have been discussed in the literature [5-14]. These models vary in their level of complexity and the feedback mechanisms they capture. Common across most these models are the state variables fat mass (FM) and fat free mass (FFM) which constitute the majority of body weight in a normal person. More detailed models may consider the stock of glycogen, protein, and extracellular fluid mass and adaptive thermogenesis among other stock variables [7, 15, 16]. While additional complexity could be important in evaluating dynamics that unfold in hours or days, results of comparative studies by Hall [8, 17] suggest that for longer term dynamics FM and FFM provide much explanatory power with very little complexity. We therefore rely on these two variables as the main state variables (stocks) in our individual model. Because we also model growth, a third stock variable captures individual's height. There is currently no unified model for childhood and adulthood body weight dynamics in the literature we therefore create one by combining insights from two of the models in literature by Hall [8] and Butte, Christiansen et al.[9] and developing a new framework that considers energy supply and demand at any point in time and allocates the supply to demand based on a set of priorities.

Energy supply comes from energy intake (EI) and consuming body mass. Total energy intake is the most important factor about food and beverage consumed by an individual Energy could also come from burning FM or FFM (either due to starvation, or if either mass is beyond what the body needs). These three sources create the total energy supply in our equations.

Factors influencing energy demand include demand for maintenance of body and energy demand for growth. The maintenance energy demand depends on resting metabolic rate (RMR) which contributes to 50-75% of energy expenditure, the physical activity energy needs, and the energy for digestion of food and nutrients consumed. RMR itself depends on the body composition (energy needs for maintaining FM and FFM are different). Energy expenditure attributed to physical activity (PA) is largely proportional to the total weight (BW=FM+FFM) and the intensity of PA. Following Hall [8] we represent the total maintenance energy demand (TME) by equation (1). Also following Butte Christiansen et al. [9] we note that $\gamma_F$and γ_L are a function of age (Tanner stage) in children, before they stabilize in adulthood.

$$TME = K + \gamma_L.FFM + \gamma_F.FM + PA_{Total}.BW + \eta_L.\frac{dFFM}{dt} + \eta_F.\frac{dFM}{dt} + \lambda.EI \quad (1)$$

We model energy demand for growth based on comparing current weight with the desired weight of individual in near future (e.g. one year ahead). The weight change rate indicated in this period is used to calculate energy needs for growth. Desired weight is determined based on the desired height and desired body mass index (BMI) for the individual, both coming from CDC growth charts, and adjusted based on variations in individual's potential height and current BMI (desired BMI is a weighted average of CDC median for that age and current individual BMI). This demand is then partitioned into energy demand for FFM (Fat Free Energy Demand: FFED) and FM (Fat Mass Energy Demand: FMED) based on regression equations that predict FFM as a function of age, gender, ethnicity, BMI, and height. The resulting gaps (or excesses) in FM and FFM determine the energy demand (supply) that comes from body's growth and BMI and body composition homeostasis processes. Included in these calculations are the energy costs for the implied tissue deposition and disintegration. These parameters are all taken from the literature [8].

Our model can take energy intake (EI) as an exogenous input. However, in practice reliable EI data is not available for large samples and over long time horizons, so we use an alternative set of expressions to endogenously generate EI values for simulated individuals:

$$\begin{aligned} EI_i = (TME_i + FFED_i + FMED_i)(1 + f(Time) + g(Age) \\ + \alpha e.Ethnicity + \alpha e * Gender)(1 + \varepsilon_i) \end{aligned} \quad (2)$$

Energy intake for individual i at time t depends on the energy demand for that individual (TME+FFED+FMED), adjusted based on time, age, and demographic effects (to be estimated from data) and an individual variation factor ($\varepsilon_i= VF(Age_i)*S_i$) that captures individual differences in energy intake. The magnitude of individual variation is age-dependent (function *VF*). Because an individual's eating habits will change only slowly the S_i term is modeled to be serially correlated, with its value at time t+dt being a linear combination of its value at time t and a new normal random number. Moreover, the variations in this term over time depend on its level: people with S_i values far from zero are more likely to change their eating habits (because otherwise they will grow exceedingly obese or starve), while those close to zero change their ε more slowly. These feedback effects are captured in modeling the auto-correlated individual variation term, S_i.

Finally, the three sources for energy demand (TME, FFED, FMED) are compared with three sources for energy supply (EI, energy from reserve FM (if any), and energy from reserve FFM (if any)). Once energy demand and supply are determined, the model uses a priority-based allocation scheme to allocate the supplied energy among demand items. If total supply exceeds demand, then additional energy will be deposited as FM and FFM, based on a partitioning function. The partitioning function we use is the empirical equation *1/(1+0.502*FM)* [17, 18] as the fraction of energy surplus contributing to changes in FFM. If energy demand exceeds supply, then shortage is covered by not supplying some energy needs or burning essential FM or FFM, depending on priorities that are summarized in Table 1. In this table, a row with YY indicates that the demand source has higher priority than supply source, therefore getting allocated from supply source as much as needed. For example body will use supply of EI to satisfy TME with no reservation. Y means the priorities are close and therefore some supply will be provided, while some of the demand may remain unmet, e.g. in case of using essential FFM to support TME. Finally N means the priority of supply source is higher than demand, and therefore no supply will be provided (e.g. essential FFM will not be used to generate reserve FM).

The model also captures the changes in individual height over time. The height equation assigns each individual a potential that modifies the desired future height for that individual around CDC growth charts median. Height will grow based on the desired values, unless energy supply falls short of demand, in which case height growth is slowed. The logic of equations is discussed above and full equations are available from the first author upon request.

Table 1. Priorities of different energy supply and demand sources in energy allocation process

Supply\demand	**TME**	**FFED**	**FMED**	**Reserve FFM**	**Reserve FM**
EI	YY	YY	YY	YY	YY
Essential FFM	Y	N	N	N	N
Essential FM	Y	N	N	N	N
Reserve FFM	YY	NA	Y	N	N
Reserve FM	YY	YY	NA	N	N

Multiple replications of the individual level model can be simulated together to generate population level characteristics of interest such as percentage of the population that is overweight or obese. However creation of the population model requires more than just replicating the individual level model. Specifically, parameters that specify individual EI variation (ε) should be estimated to match the observed behavior in data.

