13 Data interfaces for input, output, and translation between models[1]

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1. Introduction

Data processing for course of action (COA) analysis of irregular warfare (IW) scenarios differs from COA analysis of conventional warfare scenarios for many of the same reasons that social science differs from physics. A significant difference is that physics models are models of things, while social models are models of modelers because all people model their world. IW focuses on the reactions of a population of these human modelers—reactions that, unlike physics-based outcomes, are neither straightforward nor equation-based. This distinction encapsulates the challenge of processing sociocultural data. Sociocultural data processing requires interfaces between disparate models—interfaces so complicated that designing them is itself an act of modeling. Physics models, by contrast, typically implement Newtonian-based, validated data that can be held in limited repositories and require no translation because the models rely on shared and accepted concepts.

IW modeling involves reproducing a series of moves and countermoves that antagonists might use to convince populations to model and act upon events in one way and not another. How agents—whether human or software agents—react to IW moves results from their interpretations, or the way that they model the moves. Information operations (IO) present narratives to counter terrorist narratives; Civil Military Operations (CMO) embody these counternarratives. Both terrorist and CMO narratives are processed by minds that create interpretive models to determine which narratives make sense to them. A population's reaction to IW, IO, or CMO is represented by the computation in and the interfacing of models in individual agents' "minds."

Consequently, data processing for mitigation encompasses the representation of the data input, output, and trades between models, the interfaces between the models that arrange how those data are traded, and the ways in which the data are translated into the different languages of the different models. Applied to COA analysis in sociocultural scenarios, data representations include representations of strategy and narratives. They also include coevolutionary model interfaces, game theoretical arrangements of disparate models, and interfaces that preserve uncertainty.

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This chapter uses the film *The Battle of Algiers* as an example to provide context for the IW battlespace. It then discusses state-of-the-art social data representations and interfaces among social models for COA analysis of IW, giving examples of their value in the representation of social phenomena.

2. IW Strategic Scenario

To design data representations for COA analysis with sociocultural models, we must first understand how the models are used. In the context of this chapter, the moves and countermoves of IW form the crux of what sociocultural COA analysis examines. These moves and countermoves represent the antagonists' attempts to change the population's perceptions. To anchor the discussion of sociocultural data for COA analysis, we present a synopsis of the movie *The Battle of Algiers*, produced and written by the actual insurgents and shown in the Pentagon as an archetypal IW scenario in which an insurgent group used IW tactics to make the transition from unpopular to victorious (Solinas, Yacef, Pontecorvo, Musu, Haggiag, & Martin, 1976).

In 1954, the French suffered defeat at Dien Bien Phu, Vietnam, prompting French withdrawal from its Indochinese colonies. The French now appeared vulnerable, and Arab resistance elements in Algeria believed that the French would not want to engage in another colonial war. However, the French considered Algeria fully a part of France and were determined to counter any rebellion. Even so, the French public was susceptible to narratives that highlighted the political and economic discrimination that indigenous Algerians suffered. The regime deprived 10 million indigenous Arabs in Algeria of political rights, and almost all of the economy was in the hands of one million French Algerians, who enjoyed better houses and schools than the Arabs. Note that the points of vulnerability of the French, and the sources of strength for the Arabs, were cognitive: the war-weariness of the European French, the European French conviction that Algeria was an integral part of France, and the potential for the indigenous Algerians to perceive injustice were all ideas critical to motivating the popular will. IW simulations should capture such ideas, how they spread, and how they motivate IW actions.

The Algerian insurgency, known as the National Liberation Front (FLN), argued that the French Algerians did not respect their culture and incited decadent behavior such as prostitution and drunkenness. The FLN therefore campaigned to purify Algeria, imposing their own death sentences on the population for behavior that contradicted Muslim values. The movement assumed other functions of government as well, such as performing wedding ceremonies. The FLN strategy was to win the respect and support of the people and thereby secure hideouts for themselves. Ethnic violence between the French and Arab Algerians included an uprising in 1945 in which 90 French Algerians were killed, followed by a French massacre of over 40,000 Arabs. Many Algerian Arab insurgents cited this massacre as a factor in their decision to join a terrorist group. Despite this history, in 1954 every newspaper in Algeria, including the communist papers, favored elimination of the FLN. Note that the massacre constituted evidence that countered the newspapers' anti-insurgency narrative, while the contrast between French behavior and Muslim values supported the narrative that insurgents who suppressed these behaviors deserved respect.

When the French guillotined FLN leaders in 1954, the FLN complained that they were being treated as criminals rather than combatants, and organized an insurrection against the Algerian police. The police reacted by instituting curfews, checkpoints, and searches of Arabs, sometimes violating cultural restrictions on searching women. The French Algerians, together with members of the police, also bombed the Kasbah, a concentrated ethnic Arab section of Algiers, killing 75 Arab civilians. The Arab populace rushed out to demonstrate in the streets, but the FLN stopped the demonstrations, telling the people that they would be slaughtered and that the FLN would avenge their compatriots. The FLN did this because they feared that widespread killing would intimidate the people whom they hoped to rally to their side. Note that protecting the populace and avenging them supported the narrative of the FLN's legitimacy as an ally and prevented emergence of a discouraging narrative of the hopelessness of standing up to the French.

In 1956, the FLN avenged the Kasbah bombing by launching a simultaneous attack on three French civilian targets, killing many French Algerians. Some French Algerians responded by targeting innocent Arabs and even Arab children. The government of Algiers turned the situation over to the French army.

In 1957, the FLN coordinated an eight-day general strike to gain the attention and support of the international community, specifically the United Nations (UN). Despite widespread support within Algeria, the strike had little impact on the UN because the French army broke the strike in a day by forcing people out of their homes, opening the shops themselves, and compelling owners to open their stores when they tried to protect their goods. However, the government's aggressive response served to anger the Arab population further. The FLN's terrorist actions and the French retaliation led more and more people to believe the narrative that the French were the enemies of indigenous Algerians. The insurgents successfully turned the Algerian Arabs and the international community against the French government by inciting harsh reactions. At the same time they insulated the people and themselves from intimidation by timing demonstrations and strikes so that supporters would feel strength in numbers and not fear reprisal.

Both sides paid attention to the perceptions of the people and the international community by following unwritten rules of legitimate action, evidenced by their seeking to justify their actions. For instance, the insurgents sought favorable opinions by advancing the theme that the French government had crossed the line by harming civilians. The insurgents also presented the Algerian government with "damned if you do, damned if you don't" situations, where the cure had the side effect of causing more damage. For instance, by pressing the government to end checkpoints the insurgents would benefit no matter how the government responded: they would reap direct gains if the checkpoints ceased, but would obtain additional popular support by making claims about humiliating searches and violations of custom if the checkpoints continued.

