DECISION SCIENCES
A JOURNAL OF THE DECISION SCIENCE INSTITUTE

Decision Sciences
Volume 42 Number 2
2011

RESEARCH NOTE

Using Real-Time Decision Tools to Improve Distributed Decision-Making Capabilities in High-Magnitude Crisis Situations*

Herbert Moskowitz
Krannert School of Management, Purdue University, 403 W. State Street, W. Lafayette, IN 47907, e-mail: herbm@purdue.edu

Paul Drnevich†
Culverhouse College of Commerce and Business Administration, The University of Alabama, 361 Stadium Drive, Dept. 870225, Tuscaloosa, AL 35487, e-mail: dren@ua.edu

Okan Ersoy
School of Electrical and Computer Engineering, Purdue University, 465 Northwestern Avenue, West Lafayette, IN 47907-2035, e-mail: ersoy@ecn.purdue.edu

Kemal Altinkemer and Alok Chaturvedi
Krannert School of Management, Purdue University, 403 W. State Street, W. Lafayette, IN 47907, e-mail: alok@purdue.edu, kemal@purdue.edu

ABSTRACT

Multi-organizational collaborative decision making in high-magnitude crisis situations requires real-time information sharing and dynamic modeling for effective response. Information technology (IT) based decision support tools can play a key role in facilitating such effective response. We explore one promising class of decision support tools based on machine learning, known as support vector machines (SVM), which have the capability to dynamically model and analyze decision processes. To examine this capability, we use a case study with a design science approach to evaluate improved decision-making effectiveness of an SVM algorithm in an agent-based simulation experimental environment. Testing and evaluation of real-time decision support tools in simulated environments provides an opportunity to assess their value under various dynamic conditions. Decision making in high-magnitude crisis situations involves multiple different patterns of behavior, requiring the development, application, and evaluation of different models. Therefore, we employ a multistage linear support vector machine (MLSVM) algorithm that permits partitioning decision maker response into behavioral subsets, which can then individually model and examine their diverse patterns of response behavior. The results of our case study indicate that our MLSVM is clearly superior to both

*This research is partially funded by National Science Foundation grant # 0720677. The authors thank the anonymous reviewers, associate editor, and editor for their valuable comments on the manuscripts. We also thank Hoi-ming Chi and Janet Xia for their research assistance with early versions of this project. Finally, we thank both Simulex, Inc. and the Purdue Homeland Security Institute for making the SEAS technology and the Measured Response exercise data available to us for this research.

†Corresponding author.

single stage SVMs and traditional approaches such as linear and quadratic discriminant analysis for understanding and predicting behavior. We conclude that machine learning algorithms show promise for quickly assessing response strategy behavior and for providing the capability to share information with decision makers in multi-organizational collaborative environments, thus supporting more effective decision making in such contexts.

Subject Areas: Distributed Decision Making, Dynamic Modeling, Information Technology (IT) based Decision Support Systems, Machine Learning Algorithms, Multi-Organizational Collaborative Decision Making, Real-Time Decision Tools, and Support Vector Machines (SVM).

INTRODUCTION

Multi-organizational collaborative decision making in high-magnitude crisis situations requires real-time information sharing and dynamic modeling for effective response. Information technology (IT) based mobile, collaborative decision support tools can play a key role in facilitating effective and rapid response in such situations (Chu & Spires, 2000; Yi & Davis, 2001; Venkatesh, 2006; Drnevich, Brush, & Chaturvedi, 2010). Such tools allow dispersed and eclectic decision makers to address multilevel strategic and tactical problems (Goes, Pino, & Vakharia, 2008). However, having an IT-based decision support system (DSS) does not in and of itself ensure high quality decision making. There are several factors that impact decision making in a multi-organizational collaborative setting. Drnevich, Ramanujam, Mehta, and Chaturvedi (2009) observed that affiliation and situation play a critical role in how decision makers interpret information during different phases of the crisis. Further, despite the use of the best available technologies, coordination within and among teams tends to breakdown. There is also very little visibility to the process of decision making at different levels. The time lag between data gathering and its interpretation, planning and execution, mis-interpretation of intent, and the unfolding of unintended consequences characterize the high-impact crisis situation. As such, anticipation of behaviors of decision makers at different levels becomes important for an effective response. For example, decision makers in the federal government need to anticipate the response at the state and the local levels of government; likewise the state and local level decision makers need to anticipate decisions at multiple levels to inform their decisions (McKay, Chaturvedi, & Adams, 2011).