2.2 Model Calibration and Parameter Estimation

An innovative feature of this study is its methodological contribution towards estimating dynamic models based on cross-sectional individual level data from a population. No current database offers the large scale time series data typically used for estimating dynamic models similar to the one we are working with here. However, we note that the data in National Health and Nutrition Examination Survey (NHANES) provides relevant information in terms of the distribution of weight, height, and body composition for different subgroups in the population. A good population level model should be able to match those distributions closely, and the quality of that match can inform parameter estimation and hypothesis testing. If the three statistics (sample mean, variance, and skewness) for the real population match those in the simulated population, we can have some confidence about the ability of the model to recreate the historical results. Further, we can also change model parameters to reduce the discrepancy between these moments of data and model, i.e. to calibrate the model and estimate the unknown parameters. Such comparison can be scaled to many more sub-population moments to increase the precision of the comparisons, and to find better parameter estimates. This is the core idea in the Simulated Method of Moments (SMM), one of the most versatile econometric estimation methods available [19-21]. In this study we use NHANES data for 10 demographic groups (Male and Female of Mexican-American, Other Hispanic, White, Black, Other), over 5 rounds of NHANES (2000, 2002, 2004, 2006, 2008). For each demographic group we divide the population into 26 different age groups (20 groups for ages 0-20, 6 groups for ages 20 and higher, with 10 year periods, i.e. 20-30, 30-40, etc.). Finally, for each age group we use data on 10 moments (mean, variance, and skewness of body weight and BMI, mean and variance of fat mass fraction and height) to estimate the model parameters. We start the model from year 2000, using data from that year to initialize the model, and compare the moments for simulated individuals in different population groups against the next four rounds of NHANES data. This gives us 4*10*26*10 moments to compare against simulated moments[1]. Denoting $\mathbf{x}$ as the vector of observed moments for a population group, $\mathbf{x}^s(\boldsymbol{\theta})$ the simulated vector for the same moments using parameter vector $\boldsymbol{\theta}$ in the model, the following optimization problem is numerically solved to estimate the parameter vector $\boldsymbol{\theta}$:

$$\hat{\theta} = \arg\min_{\theta}[x - x^s(\theta)].W.[x - x^s(\theta)]' \tag{3}$$

For the weighting matrix $\mathbf{W}$ we use the diagonal matrix populated with reciprocal of variances for different moments. We calculate these variances by comparing, for each age group, the variation in each moment across different NHANES rounds and demographic groups. This weighting mechanism provides relatively efficient parameter estimates (for asymptotic efficiency the reciprocal of covariance matrix should be used for W; but that is computationally too expensive). Numerical optimization to find ~ 20 parameters requires in the order of one million simulations and simultaneous estimation of all population groups requires simulating over 20000 agents per simulation, which becomes infeasible for our computational resources. We therefore estimate each demographic group separately.

2.3 Initial Results

Calibration is conducted using a population of 505 simulated individuals, distributed uniformly across different age groups in year 2000 and allowed to grow and change

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[1] In practice fat mass fraction data is only available for a subset of NHANES rounds and age groups, reducing the total number of moments to slightly under 9,000.

for the next eight simulated years. Minimizing a total of 892 weighted (based on reciprocal of expected variance) moments' squared error from data across years 2002, 2004, 2006, and 2008 the calibration's error was 1045 after 582355 simulations using Powell's conjugate search method and 22 parameters to estimate. The model shows some systematic difference with data as the error value is higher than 942, the 95% confidence level for data and model being indistinguishable; however the difference is fairly limited (the difference could be attributed to only % of moments with significantly large errors) and suggests a generally good fit. The key relationships estimated are the time trends of energy intake, the age trend of variations in energy intake, and the structure of noise terms that drives energy intake (See Table 2). The calibrated model is used next to simulate the distributions of the weight, BMI, height, and fat fraction for a population of 500 white female children from year 2000, to 2008 when they are 13-15 years old.

Table 2. Overview of key estimated parameters

Energy intake for individual i :EI[i]=Expected EI[i]*(1+VF(Age[i])*S[i]) VF(x)=0.18*(1-3.79*exp(-((x-2.34)/4.16)^2/2)/4.16) See Fig. 1-a.
Expected EI[i]=DesiredEI[i]*(0.99+TF(Time)) See Fig. 1-b
DesiredEI[i]: Calculated based on individual's current state to keep her on track for a normal growth trajectory, or in equilibrium if adult. S[i]: Auto correlated noise, with half-life of $T=4.9/(1+\|S[i]\|)^{w[i]}$ See Fig. 1-c w[i]=1 if S[i]>0, w[i]=6.04 otherwise

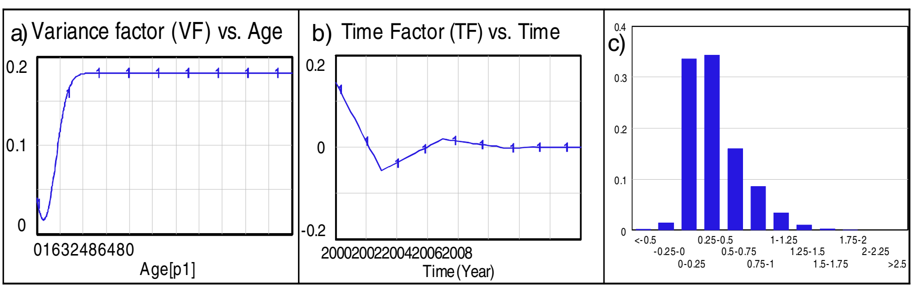

Fig. 1. Estimated relationships from calibration a) Individual variance factor (VF) as a function of age. b) Individual energy intake (TF) as a function of time and c)Distribution of individual variation in energy intake (S) resulting from estimated parameters.