Although the local population generally favored the insurgents and sheltered them, the Algerian government and the French army achieved short-term tactical success by arresting and often eliminating FLN members. The FLN instructed its adherents to remain silent for 24 hours if they were captured, which would render their knowledge of safe houses useless. To counter these instructions, the French army used brutal torture techniques to obtain information in the few hours during which it was still useful. However, the army weakened its own cause by torturing some persons who were not insurgents. This further deepened the belief that the French were the enemy of the indigenous Algerians. Over time, the Arab population and the French press learned about the torture, giving rise to an even larger insurgency in 1960. The result was a strategic defeat for the French-supported Algerian government, even though the French had "won the battle" by eliminating nearly all insurgents. The strategic defeat caused by the Algerian populace's changing beliefs ultimately led to the end of French control in Algeria.

3. Representing IW Strategic Data

In the *Battle of Algiers* scenario, insurgent moves embodied strategies to make the French act in a manner that advanced the narrative of "the French as oppressors." Although the French lacked a counternarrative, modern doctrine combines IO with CMO to support narratives reinforcing the legitimacy of the host nation or friendly forces. To represent insurgent and coalition force COAs for an IW scenario, modelers must represent the narratives, the population's reactions to the narratives, and events surrounding the narratives. Additionally, they must capture the insurgents' mental model of the population and the coalition forces' mental model of the population, if applicable, as well as the reactions of insurgents and coalition forces to each other. Steve Corman's project on Identifying Terrorist Narratives and Counter-Narratives (ITNC) at the Center for Strategic Communication and Arizona State University, John Horgan's project on Competitive Adaptation in Terrorist Networks (CATNet) at Pennsylvania State University (Horgan, Horne, Vining, Carley, Bigrigg, Bloom, & Braddock, 2011), and Jerzy Rozenblit's Asymmetric Threat Response And Analysis Program (ATRAP) at the University of Arizona (Mitchell, Craw, & Ten Eyck, 2011) present innovative ways to represent strategic ideological moves and countermoves.

According to narrative paradigm theory, people think in stories (or frames) and interpret events through these frames. Corman, Ruston, & Fisk (2012) developed a method to extract frames from text that represent cultural narratives and cluster them into groups of "master narratives" that contain archetypes. Corman uses the Natural Language Processing (NLP) technique to identify similar stories and concepts in these stories as general archetypes, and then counts how often these archetypes appear in news stories to obtain a measure of belief of the host nation. Corman examines the archetypal master narratives for evidence that friendly forces can show the host nation population to discredit terrorist narratives, on the assumption that the average person can be convinced with logical argument. He also examines possible narratives that the host nation could adopt to counter the terrorist narrative, thus helping the host nation population to interpret U.S. actions as we wish.

In the Algiers example, the host population initially internalized a narrative that they were French citizens, accepting blame for the massacre of their citizens following their 1945 uprising. However, that framing of the situation did not sit well with the indigenous Algerians: because the narrative minimized the disproportion of the response it caused cognitive dissonance. The insurgents took advantage of this dissonance by offering the population a way to resolve it cognitively, which also put the FLN in power. The insurgents' counter-narrative focused on injustice, framing the situation as a breach of contract, as well as one of moral decadence, if Algeria remained under French rule.

This theme of unjust treatment became a master narrative in the Muslim world that has persisted through the Arab Spring of 2010. The French offered only the counternarrative that individuals who joined the resistance would be tortured and the population massacred. This narrative of fear caused revulsion not only among the indigenous population but also in France proper, and was not consonant with either party's value system. The French resolved the dissonance by withdrawing their forces and granting independence to Algeria.

In Corman's unique formalization of narratives, an analyst starts with free text such as news articles, parsed with resource description framework (rdf) triplets of subject, verb, and object. The analyst identifies stories in the text, creating graphs that represent the stories. After manually dissecting many articles in this manner, the analyst clusters individual graphs to obtain an objective "story distance" measure. The analyst measures story distance by taking all triplets in one story and comparing them to all triplets in another story, scoring the same noun or its synonym with its inverse document frequency (IDF), a measure of the noun's uniqueness. If the verb is the same or a synonym (as determined by the verbNet thesaurus) its IDF score is added to the triplet distance score. The sum of the added IDF scores of all the triplets determines the similarity of the entire story to another story. Then, the analyst assumes that close stories adhere to the same general archetype, and extracts the similar nouns and verbs to make up a general story pattern and objectively measure the frequency of that pattern in news articles as a measure of belief. For example, this technique could enable analysts to measure the frequency of the master narrative of injustice in the Algerian and French press during the battle of Algiers, mapping the population's beliefs over time.

The ability to model IO, including IO content, the impact of IO on the population, and the reasons a population accepts (or does not accept) IO, remains the largest gap in IW modeling. Analysts can use Corman's objective formalization of stories as an indicator of a story's recurrence as well as an explanation of why a message is accepted or not. Modelers can use this formalization to represent the cognitions of host nation agents in simulation models, and to feed these cognitions into the agents' "minds" directly from news articles. This technique not only allows modelers to enter data into simulations and to compare simulation data against real world data for validation, but also facilitates a representation of cognition that enables models to compute the acceptance or rejection of messages. Corman's method lends validity to studies precisely because it addresses the causation behind message acceptance as it exists in cognition.

By contrast, Horgan's research describes terrorists' evolving behavior throughout a conflict or throughout the terrorist's career. Horgan is a widely acclaimed expert on terrorism; his CATNet project shapes the detailed interviews and field work he conducted into a story of competitive adaption, or coevolution, between insurgencies and government. Horgan defines competitive adaptation as the ability to learn from an adversary and gain a variety of skills in order to overcome the enemy. Horgan's methodology involves detailed, structured interviews to capture how individual terrorists learn and change throughout their careers, asking questions about what they learn from the governments they are fighting. His studies revealed that terrorists act in response to their government enemies: with every new initiative by the government, the terrorists find a new strategy to circumvent the government and enforce their will on the people. Horgan's interviews capture the coevolutionary dynamics of insurgencies in the Military Information Support Operations (MISO) moves and countermoves that are central to terrorist activities. The coevolutionary information that Horgan gathered can serve as excellent training data to tune coevolutionary agent models as well as test data against which to validate the models.

While Corman represents the narrative in text, and Horgan represents the coevolution of conflict in structured interviews, Rozenblit represents the coevolution of conflict in text. Rozenblit led development of ATRAP, a toolkit that aids intelligence analysts to find and interpret patterns in free text that could represent enemy COAs. ATRAP combines genetic algorithms, game theory, and NLP to give analysts an automated filter for documents that together create alerts and situation awareness of possible enemy actions. The system finds entities and links in text that form patterns that an analyst can mark as an indicator. The analyst can then build a threat template by stringing together indicators in parallel and in sequence to describe enemy tactics, techniques, and procedures (TTPs) or any COA.

In the context of the Algerian example, the threat template might string together the three indicators “money transfer”, “to organization”, and “related to location of interest” in parallel with the three indicators “money transfer”, “to organization”, and “related to equipment of interest.” The French forces could have applied such a threat template to unstructured text in messages, such as terrorist interrogation reports or human intelligence (HUMINT) reports on *hawala* exchanges, with a location of interest such as “Kasbah” and equipment of interest such as “explosives.” If an ATRAP template identified the money transfer as a gold transaction over $1,000, it could indicate purchase of an explosive.

