The genome-scale analysis of protein complexes in *M. pneumoniae* by Kühner *et al*. greatly expands our knowledge of protein-protein interactions within bacterial cells. Proteins often interact with one another to form functional complexes, and similar to the situation with eukaryotes (*10*), more than 90% of soluble proteins in *M. pneumoniae* serve as components of protein complexes. Surprisingly, the protein-interaction networks correlate poorly with genome organization and gene expression patterns—gene adjacency and coexpression were not good predictors of physically interacting proteins—again suggesting the presence of regulatory mechanisms not apparent from the compact genome structure.

How did these remarkable layers of gene regulation and the highly promiscuous behavior of proteins in *M. pneumoniae* arise? At first glance, these features may seem to be fine-tuned adaptations to the organism's current life-style, but this is not compatible with evidence for the reduced efficacy of selection that operates on the genomes of host-dependent bacteria. Bacteria that chronically associate with eukaryotic hosts undergo bottlenecks at the time of transmission, and such reductions in long-term effective population size result in a relaxation of selection genome-wide. This instigates the accumulation and fixation of deleterious mutations in seemingly beneficial genes due to genetic drift, as well as in those genes rendered superfluous in the nutrient-rich host environment (*11*). In both cases, disrupted genes are eliminated by the pervasive mutational bias favoring deletions that is present in all bacteria, thereby reducing genome size (*12*).

As genes are lost, their roles are fulfilled by the remaining genes, much like the members of a downsized office-staff who perform tasks that previously were carried out by former co-workers. As evidence of this process, the smallest cellular genome, currently 144 kb for the insect symbiont *Hodgkinia cicadicola* (*6*), encodes only 15 transfer RNAs (tRNAs) to specify the 20 amino acids required to synthesize proteins. It is difficult to see how this could be adaptive, or even possible, but presumably several tRNAs must be assuming multiple roles.

The reduced genome of *M. pneumoniae* belies an underlying eukaryote-like cellular organization replete with intricate regulatory networks and innovative pathways, revealing that there is no such a thing as a "simple" bacterium. The compound roles of individual genes and the need for additional regulatory mechanisms both may be hallmarks of reduced bacterial genomes, and the extraordinary information now available for *M. pneumoniae* sets a new standard for understanding systems-level questions about bacterial physiology and evolution.

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COMPUTER SCIENCE

What Can Virtual Worlds and Games Do for National Security?

Virtual environments based on behavioral models allow analysts to explore different outcomes of proposed actions in military conflicts.

V. S. Subrahmanian and John Dickerson

Military planners have long used war games to plan for future conflicts. Beginning in the 1950s, defense analysts began to develop computer-based models to predict the outcomes of military battles that incorporated elements of game theory. Such models were often restricted to two opposing forces, and often had a strict win-lose resolution. Today, defense analysts face situations that are more complex, not only in that conflicts may involve several opposing groups within a region, but also in that military actions are only part of an array of options available in trying to foster stable, peaceful conditions. For example, in the current conflict in Afghanistan, analysts must try to estimate how particular actions by their forces—building schools, burning drug crops, or performing massive security sweeps—will affect interactions between the many diverse ethnic groups in the region. We discuss one approach to addressing this prediction problem in which possible outcomes are explored through computer-based virtual-world environments.

War games (*1*) are used to play out certain scenarios that an expert has designed. Partial information games (*2*) allow machine-derived models, such as stochastic opponent modeling agents (SOMA) (*3*), to guide the actions of players in the game based on stochastic decision rules and in the presence of partial information about the other players' situation. U.S. forces might use SOMA models to understand that a particular group might respond in one of a million ways, together with a probability distribution over those million responses.

Virtual worlds provide a software environment within which players can virtually "see" these scenarios play out in front of them, understand the probabilities of the scenarios, understand what types of things another player might do, and explore "what ifs" with respect to opponents. Decision-makers gain simulated "experience" to guide real-world decisions by enumerating different ways that such complex interactions might play out over an extended period of time.

Underlying the output of a virtual world is a game tree, that is, a tree in which each node represents a "belief state." A belief state is a probability distribution over states, where a state is a set of conditions that are true in a particular node. A state may include not only what a group might be thinking, but also what its offensive capabilities are, where it has forces, or whether opponents are actively engaging them.