The weight, BMI, height, and fat fraction distributions are compared with NHANES 2008 data for the same group (only 71 subjects available). The averages are largely consistent with the data while the standard deviation of height is more in data than in simulated results (Fig. 2-a). Note that the model has been calibrated to all 26 age groups simultaneously, should calibration been conducted against only these three age groups, even better fit could be expected.

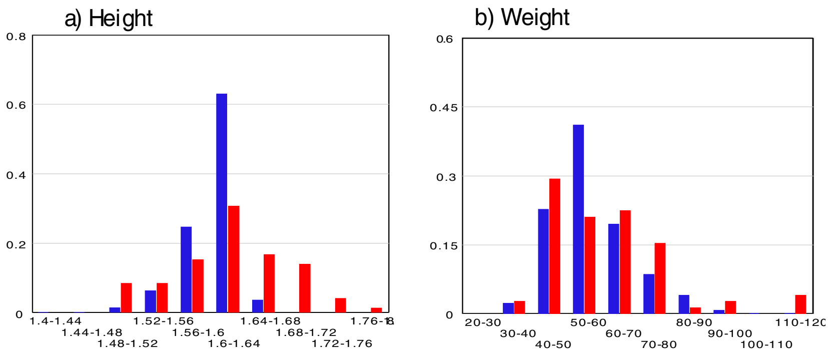

Fig. 2. Comparison of Height and Weight data (blue, right hand bars) (N=71) and simulated results (red, left hand side bars) (N=500) for NHANES 2008, 13-15 year old white female

3 Discussion and Limitations

The contributions of this work are twofold. First, for the first time in the public health literature we provide an integrated model of weight gain and loss that covers both childhood and adulthood and connect it to population level weight dynamics. The resulting model provides a flexible, validated, module to be integrated in any policy analysis project. The model is robust to extreme conditions, does not require parameter estimation, and can be plugged with any hypothetical interventions.

Second, we adopt the SMM for application to arbitrary system dynamics models to be estimated using not only panel or time series data but also cross sectional population statistics. This can open the door to much wider use of nonlinear feedback-rich models in data intensive domains traditionally dominated by simpler regression models. The results presented here provide a first cut at a complex modeling and estimation project, and future work should focus on improving the fit between the model and the data in some settings. Finally, the models main utility will be for policy analysis settings where energy intake or physical activity values are changed from their base levels; that work goes beyond the scope of current paper.

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Creating Interaction Environments: Defining a Two-Sided Market Model of the Development and Dominance of Platforms

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Abstract. Interactions between individuals, both economic and social, are increasingly mediated by technological systems. Such *platforms* facilitate interactions by controlling and regularizing access, while extracting rent from users. The relatively recent idea of two-sided markets has given insights into the distinctive economic features of such arrangements, arising from network effects and the power of the platform operator. Simplifications required to obtain analytical results, while leading to basic understanding, prevent us from posing many important questions. For example we would like to understand how platforms can be secured when the costs and benefits of security differ greatly across users and operators, and when the vulnerabilities of particular designs may only be revealed after they are in wide use. We define an agent-based model that removes many constraints limiting existing analyses (such as uniformity of users, free and perfect information), allowing insights into a much larger class of real systems.

Keywords: Two-sided markets, platform economics, platform competition, agent simulation.

1 Introduction

A *platform* is a collection of equipment, facilities, and standards that facilitates a particular kind of interaction. Telecommunications systems, social networking sites, the internet as a whole, DVD players, and credit card networks are a few examples of the platforms that increasingly mediate interactions among people and institutions. Rochet and Tirole [1] and Evans [2,3] recognized the distinctive economic features of these systems, and initiated their formal study as two-sided markets. Many important results have been derived in the short time since, however almost all are derived for systems simple enough to be treated analytically. Some common assumptions include perfect information about demand functions, homogeneity of demand, and uniformity of fees across users of a given class. Most analyses obtain equilibrium results rather than exploring the dynamics of platform development and adoption. Because the

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basic dynamics contain reinforcing feedbacks (for example platform attractiveness to prospective users increases with the number of current users) the equilibrium configuration is likely to be sensitive to small variations in development details.

Some of these analytical constraints are being removed by ongoing research. For example Alexandrova-Kabadjova et al. [4] use an agent-based model to study platform competition when geographical constraints influence interactions. The influence of platform security on users' adoption decisions has received little attention, despite the increasing use of platforms to carry personal and financial data. Creti and Verdier [5] have pioneered the study of fraud costs and liability allocation on platform selection using a staged optimization model amenable to analytical solution.

The agent-based model defined here removes constraints that analytical approaches impose. We focus on the interacting decisions of platform users and creators, including users' decisions to subscribe to or abandon a particular platform, creators' decisions to allocate tariffs and to invest in capacity and marketing. Because we are especially interested in platform security, the model includes intruders' decision to attack the platform in a way that imposes costs on users and creators. The prospect of such losses is a factor in users' adoption decisions and creators' investment decisions.

2 Platforms as Two-Sided Markets

In economic terms platforms create two-sided markets. They are used to interconnect two sets of users, which constitute the sides of the market. Sides typically play distinct roles, such as merchants and credit card customers, or application developers and application users, or musicians and audience. The two sides may use very different technology to connect to the platform, and may face different connection costs and fee structures. The platform operator creates and maintains the infrastructure, and gets revenue from one or both sides of the market.

The different costs faced by different kinds of users, and the platform operator's ability to determine prices and control access, can lead to surprising strategies for optimizing operators, such as subsidizing one side of the market at the expense of the other. The very recent recognition of two-sided markets as a distinctive category has produced important general insights of this kind; however almost all are derived for systems simple enough to be treated analytically.

The increasing variety of platforms through which economic and social interactions are conducted suggests that a model general enough to provide broad insights, yet rich enough to relax assumptions that constrain analytical approaches, would be a useful way of understanding, and setting policies for, important systems of this kind. We define such a model below by describing the essential dynamics of the system. Building from the basic interactions characteristic of two-sided markets, we demonstrate how operators' investments on performance and security can bring in new constraints on the adoption and use of platforms.