ATRAP's innovation lies in the way templates model plausible changes in terrorist TTPs. ATRAP first uses a genetic algorithm to find new patterns that resemble existing patterns in the text corpus. ATRAP then applies game theory to model how this new template, as a COA, would play out against existing defenses in a coevolutionary dialectic with counter-tactics. Staying with the Algerian example, if the insurgents had used game theory to model the new tactic of simultaneous bombing, they might have predicted that demonstrations would occur if the French employed a kinetic response to counter a simultaneous bombing. The French could counter the demonstrations with an even larger kinetic response, which might discourage the population from supporting the insurgency. To adapt their strategies, the insurgents chose to discourage the reactive demonstrations.

ATRAP could be further enhanced to include identification of terrorist and friendly narratives in data and associated actions such as CMO responses to insurgent actions. To do so, ATRAP would either have to be augmented to find indicators of narratives, or work in concert with other programs that identify terrorist narratives and counternarratives, such as Corman's ITNC. Once modelers have formalized the representation of narratives and COA templates and extracted them from the text, they become available for models to ingest as “training” data or as “testing” data to validate the model.

4. Coevolutionary Integration of Models for COA Analysis of Social Institutions

The arrangement and integration of models is another dimension in data processing for COA analysis. Model integration, because it involves interactions between disparate models through data, is a task for data processing rather than for modeling. An autonomous agent, and the way a cognitive autonomous agent models its environment, could be viewed as a complete model in itself, while the interface between agents constitutes a model integration scheme.

Coevolutionary integration of models has particular importance in COA analysis. Coevolution is a model integration scheme that can compute a population's reaction by integrating individual agents, each of which uses an autonomous machine learning algorithm for maximizing utility—that is, for best achieving goals. Such agents are autonomous because they calculate for themselves how to perceive and act to increase their utility, and do so in a way that makes sense in their individual situation. Coevolving agents determine how to perceive and act by using a method of induction, such as a neural network, genetic algorithm, Bayesian network, reinforcement learning algorithm, or even a cognitive architecture (Alpaydin, 2009; Mitchell, 1998; Sun, 2008). Inductive methods compute how an agent should perceive and act through trial and error iterations of perceptions and actions based on how these perceptions and actions affect utility. The important aspect of model integration is that the agents exert coevolutionary pressure on each other, meaning that they change each other's utility values as they act upon what they learn. Thus, although agents may have static overall goals such as "survival," the most effective subgoals to achieve these goals may change.

Integrating individual agent "minds" so that they influence each other's perceptions is a good way to model IO COAs because the purpose of an IO model is to explore why a particular belief would make sense to agents, whether human or software, in their individual circumstances. Models of IO that do not walk through sensemaking, such as homophily models based solely on copying agent neighbors, cannot explain why some IO messages are not copied, that is, why they failed to influence the intended audience, and therefore cannot test COAs. Coevolving agents are not so dependent upon each other as to be empty of thought, like homophily-based agents, nor are they fully independent thinkers that have no effect on each other: rather, they are autonomous networked beings, each of whom/which influences what makes sense to the other.

The integration scheme between individual models of thinking agents (their external interface) represents the agent's social world. Sociocultural modeling focuses on what happens in the interface: the connection between the agents' minds (in other words, their network). Understanding social behavior equates to understanding institutions. Human institutions are social because they are based on human agent's knowledge of how other human agents will react to their behaviors. For example, bribery is social because people would not offer bribes if they did not have confidence that the bribe would be accepted, or at least that they would not go to jail because of the bribe. To achieve their goals, agents learn corresponding behaviors, such as to bribe and to accept a bribe. As these behaviors become expected, they change the utility of the agent behaviors, so that bribing increases utility only if the bribes are accepted. As these behaviors become commonplace, they become institutions.

The *Battle of Algiers* scenario shows the alignment of goals into acceptable behaviors that rely upon established institutions, such as rules about actions that merit support. For example, the strike that the FLN initiated was not large enough to garner support from the UN, but the French suppression of the strike was violent enough to be distasteful to the European French and reduce their support of the war effort.

The interdependence of behaviors, to include interlocking and corresponding behaviors, causes societies to develop into distinct types in which not every possible combination is possible. Behavioral dependency makes social behaviors self-reinforcing, causing virtuous or vicious cycles. COA analysis of an entire society, therefore, amounts to the study of when society tips from one self-reinforcing set of behaviors to another, and IO COA analysis becomes the study of why a paradigm shifts from one way of viewing the world to another. That paradigm shift in viewpoint is critical to the behavioral change.

The Nexus Cognitive Agent Program (Nexus), created at the Office of the Secretary of Defense (OSD), modeled corruption and popular support in OSD's first IW Analytical Baseline, the Africa Study (Duong, 2012). In Nexus, corruption is modeled as a system of interlocking behaviors that agents learn to execute (or not) depending on how the behaviors affect utility. Utility in Nexus is defined by cultural values. For example, in the *Battle of Algiers* scenario, both the general population and the insurgents had cultural goals such as eliminating prostitution and alcohol consumption. In the Africa Study corruption scenario, software agents represented human individuals and utility was defined by African tribal cultural values. For example, a tribesman from a matrilocal tribe may care that his maternal grandmother has bought enough food in the market in the past year to sustain her health. Choices to give and receive bribes only indirectly affect utility, but indirectness is important because we can effectively explore whether bribery is effective or not under a variety of circumstances. If our simulation could produce no other outcome—that is, if bribing always generated positive outcomes and the optimizing agent has no recourse but to bribe—then we cannot report to senior leadership that we have studied bribing with scientific validity.

In the Africa Study corruption scenario, Nexus agents possessed a strategy of behaviors, telling them to bribe, accept bribes, steal, or tolerate stealing, along with a variety of network choice behaviors. Each strategy was a chromosome in a Bayesian Optimization Algorithm (BOA). Each agent had its own private BOA with 20 strategies, defined as a combination of behaviors, and executed each strategy for one year. The strategies were ranked by utility of the agents' dependents, for example, the maternal relatives of matrilocal agents. The 10 best strategies were retained and Nexus then created ten more new strategies with the same statistical properties as the ten best.

One particular analysis that can be conducted utilizing the Nexus tools involves testing the effect of transparency programs versus higher judicial penalties on the society to determine which COAs will tip the society from corrupt to noncorrupt states. For example, analysts can test for a reduction of bribery transactions between agents, such that agents no longer expect to receive bribes from other agents or feel obligated to offer them, or examine other goals that the COAs attempt to affect.