A class of decision support tools involving machine learning algorithms, especially support vector machines (SVMs), has shown promise to dynamically model and analyze incoming streams of data. SVMs have also shown good predictive and explanatory power in general management applications in support of real-time decision making (e.g., Chi, Ersoy, Moskowitz, & Altinkemer, 2007a). Thus, the purpose of this note is to: (i) Use a design science approach (e.g., Hevner, March, Park, & Ram, 2004; Holmstrom, Ketokivi, & Hameri, 2009) to develop and explore the viability and effectiveness of SVMs as a potentially more effective real-time component of integrated decision support tools which can anticipate actions that will be taken at different levels in response to a crisis situation; (ii) Follow the tradition of grounded business research (Guide & Van Wassenhove, 2007), to explore the ability of SVMs to model, explain, and predict multi-organizational collaborative decision-making behavior and response effectiveness through a case study involving a high-magnitude crisis situation. In our case study we employ an agent-based synthetic environment to simulate a crisis event, and then use SVMs to model and examine alternative response strategies to the simulated crisis as it unfolds. We find that when dealing with human behavior, particularly in a multi-organizational command and control environment, standard single stage SVMs may not adequately portray decision-making behavior across (and sometimes within) organizations. This limitation necessitated the development of a multistage linear support vector machine (MLSVM) algorithm that would sequentially permit modeling of different patterns of behavior among decision makers within and across organizations and levels.

There are two specific objectives of this research note. The first objective is to validate the effectiveness of SVMs as an automated generic IT–based decision support tool to model and improve the effectiveness of multi-organizational, collaborative decision making in high-magnitude crisis situations. The second objective is to examine the anticipatory and explanatory effectiveness of a MLSVM algorithm that would effectively capture different patterns of behavior of decision makers in a multi-organizational setting. We hope that our research will show that such a MLSVM algorithm can form the core of a set of IT-based tools to provide real time, rapid, coordinated decision support–providing a significant contribution to practice. It is technically feasible and rather easy to automate such SVM-based tools for an integrated IT–based DSS that can dynamically model real-time behavior as data and responses accumulate, as well as share this information with all involved decision makers. Such systems could also offer new directions for grounded business research (e.g., Guide & Van Wassenhove, 2007), new anticipatory capabilities not currently available to decision makers, and significantly improve response effectiveness in practice.

The limitations of the approach we develop in this research note are largely data focused. The use of SVMs in data-lean environments will be less effective, limiting the predictive and explanatory power of the developed models. Moreover, with human decision making in particular, behavior may change as people learn. Hence, the models must change as behavior changes. We can deal with this change requirement by developing adaptive SVM models that dynamically change with the requirements.

We use a case study approach (e.g., Ross, Buffa, Droge, & Carrington, 2009) involving a U.S. Department of Homeland Security training exercise called *measured response* (MR) where data streams from both a simulation and real-world decision makers to the SVM tool. Our study proceeds as follows: (i) To develop the initial design, we first review prior research on behavioral modeling of collaborative decision making and discuss the agent-based synthetic environment used to generate the data to train and test the MLSVM algorithm; (ii) We then develop the MLSVM algorithm employed in our analysis; (iii) Next, to evaluate and refine our solution, we compare the performance and behavioral implications obtained from our MLSVM with other machine learning and multivariate statistical modeling tools such as linear and nonlinear single stage SVMs as well as linear and quadratic discriminant analysis (LDA, QDA); and (iv) We conclude with a discussion of the results of our exploration, their implications for future theory development and practice, and offer suggested extensions for our research and its applications.