3 Model Components and Behavior

The model includes the basic classes of Platform, Operator, and User (Fig. 1). The systems of interest typically have two major subclasses of Users which define the sides of the two-sided market. One class is often a Producer of some good or service or content, while the other is a Consumer. Figure 1 shows the three principle classes and the flows of value considered in the model. These values create motivations for the actions of each class of decision maker. How the Platform creates these values depends on intrinsic features of the domain, performance properties of the Platform, and the number of users of the Platform. The model can be applied to specific cases by specifying parameter values, however the components of the model and their dynamics are meant to be generally applicable.

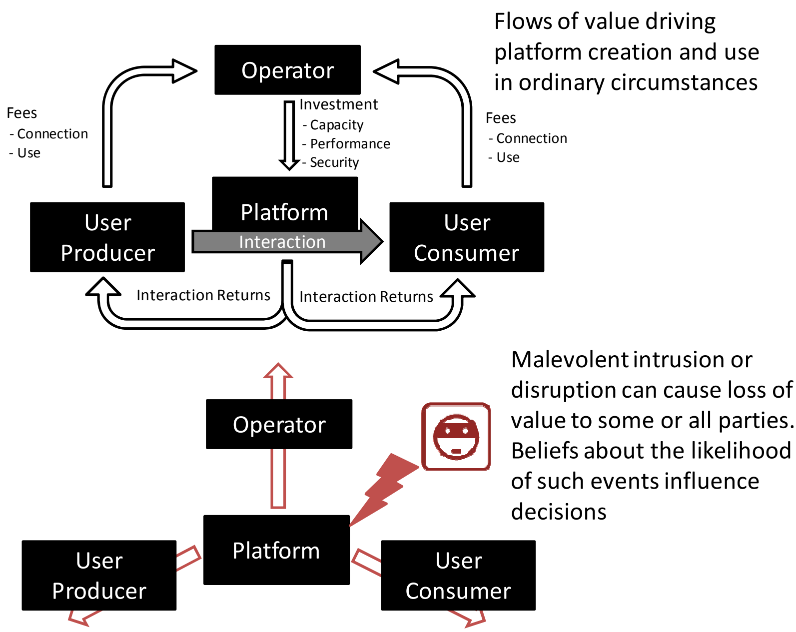

Fig. 1. Main classes in the platform model, and flows of value created by platform use and intentional disruption

Users derive some benefit from interacting on the Platform, and pay fees to the Operator, generally for both access and for usage. Often these fees are explicit; however they might be imposed indirectly, by means of advertising for example. There may be more than one Platform available to Users, so that Users can choose to subscribe to or use alternatives on the basis of their costs and returns. Operators can set the subscription and usage fees borne by each user, and these might vary across users.

Some platforms, especially those mediating financial transactions, compete on the basis of security. We include security as a consideration by means of random acute costs, which can be imposed on individual Users, on groups of Users, and on the Operator. These costs represent losses that would occur as a consequence of a security breach, such as theft of assets or expenses incurred as a result of identity theft. User's expectations about such costs will influence their platform choice and use. These expectations are based on prior beliefs, on the actual security history for the platform, on reports of trusted social contacts, and on marketing messages created by the Operator. Operators, in turn, may invest in security measures that reduce costs or probabilities of a breach as well as in marketing messages designed to shape Users' beliefs about the security of their Platform and other Platforms. Operators' interest in maintaining security comes both from costs they might incur as a direct consequence of a breach and costs of any loss of subscribers or usage arising from Users' changed perception of risk.

3.1 Model of Producer and Consumer Behavior

The success or failure of a particular platform, and the value produced for its users, are the result of interacting decisions by the Operator and by members of the two subclasses of User, Producers and Consumers. We assume Users derive some specified basic value from conducting a single transaction of the kind the platform supports. This basic value may be different for Producers and Consumers, but is the same for all platforms that compete for Users' business. Platforms differ in the number of transaction opportunities they provide, and in the costs they present to Users. Some of these costs can be directly controlled by Operators, while others are the indirect consequences of decisions Operators make, such as investments in capacity and security. These costs and decisions are the strategic variables that Operators use to compete for market share and profit.

The dynamical model of Users' decisions about their participation in a particular platform is shown as a causal loop diagram[1] in Figure 2. The defining dynamical feature of platforms is the reinforcing feedback that causes an increase in the number of producers using the platform to attract additional consumers, and vice-versa. Such two-sided network effects have been identified in many technological systems [6].

This reinforcing feedback can lead to exponential growth in platform users, as well as to exponential collapse, depending on how users' costs compare with the benefits they obtain from using the platform, and the costs presented by competing platforms. The basic value that a user obtains from a single transaction on the platform is exogenous. The model distinguishes subscription to the platform, which involves getting whatever equipment and authorization is required to use it, and usage, which involves conducting transactions on the platform. These two actions may have very

[1] Causal loop diagrams are qualitative model specifications showing the variables considered in the model and the causal relationships between pairs of variables. The effect of increasing the value of a variable on causally dependent variables is indicated by a +/- sign near the arrow to the dependent variable.