In the Nexus Africa Study's popular support scenario (Marling, Duong, Sheldon, Stephens, Murphy, Johnson, & Ottenberg, 2008), every agent maintained a neural network with which to induce popular support and determine whom to credit and whom to blame for actions based on consistency theories in social psychology. The model implemented Festinger's cognitive dissonance theory (Festinger, 1957), Heider's balance theory (Heider, 1946), and Fischer's narrative paradigm (Fischer, 1984). Nexus assigns each agent a constraint satisfaction neural network, specifically, a Boltzmann machine, to represent the mind. In this network other agents tend to be supported if they treat the agent well and support the agent's "friends," and tend not to be supported if they treat the agent poorly or do not support the agent's friends. Historical actions and a network of support all contribute to an agent "schema" of support. That schema consists of a set of reinforcing facts that cause an agent to polarize friends and enemies, and perhaps to blame its enemies for more than they have done while perhaps supporting its friends more than they deserve. Support relations, such as coalitions, that link the agents arise from these schemata in the form of public declarations of support; because they are self-reinforcing they tend to tip the society between states. The schema enables COA analysis of popular support, such as how coalitions change as a result of exogenous interventions. The coevolutionary integration scheme between autonomous agent models is critical to the COA analysis, because popular support takes the form of data traded between the models, and coevolution of this data represents how individual agents change each other's minds.

5. Game Theoretical Integration of Models for COA Analysis of Strategic Moves and Countermoves

Recall that not only software agents but also their cognitions about their environment are individual models. Models can represent a strategist agent's situation awareness, and can be executed in a way that represents each side's mental model of the enemy and of the host population. Thus models can be integrated in a game-theoretical manner for analysis of strategic moves and countermoves. In this way they can represent a mental model, or "what if he thinks X…" scenario, even if they were designed as models of the environment. For example, the eXtensible Behavioral Model integration framework (XBM) project led by Impact Computing (2013) is an open source tool that enables the representation of a strategist agent's situation awareness by running any models (not just cognitive models) as though they were the strategists' mental models.

XBM runs models in innovative strategic combinations with each other for COA analysis. Specifically, it supports the concept of *strategic data farming*, a variation of data farming that utilizes game trees to detect best COAs during scenario runs (Duong, Brown, Schubert, McDonald, Makovoz, & Singer, 2010). Data farming is a form of COA analysis by testing parameter sensitivity through a very large number of model execution runs. One way to test COAs with computer simulations is to trace which inputs, such as IW actions, lead to which outputs, such as popular support. Again using the *Battle of Algiers* scenario, inputs for the French commanders could be kinetic strategies to eliminate the insurgents through checkpoints, curfews, and harsh treatment, while outputs of interest would include estimates of popular support among the indigenous Algerians and the European French. Data farming is complicated because the large number of parameters in sociocultural simulations typically precludes testing every parameter in combination with all the others to see what combinations of inputs lead to what outputs. Testing parameters in combination could require billions and billions of simulation runs; a stochastic simulation would demand an order of magnitude more runs to cover the space of possibilities.

Data farming covers the parameters as evenly as possible by applying methods such as Cioppa's "orthogonal Latin hypercubes," which optimize parameter coverage on a simulation treated as a black box (Cioppa & Lucas, 2007). Strategic data farming has a different focus: rather than examining all possible outputs from the simulation, it performs risk-based COA analysis by sampling the output space in proportion to likelihood. For example, in the Algerian scenario, kinetic input moves of the French government would usually correspond to input moves of the insurgents such as strikes. Because simulation parameters are not in fact orthogonal, strategic data farming inputs parameters proportionately to generate a proportional output space.

Using strategic data farming, XBM can also represent deception, a concept central to IO campaigns. In XBM, an analyst may execute a model scenario depicting the red side's concept of the blue side's concept of the battlefield. One example of deception is the IW tactic of trying to incite trouble so that the other side seems brutal and receives the blame of the population. This tactic appeared in the Algiers example when the insurgents bombed French citizens, eliciting a harsh reaction from the French police. XBM could execute a model that represents the indigenous Algerian population's reaction to French kinetic and nonkinetic moves as the insurgents' cognition regarding the consequences of their own actions meant to incite the French. Executing these coexisting situation awarenesses and resultant behaviors results in a COA analysis based on strategic moves and countermoves.

Analysts at the U.S. Army Training and Doctrine Command Analysis Center (TRAC) applied strategic data farming to an IW IO scenario using XBM and Nexus. The research evaluated moves, countermoves, and strategies from TRAC's tactical wargame to determine the best COAs under certain conditions. The research also provided insight into the population's attitude toward the host nation and insurgents, and helped identify tipping points where the population may shift allegiance.

XBM performs dynamic moves to achieve agent objectives by implementing the following three capabilities: (1) assessing indicators that measure how far agents are from their goals at specific time intervals, (2) saving and precisely restoring the simulation state (checkpoint/restart), and (3) implementing moves. XBM defines player strategies, and players' perceptions of other players' strategies, in advance. In strategic data farming, a strategy consists of the following elements from the Military Decision Making Process (MDMP):

- Decision points – conditions under which a change of Concept of Operations (CONOPS) is to be considered
- Branches and sequels – doctrinal guidelines that constrain and define possible moves

- Goal states – ultimate objectives
- Subgoal states – proximate short-term objectives

XBM maintains “ground truth” that represents reality as opposed to any particular player’s view of reality. When a player’s decision point has triggered and the player must choose among doctrinal moves, the simulation is executed from the viewpoint of the decider (decision maker). In other words, the simulation executes the decider’s idea of the other players’ points of view as the decider looks ahead (mental model) to what might happen. If perception and deception are excluded only one model is needed, because blue’s view of red’s plans and what red sees are assumed to be correct and vice versa.

When the decider reaches a decision point, or believes that other players have reached a decision point, the simulation branches (along the game tree) according to the top *n* moves of that player’s strategy. Other player’s moves are translated back to the decider’s simulation, which represents the decider’s ground truth. This pattern recurs until a certain number of decision points have been reached, and then XBM judges each separate simulation according to the decider’s idea of the other player’s goals. XBM sends the score of the simulation back up the mental model game tree, assuming each player selects actions that lead to the most favored condition. The decider then picks its next move with the assumption that each player is optimizing its goal at every decision point. All players decide their next moves in the same manner, and then the ground truth simulation advances to the next decision point.

Figure 1 illustrates a small portion of a game tree in which blue looks ahead for six decision points. Ratings are shown for each simulation state from the bottom of the tree (not shown).

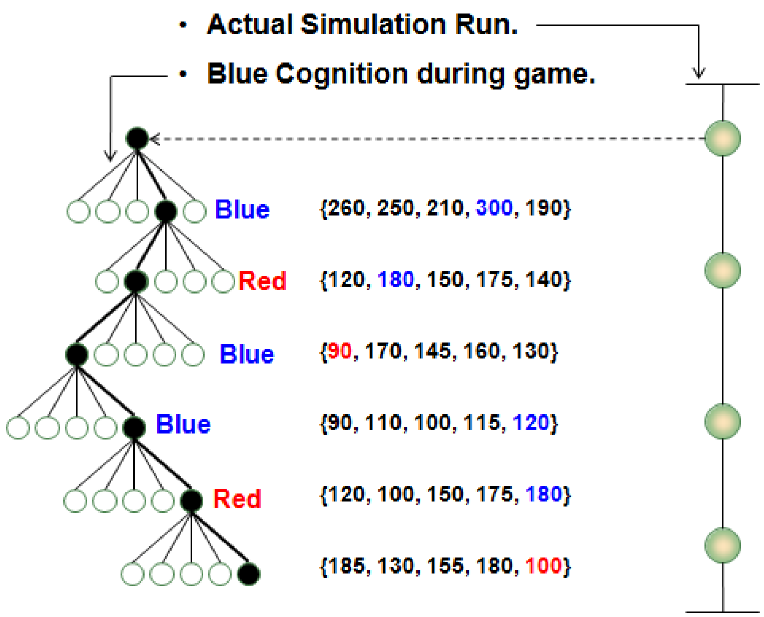

Figure 1. One decision point is reached in a simulation, causing blue to examine six decision points and choose a COA according to its CONOPS.