THE STUDY

Related Research on the Decision Problem

Prior related research on collaborative decision making in crisis response has examined a wide variety of issues including goal competition and conflict (Kumar & Van Dissel, 1996; Osborn & Hagedoorn, 1997; Westley & Vrendenburg, 1997; Hardy & Phillips, 1998; Kumar & Niti, 1998; Drnevich et al., 2009), decision-making effectiveness (Lin & Carley, 1993, 1997; Drnevich et al., 2010), response strategies (Carley et al., 2004; Green & Kolesar, 2004), and behavior anticipation and shaping (McKay et al., 2011). One common thread in this body of work is that multi-organizational collaborative decision making is a multifaceted issue, and research on this topic may take a variety of forms. It involves different schools of thought, focus areas, and various methodological approaches (Osborn & Hagedoorn, 1997). However, there exists a marked lacuna in the study of IT-based decision support tools for collaborative decision-making, its underlying methodological modeling (Chu & Spires, 2000; Yi & Davis, 2001; Sexton, Sriram, & Etheridge, 2003; Venkatesh, 2006; Drnevich et al., 2010), and tactics, techniques, and procedures to operationalize it. To improve the capabilities of IT-based decision support tools, we examine the viability of SVM to dynamically model and analyze incoming data to support real-time decision making. We next discuss the intelligent agent-based synthetic environment used to simulate the crisis event for the decision makers in our case study and then later discuss the development and testing of an SVM-based decision support modeling tool.

Study Setup and Methodology

We use a design science approach to construct a synthetic environment for this study. We utilize data from the MR homeland security training exercise (Drnevich, Mehta, & Dietz, 2006), which combines agent-based simulation with experimental gaming techniques, making it particularly useful for large and complex experiments. MR features include scalability (the ability to run hundreds of thousands of agents), *human-in-the-loop* capability (live human players in real-time experiments), configurability (easy set up and modification), and modularity (multiple different scenarios and organizational teams developed and integrated as needed). The MR exercise simulated a bio-terror attack on a major U.S. city utilizing tens of thousands of artificial agents to represent the citizens of the simulated population. Agents consist of four layers of models to represent position, mobility, infectability, and well-being, each calibrated in accordance with relevant research (Drnevich et al., 2006). The intelligent agents ran on a distributed grid-computing platform comprised of two supercomputers connected by a gigabit network for large exercises that can scale down to run in a client–server environment for smaller applications.

The MR scenario provides multilayer geography (federal, state, and local) to enable multiple agencies at each level to participate in a joint experimentation environment. MR provides the ability for many human-in-the-loop players to participate in an experiment alongside simulated entities. Players representing each agency can execute their actions within the response framework in the scenario. MR simulates the outcome of these actions in the context of scenario conditions to project outcomes over time. The outcomes of multiple courses of action can then be compared to evaluate the benefits. Throughout the simulation, human players (agents) from different government agencies make decisions that affect the outcome. These agents represent nine government entities, three each at federal, state, and local levels. The agencies represented at each level are: the Department of Homeland Security (DHS), the Department of Transportation (DOT), and the Department of Health and Human Services (HHS). The responsibilities of each agency differ based on both size and scope. Thus, although each shares common goals, the means with which they can accomplish those goals varies within and among agencies. For more information on the simulation platform and MR training exercises reference Drnevich et al. (2006) and Chaturvedi, Dolk, and Drnevich (in press).

Development of the High-Magnitude Crisis Decision Model

We limit our focus to developing and applying an MLSVM algorithm to model and predict what decision makers in organizations would do in response to a simulated high-magnitude crisis. Background and specifics on the development of the high-magnitude crisis decision MLSVM model we employed are available in Appendix A.

Decision Application

Discussion of decision context

Crisis situations of all types, by their general nature, involve nonroutine situations that a single organization or their decision makers are unlikely to have faced. As such, responding effectively to a crisis situation often involves drawing upon the expertise of multiple decision makers from several organizations. In these decision-making situations access to information across organizations and information sharing within organizations is important for response effectiveness. In high-magnitude crisis situations (i.e., those with significant threat to survival), speed of response is also important for effective decision-making due to the generally dynamic nature of the situations. Such situations often involve rumors and inaccurate information, and a lack of visibility of actions taken at different echelons of decision making, resulting in an incomplete and often conflicting understanding of the situation. Consequently, effective multi-organizational collaborative decision making involves both combined real-time information sharing and dynamic modeling for effective response. In the remainder of this section, we provide an overview of the decision making in the exercise and discuss the application of our MLSVM model.