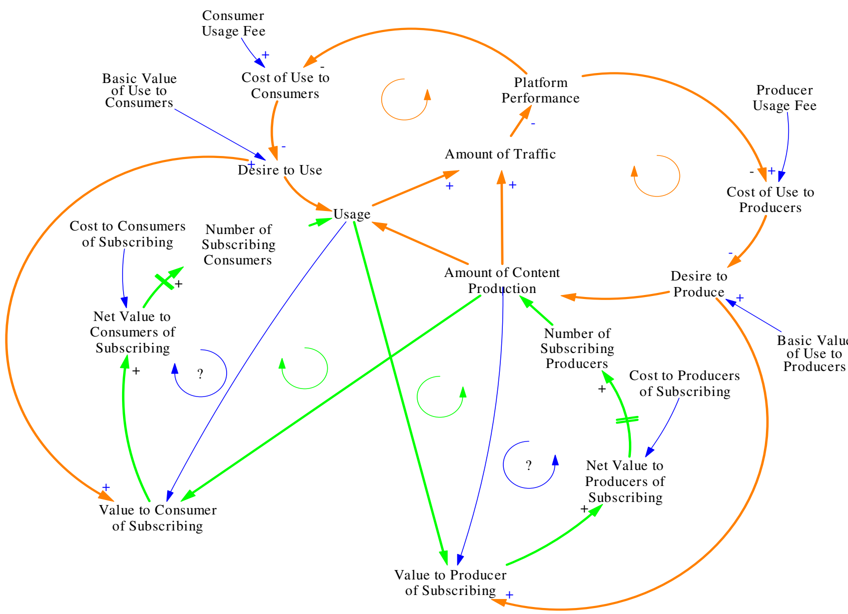

Fig. 2. Causal loop diagram showing the dynamics of platform subscription and usage by producers and consumers. The central reinforcing feedback can lead to exponential growth (or collapse) as additional users of one kind increase the value of using the platform to users of the other kind. Increased traffic on the platform may degrade users' perceived performance and limit growth.

different costs, which differ between producers and consumers. Platform operators can try to encourage growth by manipulating those aspects of costs that they can control. For example a new platform with few producers or consumers will present little value for either side to subscribe. Initial subsidies for subscription, reducing or inverting subscription costs, may attract enough initial users to allow the subsidy to be eliminated for later subscribers. The subscription costs and usage fees in Figure 1 are two important targets of operators' decision-making.

3.2 Model of Operator Behavior

Many existing analyses of two-sided markets derive pricing strategies for operators which maximize their profits, given differing price sensitivities of producers and consumers [1]. In these analyses Users' costs can be directly controlled by Operators. Many systems impose significant indirect costs on Users which may have considerable influence on their decisions, but which are not directly controllable by operators. We include the effects of platform performance and security as indirect costs. Figure 2 shows the potential for increased platform usage to degrade performance and so increase the usage costs of consumers or producers. This increased cost can place limits on prospective users' uptake of a platform. Investments in capacity can be used to improve performance and encourage further growth. The transactions hosted on many platforms have a financial component, and some platforms (such as credit cards) are specifically designed for financial purposes. The security of such platforms is a special concern to users. Security compromise might lead to loss of personal information, initiation of fraudulent transactions in the guise of legitimate users, corruption or blockage of transaction data, and many other undesirable consequences. Such events might lead to direct financial loss to users, or simply to inconvenience and delays which we represent as an indirect cost. Users do not need to experience such events directly in order to weigh such costs in their decisions to subscribe to and use the platform. The expectation of loss from lax security, which includes both the prospective cost of a breach and the users' probability that a breach will occur, is included as a component of cost. Managing platform security, and users' perceptions of security, is a second means by which operators can indirectly control costs.

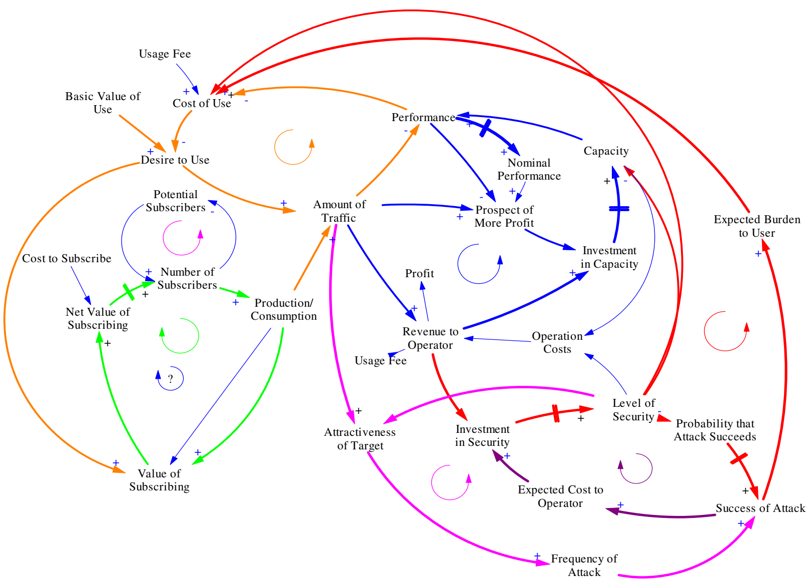

Fig. 3. Causal loop diagram showing the dynamics of platform operator's behavior. Platform growth can be driven by investments leading to improved performance and greater security. Perceptions of improved security may lag investments in security, and reductions in security may take time to manifest as attacks. These delays can create oscillations in security investment.

Figure 3 elaborates the causal loop diagram to include the dynamics of operator behavior. In this diagram the two kinds of platform user have been collapsed into one in order to simplify the picture. Operators receive revenue through platform use. They invest in both expanding platform capacity and in securing access and traffic from this revenue. The linkage between revenue and investment reflects the possibility of direct reinvestment as well as loans secured by future revenue.

The platform operator can encourage growth by making investments that improve platform performance and that increase security. Both kinds of investment tend to lower the effective cost to a user of transacting on the platform. Performance improvements are shown as coming from an increased capacity, although other platform changes that facilitate use (such as redesigning interfaces) can have a similar effect. Capacity investments may be reactive – driven by performance problems with the existing system – or proactive – driven by trends in the current usage which anticipate constraints on performance.

Investments in security are motivated by threats of attack. The kind of attack that might be staged and the costs imposed by successful attacks depend on the specific platform being considered. A denial of service attack for example might delay users' business operations and might degrade the reputation of the platform operator. Theft of credit-card data might lead to financial losses to issuing banks and inconvenience costs to cardholders. A successful attack will increase (to some degree) both the operator's and users' estimated costs, leading to increased investment in security by operators and possible changes in usage. An increased investment in security will reduce the probability of successful attack to some degree, lessening users' perceived costs and encouraging growth in platform use. There can be significant delays in this process, both in deploying security measures and in changing users' perceptions, so that the return on security investments may come long after expenses are incurred. Heightened security can impose burdens on the system and its users. These effects are shown in Figure 3 as a possible reduction in capacity and a possible increase in user costs driven by increases in the level of security.