Figure 2 illustrates an example run of the Nexus model. In the Africa Study, Nexus modeled and measured intergroup support levels. Nexus represented a "group mind" for each tribe and computed support levels based on past historical events and support networks. The study measures intergroup/alliance strength by executing stochastic Nexus ten times. If a group mind was positive about another group in every case, then the alliance was deemed solid. If a group mind was positive about another group half the time and negative half the time the alliance was deemed tippable.

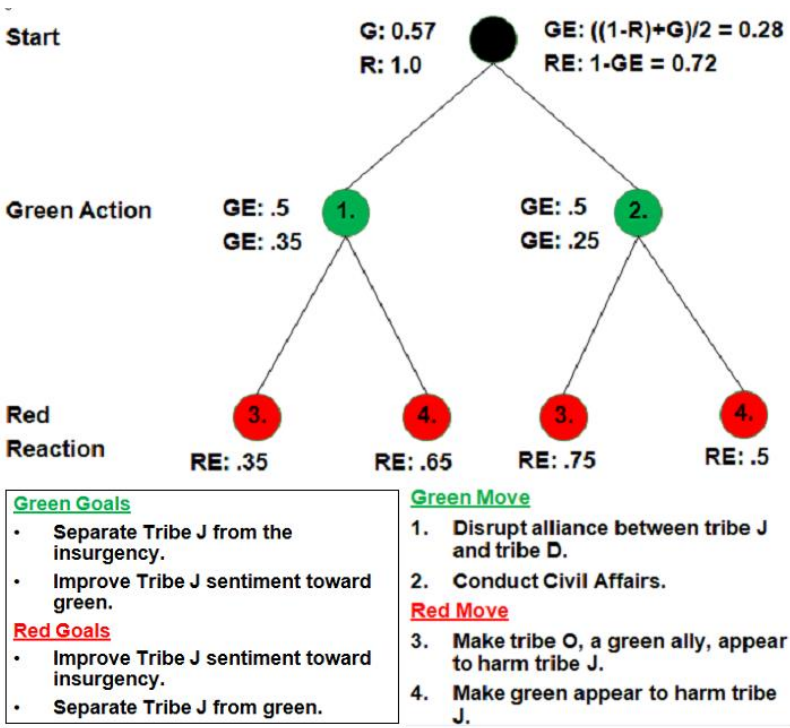

Figure 2. Goals, doctrinal moves, and evaluation function (GE and RE) of a Nexus strategic data farming walkthrough.

In this scenario, green represents the host nation government actions and red represents insurgent actions. Both green and red focused their attention on the opinion of Tribe J, the main tribe from which the insurgency recruited its members. All the people of Tribe J initially had positive views of the insurgents, even though 57% of Tribe J also had positive attitudes towards the green government.

Green wanted to act in the region because its popular support had waned. The objective function was to form a more solid alliance with one's group and a more solid opposition with the opponent.

Green's evaluation function was: GE= ((the ratio of times green's support node was illuminated in Tribe J's brain) + (the ratio of times red's support node was illuminated in Tribe J's brain))/2. Red's evaluation function was: RE = 1– GE. An increase or decrease in the evaluation function served as the decision point. Fully executing the single mind of Tribe J in Nexus with no moves, to get a baseline of what would happen in the simulation had no party intervened, resulted in a tight alliance between Tribes J and D, and a GE score of about .28.

Assume green's strategy involves a choice of either performing positive civil affairs actions or trying to disrupt the alliance between Tribes J and D by causing ethnic tension (for example, having a Tribe J member provoke an attack by Tribe D members, filming it, and broadcasting it to Tribe J members). When green assesses these moves in isolation, both increase GE to 0.5. To differentiate between the two, green must look at the vulnerabilities its actions may have created for red retaliation. Say that the red strategy only includes making others look bad (for example, by provoking green into acts of violence against Tribe J, and by inciting ethnic tensions between Tribe J and a green ally, Tribe O). If green only performs civil affair actions, inciting tension between Tribe J and Tribe O causes RE to reach 0.75. Green acts of violence against Tribe J result in an RE score of 0.5. Thus, since red would choose to incite tension (because it would cause more damage), the true value of the civil affairs action to green is GE = 1 – 0.75 = 0.25.

On the other hand, if green first causes ethnic tension with Tribe D and red retaliates by causing ethnic tension with Tribe O, then RE = 0.35, and if red retaliates by inciting acts of violence by green against Tribe J, RE = 0.65. Thus, in this case, red would again choose to incite acts of violence against Tribe J, the action with the strongest effect. Apparently, if green incites ethnic tensions first, it is protected from the effects of red actions later. Accordingly, the value of inciting ethnic tensions to green is GE = 1 – 0.35 = 0.65. Since 0.65 is greater than the present value of 0.28, it is to green's advantage to take this action, given the strategy and goals of both sides.

Another model that integrates agent minds that interact and think through consequences of their behavior is Senturion, a proprietary model of Sentia, Inc. (Kugler & Abdollahian, 2013). Senturion simulates the political bargaining process on the basis of two economic theories: median voter theory and expected utility (EU) theory. Median voter theory is a technique for predicting the stance that stakeholders (for example, a political candidate) might take on an issue in order to win the most support. Senturion uses game theory and the assumption that the candidate sells out his actual position in order to win votes, where the winning position is the median.

Senturion uses EU theory to incorporate a form of perception and cognitive bias – risk aversion – into this purely rational game theory technique. Instead of assuming that the politician will do anything to win, Senturion calls the selling out of one's beliefs "risk aversion" and represents the tradeoff between that and retaining one's beliefs as "risk acceptance." Senturion identifies the stakeholders near the median issue stance as risk averse and likely to give in, while stakeholders far from the median accept risk and are unlikely to move far from their positions.

Senturion uses parameters that include the salience of an issue to a stakeholder, and stakeholder influence, to calculate a "weighted median." In each iteration of Senturion, agents make proposals to all other agents regarding position change, and every agent then chooses one proposal and moves toward it. In deciding what proposal to accept agents consider how much influence a stakeholder wields and how important the issue is to the stakeholder. Additionally, a risk-averse decider magnifies how much power another stakeholder has, while a risk-acceptant decider disregards another stakeholder's power. Agents assess where they would land if they took an offer, and then choose the offer that causes them to move as little as possible from their present position.