Each outcome of a player's actions drops the game a level in a tree. For example, the U.S. might play, with a group playing at the

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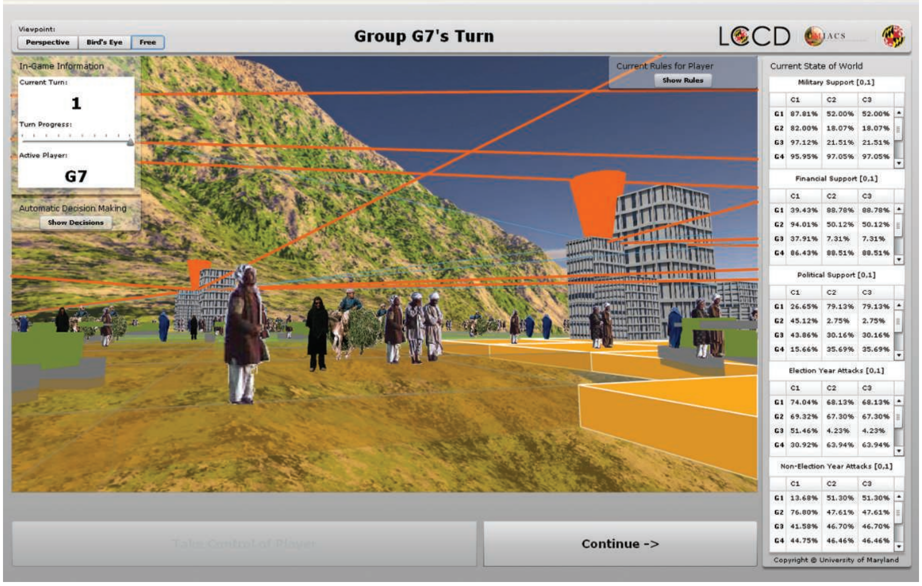

A virtual-world terrain representation. In this example, an Afghan cultural island representing a town might be populated with realistic looking "avatars" representing Afghan men, women, and children whose actions are in accordance with behavioral models. If the town is 65% Pashtun, 30% Hazara, and 2% each of Tajik and Uzbek, with a smattering of other groups represented, then the avatars should follow this distribution as well. The accompanying video describes a set of different outcomes of analyst actions within this representation, which is an example where artificial groups are used.

next level, a second group playing at the level after that, and so forth until it is the U.S.'s turn to play again. A specific U.S. move will transition the belief state from one node to an outcome (or "child") node, but the outcomes cannot be known with certainty. A game tree can easily exceed $10^{1,000,000}$ nodes in size, even to model interactions over a short time frame involving a small number of groups. In the Afghanistan conflict (*3*), for example, different rates of improvised explosive devices attacks in one town represent several branches coming from one node in the game tree. New approaches that limit the number of options use a mix of computational behavioral models (*4*) and forecasting techniques (*4*, *5*) as well as game-theoretical algorithms (*6*). This hybrid analysis model leverages analysts' knowledge with a mix of gaming and virtual-world technology.

A number of virtual-world environments such as *Second Life*, *World of Warcraft*, and others have emerged as online phenomena. However, they do not provide direct support for game theory because neither platform includes real-world models of terrorist groups or sociocultural groups that their forces may encounter. In addition, these platforms do not provide explicit programming for game-theoretic reasoning, although characters can be inserted who perform according to game-theoretic reasoning. For instance, *Second Life* and *Olive* provide an environment where users can adopt a virtual persona that engages in various virtual activities, such as building a house, adopting a profession, and building friendships, but do not provide the interaction environment between groups. *World of Warcraft* provides an environment within which users engage in combat on a virtual battlefield that continuously changes conditions, but it does not consider why groups are fighting or how one group may reason about other groups.

Cultural islands developed at the University of Maryland (*7*), and shown in the figure, provide a virtual-world representation of a real-world environment or terrain, populated with characters from that part of the world who behave in accordance with a behavioral model. For example, the CONVEX (*8*) forecasting engine has been validated on historical data for about 100 groups and found to be more than 90% accurate. The CAPE forecasting engine (*4*), which focuses only on predicting behavioral changes, was validated on historical data for seven groups and had about 69% accuracy in predicting behavioral changes.

U.S. defense analysts can use such virtual worlds to interact with models of the behaviors of these groups and understand how certain actions they might take will affect the short-term and long-term behaviors of these groups. At any given point in time, the game has a "state" describing, for instance, the situation in a town. When U.S. forces or a local government takes actions such as opposing a local leader, that state is altered. A group may react in one of several ways in accordance with a probability distribution.

Although behavioral models can be rerun several times to check for robustness, the intent of the virtual worlds is to allow defense analysts to bring their own expertise into the game to explore how the U.S. or a particular group might act and look for favorable outcomes. Analysts can also make these virtual worlds more efficient by using their intuition to prune large parts of the enormous game tree. For instance, a behavioral model of the Pashtuns in a virtual world may display only the 20 most probable reactions to the analyst, which reduces the number of options to be searched by 98%. Thus, a human analyst playing the role of Hezb-i-Islami may examine the 20 most probable things this group might do and then choose just one of these options.

Defense analysts can understand the repercussions of their proposed recommendations for policy options or military actions by interacting with a virtual-world environment such as CIG (computational intelligence and games) (*7*), which already comes equipped with connections to behavioral models, or other sophisticated virtual-world environments, such as *Second Life* or *Olive* (*9*), both of which may be augmented with appropriate behavioral models. They can propose a policy option and walk skeptical commanders through a virtual world where the commander can literally "see" how things might play out. This process gives the commander a view of the most likely strengths and weaknesses of any particular course of action.

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