The threats faced by a particular platform are also dynamic, and the model includes two important factors influencing the attractiveness of the platform as an attack target. The current level of security can deter attack or cause it to be directed elsewhere. The amount of traffic on the platform is assumed to make it more attractive as a target, whether the object is financial gain or spectacle. Increased attractiveness leads to more frequent attack attempts, and a greater incidence of successful attack.

4 Model Analysis and Development Status

The causal model defined above represents the processes that can determine the outcome of competition among platforms when the operators of those platforms adopt different strategies. Even without a precise formulation of the relationships represented by the causal links, the basic feedback structures can produce insights into possible behavior. For example Figure 3 suggests two mechanisms by which an operator might try to expand their platform: investing in capacity to improve nominal performance; and investment in security that decreases users' expected costs. While there are potential delays in realizing performance improvements through new capacity, the delays between an investment in security and an improvement in users' perception may be much greater, especially in system characterized by infrequent but costly attack. This suggests that a strategy emphasizing capacity expansion might out-compete a strategy emphasizing platform security, particularly in a market with rapid growth rates.

A mathematical specification of the causal links illustrated in Figures 2 and 3 is necessary to study particular systems. Such specification allows simulation of possible histories of subscription and use resulting from different user dispositions, costs, and operator policies. We are currently developing an application to retail payment systems, using an agent-based framework that allows for heterogeneous populations of Consumers and Producers, price differentiation by Operators, and other properties that characterize the real system but that make analytical approaches intractable.

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The Impact of Attitude Resolve on Population Wide Attitude Change

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Abstract. Attitudes play a critical role in informing resulting behavior. Extending previous work, we have developed a model of population wide attitude change that captures social factors through a social network, cognitive factors through a cognitive network and individual differences in influence. All three of these factors are supported by literature as playing a role in attitude and behavior change. In this paper we present a new computational model of attitude resolve which incorporates the affects of player interaction dynamics that uses game theory in an integrated model of socio-cognitive strategy-based individual interaction and provide preliminary experiments.

Keywords: Computational model, attitude change, cognitive modelling, social modelling, game theory.

1 Introduction

Attitudes are "general and relatively enduring evaluative responses to objects" where objects can be "a person, a group, an issue or a concept" [1, Page 1]. Attitudes are shown to have an impact on, and can sometimes predict, the behaviors of individuals (e.g., voting behavior [2], consumer purchases [3,4]).

Understanding population wide attitude change is thus an important step to understanding the behavior of societies. For instance, consider the change in attitudes towards global warming and the environment that has resulted in a significant change in public policy and national priorities [5].

While there are a number of factors that influence attitude change [6], we will focus on three in this paper. The first is social – individuals are exposed to various attitudes and information through interaction with others. Family, friends, acquaintances, and the media all influence the attitudes of individuals by providing new information/opinions.

The second factor is cognitive – individuals tend to hold a set of attitudes that are consistent with each other [7,8,9]. According to *cognitive consistency theories*, an individual holding a strong positive attitude towards environmentalism should also hold a strong positive attitude towards recycling; if they do not, the attitudes are inconsistent with each other and could cause an uncomfortable feeling (i.e. *cognitive dissonance*) which tends to result in either attitude or behavior change [6].

The third factor is individual differences in influence. Intuitively, some individuals seem more likely to change than others. This intuition has been supported

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by research from the marketing and social psychology fields (see Section 2 for more details).

Previous work [10,11] has described a socio-cognitive model that captures the social and cognitive aspects of attitude diffusion in individual interaction in a social setting. This work extends previous work by incorporating individual differences in influence. In our model we have two types of individuals, "susceptibles" and "advocates". "Susceptibles" represent individuals that are strongly influenced by others. Thus in any interaction they change significantly. "Advocates" represent individuals that do not change as much.

In this paper we present preliminary work on a new model that captures these three elements together to help understand how information, in the form of attitude, is spread in a social setting. In our model, individual differences will be modeled using *game theory*. We describe the basis of this model, then show some simple simulations that explore the dynamics of this model.

2 Theoretical Basis

Intuition and common experiences seems to indicate that people vary in how they are influenced by others. Some people stand firm and rarely change their attitude opinion, while others often vacillate. Research in social psychology and marketing has provided some evidence to this folk psychological idea.

Decades of research has occurred in the marketing domain to understand how consumer purchasing decision are influenced by others. Two types of influence are usually described, (1) informational – where individuals are influenced by obtaining new information from peers; and (2) normative – where individuals are influenced to conform to others decision in order to be liked [12]. The unit of analysis here is on individuals, and the demographic characteristics that can make them change, such as age or gender [13].

Another branch of research has focused more on attitudes themselves rather than individuals. *Strong* attitudes are: "resistant to change, stable over time, and have powerful impact on information processing and behavior" [14, page 279]. Several characteristics of an attitude, such as its importance to an individual or its accessibility, can influence it's strength.

3 Model Description

An attitude dissemination model consists of various levels of interactions. At the social level, some mechanism selects which agents are to interact with one another. Numerous possibilities exist such as teacher-student interactions, co-worker interactions, or a discussion amongst friends/peers to name a few. Each of these interaction types may have subtle effects with regards to how the selected interacting agents affect one another. Upon selecting the interacting agents, their affect upon one another must be assessed in some manner. And finally, at the individual level, any internal changes brought about by the social interaction may lead to a cascade of changing beliefs or a resilience of the agent's original attitudes.

Game theory is a branch of mathematics pertaining to strategic interactions. As such, it is applicable to the development of a framework which can address each level of interaction in an attitude dissemination model. In this work, we have investigated applying game theory to the agent interaction level. Before describing our game theoretic approach to agent interaction, we will first give an overview of the cognitive and social aspects of our model (for a more detailed description see [11]).