EU is well vetted and accepted by the modeling community. It combines the two most important components of decision making: rationality and bias. Thus, EU captures the tradeoff between the idealist's adherence to principle and the practical bow to social pressure that permeates politics.

Senturion is the best current model of political bargaining, and is highly useful for the study of IW. In the Africa Study, Senturion represented popular support of the host nation as the issue about which the stakeholders should arrive at consensus. In the *Battle of Algiers* scenario this would be the equivalent of modeling the insurgents, the Algerian indigenous population, the French Algerians, and the European French as stakeholders, inserting kinetic and nonkinetic COAs for each, and computing their compromises based on their relative power.

6. Preserving Uncertainty for Risk-based COA Analysis

New data processing methodologies for COA analysis include representations of narratives, COA templates, and elements of the MDMP. They also include methods for integrating models to compute social network behaviors to test interventions, as well as the strategic interactions of IW. However, one especially important methodology that research must advance is tracking uncertainty for risk-based COA analysis. In conventional warfare analysis, uncertainty stems from a few random variates from distributions inside physics-based models. IW analysis must take into account uncertainty in data, uncertainty on the correctness of social theory, uncertainty on the correctness of the representation, uncertainty in the way to translate data between disparate models and data created for different purposes, and even intrinsic uncertainties of human behavior.

Innovative methodologies help track these uncertainties. For example, researchers could mitigate the uncertainty about social theory by testing the theories underlying different models in proportion to their reliability and testing strategies for robustness against all theories. Because there are so many possibilities, sociocultural analysis requires multiple models that depend on integration frameworks to track the uncertainty. Integration frameworks such as Oz, Global Information Network Architecture (GINA), XBM, and SIMmiddleware translate between models using ontologies in hub-and-spoke arrangements. An ontology is a grouping of data into the language of a domain, along with the rules for grouping the data. Ontologies are used for translation because they define their terms precisely. A probabilistic ontology additionally represents uncertainty in knowledge about how data are grouped and how they should be translated by combining crisp ontological logic with Bayesian inference.

For the TRAC tactical wargame, SIMmiddleware integrated hub, spoke, and mediation probabilistic ontologies to support analysis (Duong & Bladon, 2012). These ontologies tracked the uncertainty of data translation so that the results kept track of the likelihood of a particular outcome. The uncertainties within the ontologies were combined using rule-based systems. For example, the translation between the Cultural Geography (CG) model (one of the tactical wargame models) and the hub model required probabilistic translation. Specifically, analysts created a one-to-many mapping of CG moves to hub model moves that SIMmiddleware implemented using probabilistic ontologies. Probabilistic ontologies were also used to assess crisp rules to fire decision points based on popular support indicators. Probabilistic ontologies such as Bayes Owl combine probabilistic and crisp logic (Ding, Peng, & Pan, 2004).

XBM provides a way to take data credibility into account in a proportionate output using a mixing function. A mixing function draws proportionately from input data sets according to their reliability, using XBM's probabilistic ontology, ProbOnt. SIMmiddleware provides a way to track these forms of uncertainty, data pedigree, social models, and model translation, so as to output the results of multiple runs proportionately into a Markov process. A Markov process, a node-and-link graphical model that displays the probability of going from one state to another, describes the state space (all possible states) probabilistically. The Markov process can be used to analyze likely tipping points. For example, to measure the effectiveness of an action, the process can calculate the likelihood of reaching any state from the point of the action and can show whether selected actions can achieve desired goal states. The process can also analyze actions that drive the system to states in which the goal is more easily attainable.

7. Data Processing Implications of Validation of COA Analyses

Although IW scenarios in simulation models are individualistic, research can and should extract generalities from these scenarios. For example, analysts can measure whether the correlation of states in the model mirrors their correlation in the real world, for the purpose of validation. Generalization is most fundamentally an issue of data representation, and finding the right level of generalization in an ontology that best establishes a correlation is a data processing issue.

TRAC used SIMmiddleware to study the validity of models of its 2010 tactical wargame by comparing model output to Afghan Nationwide Quarterly Assessment Review (ANQAR) data from the same year portrayed in the tactical wargame. Analysts calculated a probabilistic distance between the model and the real-world data using the Kullback-Leibler convergence probabilistic distance function. This equation represents the information lost when one Markov process is substituted for another; specifically, the number of bits needed to make the output of one match the other. The Markov process shown in Figure 3 illustrates results of the validity research from tactical wargame 2010. Nodes indicate types of player actions and the popularity of a coalition player. Arcs represent the likelihood of transitioning between node states. Green areas represent 'good' states (popular) while red areas represent 'bad' states (unpopular). The probabilistic distance between the model and the real-world data shows a score of 0.21, a relatively low probabilistic distance (lower is better). This score served as evidence for the validation of the tactical wargame model at a rudimentary level. Since SIMmiddleware and its implemented probabilistic ontologies preserved the uncertainties in the data, models, and translations between models, the Markov process represents the best estimate of the probabilities of arriving at different states of interest (Duong & Bladon, 2012).

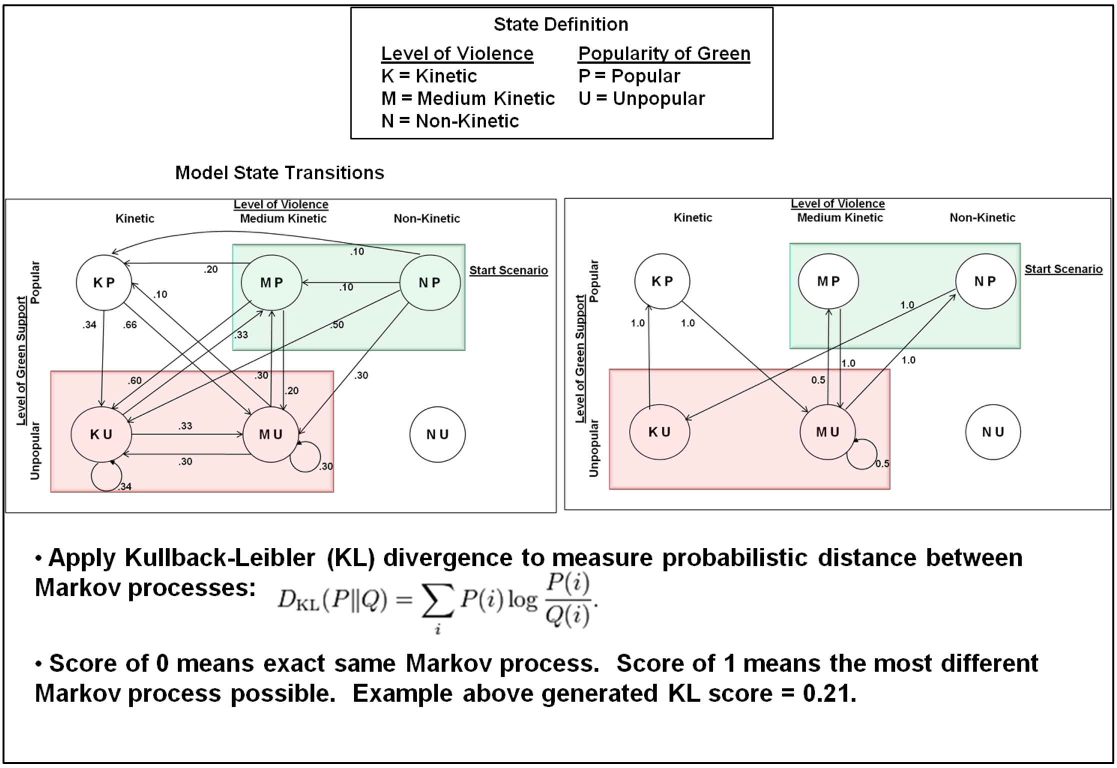

Figure 3. Comparison of Markov processes for validation score.