Model validation

We validated our multistage machine learning algorithm by applying it to the MR training exercise. We attempt to anticipate and explain the intervention strategies of each decision maker in response to the simulated crisis event, with the ultimate intention of providing such information as automated feedback either in real time during a crisis situation or as lessons learned as part of a digitized, integrated DSS. Part of our objective was to assess the value added by our algorithms vis-à-vis traditional single stage multivariate statistical and SVM algorithms. We use a total of 135 samples from the survey and simulation data collected in the MR exercise. The dataset contained 15 explanatory variables, 6 of which were quantitative, depicting the simulation environment. The remaining nine were indicator variables representing background information for each responder (e.g., level of position (federal, state, or local), affiliated departments (DHS, HHS, DOT), and interaction between levels and departments). We originally categorized the response variable, quarantine strategy (QS), into one of five classes (QS1, QS2, Q3, QS4, QS5). This set of response decisions ranged on a five-point ordinal scale from no intervention (QS1) to moderate (QS3) to extreme (QS5) intervention (quarantine) responses. The moderate response strategies (QS2 and QS3) involved city block quarantines (CBQ), whereas the extreme response strategy (QS4 and QS5) involved a full military-enforced mass quarantine (MQ). Of the 135 responses (data points), only eight chose QS2 and four chose QS5. Thus, we treated these as QS1 and QS4, respectively. Hence, the five classes were aggregated into three, corresponding to QS1 (no quarantine), QS3 (city block quarantine), and QS4 (military or extreme quarantine). We provide a description of the simulation and survey variables from the exercise used in the validation in Table 1 and the descriptive statistics of the simulation variables in Table 2. More information on the decision-making criteria, processes, and outcomes in the MR exercise is available in Drnevich et al., (2006, 2009, 2010).

Table 1: Measured response exercise simulation and survey variable descriptions.

Variables	Input/Output	Type	Description
AEL (X1)	Input	Indicator	Appointed or elected participant
Fed (X2)	Input	Indicator	Federal level participant
State (X3)	Input	Indicator	State level participant
DHS (X4)	Input	Indicator	DHS
HHS (X5)	Input	Indicator	HHS
Fed*DHS(X6)	Input	Indicator	Interaction between Fed and DHS
Fed *HHS(X7)	Input	Indicator	Interaction between Fed and HHS
State *DHS(X8)	Input	Indicator	Interaction between State and DHS
State *DHS(X9)	Input	Indicator	Interaction between State and HHS
HI (X10)	Input	Real	Priority of health issues
TIN (X11)	Input	Discrete	Total number of people infected
TPM (X12)	Input	Real	Total public mood
TD (X13)	Input	Discrete	Total number of people deceased
Round (X14)	Input	Discrete	Round of exercise played
QS_prev (X15)	Input	Discrete	Previous round QS choice
QS (Y)	Output	Discrete	QS

Table 2: Simulation variable summary statistics and correlation matrix.

Quantitative Variables	Mean	*SD*	Min	Max	Correlation Matrix[a]				
1. HI	3.56	0.62	2.00	4.00	1.00				
2. TIN	566	375	117	1208	0.068	1.00			
3. TPM	3.97	0.15	3.81	4.4	−0.14	−0.14	1.00		
4. TD	4.60	3.84	0	9	0.021	0.95*	0.086	1.00	
5. Round	3.00	1.42	1	5	0.034	0.86*	0.11	0.96*	1.00
6. QS_prev	1.98	1.48	0	4	0.050	0.67*	0.062	0.69*	0.71*

*Denotes significance at $p \leq .05$.
[a]Although some variables were significantly correlated, we kept them in the model, because they were the decision variable available to the responders during the simulation exercise. In this way, we could investigate the influence of each of these features on choice behavior.