Within each agent in the model is a Parallel Constraint Satisfaction (PCS) model to represent their individual cognitive network. A PCS model is a type of connectionist, attractor neural network. Nodes within an agent's cognitive network represent concepts, hypotheses, or information. These values are continuous and range from -1 (min) to 1 (max). Weighted links between concepts (w_{ij}) indicate the strength of influence between the concepts. PCS models utilize a connectionist approach to find a consistent set of concepts: the value of each concept is updated according to a non-linear *activation function*. One activation function that is often used is [15],[16]:

$$a_j(t+1) = a_j(t)(1-d) + \begin{cases} net_j(\max - a_j(t)) & \text{if } net_j > 0 \\ net_j(a_j(t) - \min) & \text{if } net_j \leq 0 \end{cases} \tag{1}$$

where:

$$net_j = \sum_i w_{ij} a_i(t) \tag{2}$$

and d is a decay term that is set to 0.05. This update rule modifies the value of a concept based on the values of other concepts. An agent synchronously updates all concepts in their network and repeats this process a finite number of times defined as the cognitive effort.

Given this basic inter-agent cognitive framework, our overall model is then composed of three elements:

$$< A, G, C > . \tag{3}$$

A represents a set of n agents that represent individuals, C is a *cognitive consistency network* that represents the internal cognition that drives change in an attitude, and G is the social network graph that defines the social structure of the population. Each agent has the same number of concepts (m), and the same weights between concepts (W), however each agent can differ in the value of those concepts.

We assume turn based dynamics for simulation of individual interaction – where at each timestep the following actions are taken:

1. A single agent is randomly chosen from the population, uniformly across all agents. We call this agent the *speaker*. One random neighbor of the speaker is designated the *hearer*, chosen uniformly from all neighbors.
2. A single concept is chosen as the *topic* of communication.
3. The speaker and hearer communicate with one another regarding the topic of communication. This is the *communication* step.

4. The interacting agents engage in an *information integration* step.
5. The interacting agents modify the values of their individual PCS model cognitive networks in order to find a more consistent set of beliefs. This is the *agent update* step.

In the communication step, our game theoretic approach to agent interactions incorporates agent personality types such that each agent is either an *advocate* or *susceptible*. Much like the canonical Hawk-Dove game, this approach yields differing payoffs depending upon what types of players interact. If an advocate speaks to a susceptible agent, then the advocate will have great success in influencing the suspectible agent towards their attitude with little concession on their own part. However, if two advocates interact with one another, neither is able to persuade the other to budge in their attitude. When two susceptibles interact they are both moderately successful in influencing the other. And so, while being an advocate and aggressively trying to influence the agent you are interacting with is quite successful when dealing with susceptible agents it is a poor strategy in dealing with another advocate. The level of influence one agent has on another is the information integration step. Consequently, new strategic dynamics emerge regarding societal interactions.

Formally, the following update equations govern this agent interaction. Let $x_i(t+1)$ be the activation of node x for agent i at time $t+1$. Let $u_a \in [0,1]$ be the strength of influence of an advocate. Let $u_s \in [0,1]$ be the strength of influence of a susceptible agent. Let $u_a + u_s = 1$, where the update equations are:

$$x_i(t+1) = \begin{cases} u_a x_i(t) + u_s x_j(t) & \text{for Advocate } i \text{ and Susceptible } j \\ u_a x_j(t) + u_s x_i(t) & \text{for Susceptible } i \text{ and Advocate } j \\ 0.5x_i(t) + 0.5x_j(t) & \text{for Susceptibles } i \text{ and } j \\ x_i(t) & \text{for Advocates } i \text{ and } j \end{cases} \tag{4}$$

4 Experimental Results

4.1 Parameterizations

In order to select functionally realistic values for the influence strengths of both the advocate and susceptible agent types we performed an empirical value sweep and found intuitively plausible behaviour to occur with an advocate agent influence strength (u_a) of 0.7 and susceptible agent influence strength (u_s) of 0.3. Weights between concepts in each agent's PCS network were set at 0.05, and we selected a small percentage (10% to 30%) of the population of agents to be of the advocate type while the rest became susceptible agents.

4.2 Experiment 1: Number of Advocates

To visualize and more easily understand the influential power of advocates who may significantly change susceptible agents and are not easily influenced themselves, we experimented with small, randomly connected networks and varied the percentage of advocates in the overall population (see results below). We used the same three node cognitive consistency network in each agent and initialized all of their networks to be cognitively consistent with an attitude value ranging from zero to the minimum defined by the negative attractor value (determined by the weight values in the PCS model). Then we selected a minority percentage of agents to adopt the opposing positive attitude value (ranging between 0 and the maximum postive attractor value, again determined by the weights in the PCS model). The negative attitude value agents are susceptible agents and the positive attitude value agents are advocates.

Iterating over this initialization, we investigated whether 10, 20, or 30 percent positive attitude advocate agents would be sufficient to persuade the opposing majority of susceptible agents to change their attitude belief or conversely if the majority of susceptible agents would be able to overwhelm the minority advocates.

4.3 Experiment 2: Position of Advocates

Beyond investigating the affect of the number of influential advocates in a network, we also examined the significance of the particular position of an advocate within the social network topology. To place advocates in a meaningful location we used small hierarchical and ring network topologies in which we could manually determine specific agents as advocates due to their connectivity or position within the topology.

5 Discussion

5.1 Experiment 1

We have used a small ten node, randomly connected network so that it is tractable to visualize and analyze the interactions and attitude values over each time step of our simulation. A single advocate (ten percent of the population) was never able to convert a single susceptible agent and eventually is overwhelmed to adopt the negative attitude itself. Using two advocates (twenty percent of the population) allows for possible advocate-advocate interactions as well as doubles the possible conversion influence. We began by randomly selecting two random agents as advocates and as before, despite their increased influential capabilities, the two minority advocates were not sufficient to persuade the majority of susceptible agents. Selecting two connected agents, each with low social connectivity, as the advocates was sometimes able to convert the opposing eight susceptible agents. Increasing the advocate population to three (thirty percent) typically was sufficient to convert the seven opposing attitude susceptible agents simply by using randomly selected advocates.

5.2 Experiment 2

To study the significance of the position of advocates within a network, we used the small ring and hierarchical network topologies shown on the left and right side of Figure 1 respectively.