The concepts of a social theory should enable output data from IW models to correspond to real-world data. The validation analysis from Figure 3 compared model and real-world data regarding simple concepts such as popularity and kinetic actions. However, IW concepts are much more complex, and models representing IW concepts must be formalized to determine whether they align with theory.

The U.S. Army Engineer Research and Development Center's (ERDC) Cultural Reasoning and Analysis for the Tactical Environment (CREATE) offers a good example of such a formalization that could be used to objectively score how closely a simulation conforms to theory (Whalley, Perkins, Krooks, Hargrave, & Rewerts, 2012). CREATE is unique in its formalization of the arguments from social literature that frame the situation in a host country. CREATE's factor map formalizes the social literature on CMO with an augmented version of Shum's Naturalistic Argumentation upper ontology (Shum, Uren, Li, Sereno, & Mancini, 2007). Shum's ontology consists of relations between entities that indicate the degree to which social literature claims support or refute one another. The social literature is annotated with these relationships, so that the analyst can easily query scenario data that support the social model/frame/theory. For example, a theory may claim that insurgency is political in nature while another theory may identify poverty as the root cause of insurgency.

Using CREATE's annotation user interface, an analyst can manually mark claims in the text as major claims of the article, and then mark all supporting claims with links labeled "is evidence for," "proves," etc. (see Table 1). The claims and the link between them form an rdf triplet for a Web Ontology Language (OWL) ontology. The links are weighted to show the level of support (or refutation) one claim has for another. These claims are then linked to claims in other articles as well, to include link labels such as "is inconsistent with." The claims may represent any level of generality, from generalizations about insurgency to specific facts about the insurgency in Kenya. Use of CREATE results in a summarized understanding of the situation in terms of the processes that belong to a frame (for example, whether the insurgency in Kenya is caused by poverty, and if so, the effectiveness of the intended CMO interventions).

Table 1. *Shum's Naturalistic Argumentation Upper Ontology*

Relation Class	Dialect label	Polarity/ Weight
General	is about	+/1
	uses/applies/is enabled by	+/1
	improves on	+/2
	impairs	– /2
	other link	+/1
Problem Related	addresses	+/1
	solves	+/2
Supports/ Challenges	proves	+/2
	refutes	–/2
	is evidence for	+/1
	is evidence against	–/1
	agrees with	+/1
	disagrees with	–/1
	is consistent with	+/1
	is inconsistent with	–/1
Causal	predicts	+/1
	envisages	+/1
	causes	+/2
	is capable of causing	+/1
	is prerequisite for	+/1
	prevents	–/2
	is unlikely to affect	–/1
Similarity	is identical to	+/2
	is similar to	+/1
	is different to	–/1
	is the opposite of	–/2
	shares issues with	+/1
	has nothing to do with	–/1
	is analogous to	+/1
	is not analogous to	–/1
Taxonomic	part of	+/1
	example of	+/1
	subclass of	+/1
	not part of	–/1
	not example of	–/1
	not subclass of	–/1

Note: Table adapted with permission from Shum, Uren, Li, Sereno, & Mancini (2007)

Applying this method to an example from the *Battle of Algiers* scenario, we might find that a news article states that many of the insurgents are well educated. That would conflict with the social theory that poverty leads to insurgency, stated in another theoretical journal article. In this case, the triplet for the news article may be <Ahmed, education level, PhD> and the journal article triplet <Insurgents, economic class, poverty>. The Shum ontology triplet would be <<Ahmed, education level, PhD>, is evidence against,<Insurgents, economic class, poverty>>. When this connection is found, the social theory that poverty leads to insurgency would receive a "–1'. Even an analyst who lacks a formal background in the social sciences can rapidly assess the arguments and evidence that explain the social situation and comprehend the advantages and disadvantages of varying perspectives.

Formalizing the claims of social science and applying them to particular scenarios of IW aids in model validation. The numerical degree of refutation or support of a theory encoded in the Shum ontology links can form an objective measure of how much the model output matches particular social theories. Methods that enable objective measurement of models significantly advance sociocultural model validation requirements.

Although the CREATE methodology was designed for analysts rather than computer models, its formalization of the ideas of sensemaking can model the insights that MISO makes regarding the host population, which in turn are instantiated in CMO interventions. The usefulness of CREATE for modeling CMO resides in its potential for modeling effects of a MISO argument on a host nation population and to counter a terrorist narrative. A major gap in the ability to model the effect of CMO on the host population is the ability to model MISO. Doctrine states that CMO is the evidence of MISO, and that the purpose of CMO is ultimately to influence popular support. However, almost all models of popular support are based on message dissemination dynamics by affinity rather than on the content of the message itself and why that message would resonate with the people.

To model MISO, we must therefore model why a MISO message will resonate with the population and how CMO supports the message. In terms of natural argumentation, the host nation population would have several ways of framing the situation: in terms of their cultural narratives, the CMO actions and the MISO that depicts them, and past perspectives. Insurgents would give evidence that supports some of the population's frames and refutes others. Introducing message content into the modeling of MISO would be a vast improvement over existing algorithms.

8. Model Process Control

Model process control (MPC) uses feedback between data and models to improve both the interpretation of the data and the accuracy of the model. We have described methodologies to extract data, input and execute data in models, and compare model output to real-world data. One data processing methodology for COA analysis involves putting all of these activities together into a feedback loop that interprets data and refocuses models on more salient data. A feedback loop benefits all stages of data fusion because even such fundamental steps as the parsing of free text data depend on meaning. For example, the difference in the parse of the statement "Jack ate the salad with chopsticks" and the statement "Jack ate the salad with croutons" results entirely from the meanings of words. Applied to the *Battle of Algiers* scenario, a text may mention a man named Ahmed who bought fertilizer—a substance that may be used to nourish crops or to make bombs. The first interpretation would be the triplet <Ahmed, purchase, bomb-materials> and the second <Ahmed, purchase, farming-materials>. A model might retain both interpretations until one or the other approaches certainty. A model can help analysts determine how the interpretation fits in with everything else known about Ahmed. For example, the model could posit that Ahmed was buying bomb materials, but through a motivation-based simulation might determine that at this point in time the insurgent group is highly unlikely to find bombing acts to their advantage (e.g., if the French populace were leaning toward pulling out of Algeria, a bomb attack would be interpreted as a reason to stay in the country). The MPC might then accept the interpretation that Ahmed was a farmer, and refocus its data collection on plans for strikes, which would better achieve the goals of the insurgency at the present stage in the game.

The U.S. Army Intelligence and Information Warfare Directorate (I2WD) is pursuing an MPC project for the Intelligence Community that implements automated feedback loop concepts. Through its Soft Target Exploitation and Fusion (STEF) program, I2WD has previously sponsored projects that can serve as part of the feedback loop. For example, Indra, an NLP program, can enable real-time, evolving data to conform to a model's requirements. Indra generates ontological categories of social roles and role relations that emerge from text and translates them into the particular ontology of a computer model (Duong, Stone, Goertzel, & Venuto, 2010).

One aspect often neglected in sociocultural modeling is the capacity of the model to absorb data. Nexus can serve in another part of a feedback loop by helping a model conform to the data. Nexus uses coevolutionary pressure to explain the statistical patterns in the data through the motivation of the agents, so that the simulation can recreate the same vicious and virtuous cycles that created the data in the real world. This allows interventions to be tested on a natural, self-reinforcing system (Duong, Pearman, & Bladon, 2013).

The capacity to absorb data in simulations is important to federations of models because it enables participants to assume new consensus states. Data processing for COA analysis should account for conflict resolution not only in the data fed to simulations, but also in federated models that overlap. Models that overlap in function can resolve conflicting results using voting techniques to achieve consensus.

Another technique for arriving at consensus related to competing or overlapping functions involves the use of Nexus's neural network for constraint satisfaction. The neural network can place positive links between event relations that are positively correlated in the real world, or that CREATE determines to be consonant with theory. Conversely, the neural network can place negative links between events that are negatively correlated in the real world, or that CREATE determines to be dissonant with theory. Nexus could execute the network to determine simulation outputs that fit best both theory and the real world, and enter them back into all federated models as the consensus state. In this way, the computations that federated models make in an MPC system could include a validation step. The MPC would retain the most valid simulation states that are both consistent with each other and consistent with theory.

9. Science and Technology Gaps in Data Processing for COA Analysis

Industry, government, and academia have all recently made important contributions to data processing for COA analysis in the areas of both model integration and formalization of COA concepts in data. In industry, Impact Computing's XBM integrates models to represent interactions among strategizing minds in general, while Sentia's Senturion integrates a specific cognitive model for political COAs. In government, OSD has researched coevolutionary integration of learning mental models in Nexus, and TRAC has preserved uncertainty in data and translation for risk-based analysis and validation using SIMmiddleware. Additionally, ERDC has formalized evidence and sensemaking data in CREATE, and I2WD is advancing the science of MPC to integrate models in a feedback loop. The Naval Postgraduate School's Simulation, Experiments and Efficient Design (SEED) Center has advanced the science of data farming. In academia, researchers at the University of Arizona, Arizona State University, and Pennsylvania State University have improved the representation of COA extraction from text, narrative extraction from text, and a coevolutionary framework for terrorist learning, respectively. The Department of Defense (DoD) has supported many of these advances. However, gaps remain in the underpinnings of how to use all of these ideas together in a scientifically valid analysis.

Although the tools mentioned in this chapter offer a promising start, they have not solved the problem of valid scientific analysis of social phenomena. These tools begin to deal with the most important data processing gaps for COA analysis—automation, uncertainty, and risk-based analysis—but do not yet form a complete program that has the blessing of the scientific community as the best direction to take, and that can be translated into formulas for use for operational personnel.

In the past, models of conventional warfare only needed a limited amount of pre-validated, physics-based data. In contrast, the IW models of today demand far more data because they are based on the scenario-specific data of social processes. Little scientific research has focused on automating the use of "big data" from the internet. For researchers to use the data live or with any scalability, automated tools must automatically put these data into the ontology needed by the model. Further, models should be modified to accept data that they do not anticipate. Because social science is scenario specific, the social model should not predetermine all of the processes simulated; instead, the data should determine the specific processes while the model only holds general forms of social processes as true. The capacity to automatically absorb data for models goes hand-in-hand with the capacity to automatically represent data for model consumption. Once tools can automatically place the big data of the internet in the correct ontology and resolve conflicts within the data, the data base can become more reliable than the individual data that comprise it. The data can then serve as both a training set for model creation and a testing set for validation.

Uncertainty is another important data processing gap for COA analysis. Non-validated data can potentially conflict. Closing the technological gap by taking advantage of the amount of data for the resolution of conflict in the data, perhaps in a type of automated crowd sourcing technique or other voting system, will permit disparate, conflicting data to form a coherent picture.

Conflict occurs not only in data that go into models but also in data produced by federated models. Overlap in model functionality has benefits because the models can clarify and vote on conflicting areas. Such overlap enables users to test CONOPS for robustness against every plausible model of every school of thought. Data processing techniques of integration, such as voting systems, switching in and out in proportion to pedigreed credibility, or constraint satisfaction systems can handle functional overlap and conflict resolution in models.

Furthermore, risk-based analyses should measure uncertainty and conflict in the data coming into the models and going out of the models. To build scientifically valid models for COA analysis, we must advance the science of data processing to make data available for validation. We also need feedback from data to identify the most promising new scientifically based model technologies. The confidence that analysts have in the data, in the translation of the data, and in the output data should be kept in proportion so that the end result of the analysis retains a probability. The parameters of multiple model runs should be chosen according to their likelihood given other parameters, so that they are realistically correlated. The DoD as a whole would likely have benefited from additional investment in the science of valid social analysis, whether focused on models or on data.

10. Technology Transfer of Data Processing Techniques for COA Analysis

Today knowledge gaps exist regarding processes for integrating new technologies from government, industry, and academia into operational use. This gap in knowledge of the science of IW analysis hinders operators from selecting sociocultural products that could support scientifically valid analysis. Operators need not only the products, but also guidelines for carrying out COA analysis that rest on both scientific theory and the big data of the internet, and that are comprehensible to non-scientists.

Control of operational analysis that uses sociocultural modeling should remain in the hands of scientists until the scientific community comes to a consensus on the direction that scientific modeling of social phenomena should take. The DoD should not prematurely choose a particular direction or constrain the science through standardized procedures of analysis before the natural process of scientific argumentation, experimentation, and validity has reached a consensus from which to draw a procedure. The DoD should not spend 6.4 (demonstation and validation) funds until 6.1-funded (basic research) products are mature, no matter how frustrating the wait. Scientific competition in argumentation and experiment should ideally enable the best ideas to bubble to the top. Short of that, the DoD should hire scientists to spot the best new ideas, rather than having operational personnel under resource constraints control social model analysis.

Once scientists have established and advocated scientifically sound criteria for usage of individual methods, and schools of thought have explored competing paths toward scientific analysis, the scientists can lay out entire maps of the procedures that operations personnel should perform as part of scientifically valid analysis. Without careful review by the best scientists of the day, operational analysis of social phenomena will fail to meet the stringent criteria for scientific validity.

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