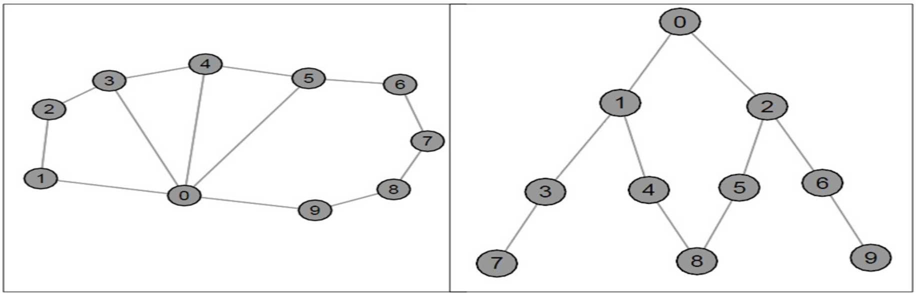

Fig. 1. Small ring and hierarchical network topologies

For the ring network we experimented with setting agent 0 as the sole advocate since it is the most connected agent. However, despite being the most connected agent it was unable to overcome the nine opposing attitude susceptibles. As one might expect, it was able to raise the attitude values of the agents it was connected to, but not sufficiently enough to convert any of them to the postive attitude. Additionally, we also experimented with setting agent 2 as the sole advocate. As a member of the perimeter of the ring which only interacts with its two adjacent neighbors agent 2 was also unable to convert the opposing 9 susceptibles. Finally, setting both agents 0 and 5 as advocates was typically enough to convert the other 8 agents despite the fact that neither is directly connected to many of the other agents in the ring. In this pairing, agents 0 and 5 were able to reinforce one another and eventually persuade the other agents despite being outnumbered.

Figure 2 depicts the affect of different advocate positions within a network. This image plots each agent's attitude value across time. On the left half of Figure 2, two arbitrary agents were selected as advocates, and were unable to persuade the other agents to adopt the positive attitude. In fact these advocates were themselves converted. This is illustrated by by the full convergence of all agent attitude values to the negative attractor at -0.33. Alternatively, the right half of Figure 2 plots the simulation results where agents 0 and 5 were selected as advocates. Although they were the only two agents initially in favor of the positive attitude value, over time they are successfully able to pull all the other agents attitude values up to the positive attractor at 0.33.

For the hierarchical network (seen in the right half of Figure 1), we likewise began by experimenting with single agents as the lone advocate and investigated whether the position at the topmost node in the network would be sufficient to propagate down and convert the rest of the nodes, or whether being a bottom node would be able to spread upwards and convert the others. In both cases, neither sole advocate was sufficient to overcome the other nine susceptibles. Alternatively, utilizing both a top down and bottom up influence by setting agents 0, 7, and 9 as advocates was largely sufficient to spread their attitude and convert all of the remaining agents despite the fact that their influence is

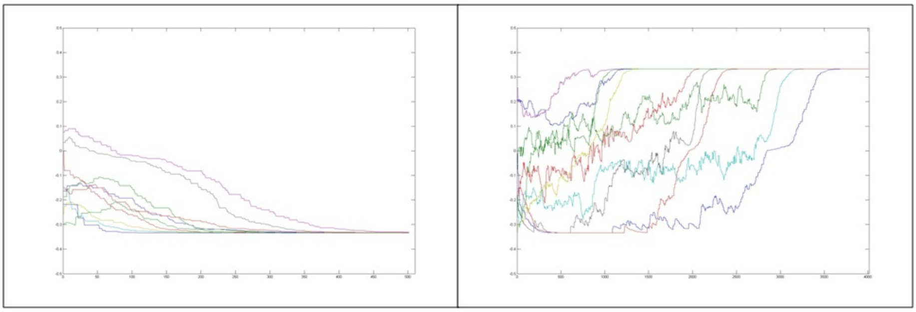

Fig. 2. Drastically different results for different advocate positions within a network

constrained such that they can only interact with one or two other agents whom they must convert and in affect those most continue the spread with their further neighbors.

6 Conclusion and Future Work

6.1 Conclusion

In this paper we have presented a new computation model of attitude resolve which incorporates the affects of player interaction dynamics using game theory in an integrated model of socio-cognitive strategy-based individual interaction. Running a variety of experiments on this model with different network topologies and population mixtures we have investigated attitude adoption and resolve within small networks. These experiments have indicated that selecting specific advocate locations within a population tends to result in a stronger spread of influence, even with only a few advocates in a small network, as opposed to random placement. And the enhanced spread of influence can be observed by the ability to convert agents with opposing attitude values that greatly outnumber the advocates as well as through lower diffusion time (iterations in the PCS network - also referred to as cognitive effort) for the adoption of the opposing attitude.

6.2 Future Work

Having investigated interaction dynamics on computationally tractable small networks, we would like to extend this work to larger real world networks to assess whether the same behavior occurs. Additionally, we can also extend the model to incorporate factors such as more sophisticated cognitive networks.

In addition to incorporating game theory at the agent level we are also interested in looking at the affects of applying game theory at both the social and individual, cognitive level. At the social level, agent interactions are typically dictated by given static social network topology. An alternative approach would be to investigate coalition formation games from coalitional game theory. This particular branch of game theory seeks to build network structure in a strategic manner. Furthermore, if a particular agent, selected as a speaker, is seeking to maximize the spread of their influence they might want to select the hearer they share their attitude view with strategically rather than randomly from everyone they know. Various aspects of game theory such as coalitional graph games or network routing could provide an alternative framework to model this interaction.

As an alternative mechanism to implement parallel constraint satisfaction (PCS) attitude updates within a single agent, a game may be played amongst two attitudes competing to influence one another. Rather than requiring multiple iterative updates the effect is achieved by a single instance of the game. For attitude nodes connected to (influenced by) several other nodes, the game is played simultaneously with all neighboring nodes and the net attitude change is a synchronous aggregated update of all games played in a pairwise interaction with neighbor nodes.

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