We partitioned our data analysis approach into two major categories: Analysis of decision (choice) performance of responders and analysis of the MLSVM model with relative and absolute performance and behavior. We compared responder performance across government levels, departments, and decision rounds. We evaluated the MLSVM model in terms of model performance (y) as well as a comparison of choice behavior among the governmental entities and factors (x) used by these responders to make a quarantine choice. We then investigated the factors by decision round to observe how their importance may have changed as new results became available, as well as how current quarantine decisions were affected by the most recent previous quarantine choice.

Results of Model Validation

To validate the MLSVM model we first standardized the input variables and then randomly selected 90 of the 135 response decisions as the training set. Of these data points, 32 responses involved no intervention (QS1), 36 responded with a moderate CBQ (QS3), and 22 responded with a more extreme MQ (QS4). The remaining 45 data points served as the testing (validation) set of which 17 involved QS1, 18 involved QS3, and 10 involved QS4.

We based MLSVM model performance on its ability to accurately predict a responder's decision (classification) regarding QS1, QS3, and QS4. Using this criterion, we compared MLSVM performance to the following algorithms: (i) a single stage linear SVM (SLSVM), (ii) a single stage second-order polynomial (quadratic) SVM (SPSVM), (iii) LDA, and (iv) QDA. We implemented the SVM models in MATLAB using SVMlight (Joachims, 1998, 2002) and its MATLAB interface (Schwaighofer, 2005).

We summarize the training and testing overall classification prediction accuracies for each modeling algorithm in Table 3. LSVM and LDA exhibited the lowest training and testing predictive power. Our SPSVM algorithm showed the highest training accuracy (94.44%), but its testing accuracy was only 64.44%, due to overfitting (resulting from the addition of interaction and squared terms in the model). Our MLSVM algorithm achieved a training accuracy of 82.20% and the highest testing accuracy of 68.89%.

Table 3: Standardized coefficients of explanatory variables.

	Stage One				Stage Two		
	QS1	QS3	QS4		QS1	QS3	QS4
BIAS	−1.59	0.97	−1.32	BIAS	−1.71	1.00	0.31
AEL	0.00	−1.72	0.78	AEL	0.00	−2.00	0.63
FED	1.54	−2.27	0.75	FED	−1.36	−2.00	1.03
STATE	0.36	−0.52	0.38	STATE	2.15	−2.00	−1.77
DHS	−0.04	1.72	−1.74	DHS	1.65	−2.00	−1.70
HHS	0.00	0.59	−0.96	HHS	0.18	0.00	−1.08
FD*DHS	−0.60	−1.72	1.74	FD*DHS	−1.65	2.00	1.70
FD*HHS	1.66	−1.70	−0.54	FD*HHS	−0.18	2.00	−0.21
SD*DHS	0.63	−2.54	0.26	SD*DHS	−1.11	2.00	0.42
SD*HHS	0.00	−0.14	−0.26	SD*HHS	0.36	0.00	−0.22
HI	−0.04	0.00	0.32	HI	−0.53	0.00	0.37
TIN	−3.74	7.55	−4.06	TIN	10.15	−0.01	−6.90
TPM	−0.21	1.15	−0.54	TPM	2.51	0.00	−1.77
TD	7.81	−11.32	3.51	TD	−12.86	0.01	9.04
ROUND	−4.19	5.53	−0.74	ROUND	4.39	0.00	−3.76
QS_Prev	−1.18	−0.41	1.16	QS_Prev	−2.10	0.00	1.46

	Stage Three		
	QS1	QS3	QS4
BIAS	−2.50	−1.00	−0.14
AEL	0.00	0.00	0.00
FED	1.67	0.00	1.77
STATE	2.12	0.00	−1.11
DHS	1.78	0.00	−1.38
HHS	1.79	0.00	−1.38
FD*DHS	−3.20	0.00	1.77
FD*HHS	−1.79	2.00	0.00
SD*DHS	−1.78	0.00	0.55
SD*HHS	−1.79	0.00	0.27
HI	0.00	0.00	0.28
TIN	0.96	0.00	−8.70
TPM	0.46	0.00	−2.00
TD	1.78	−0.01	12.26
ROUND	−2.45	0.00	−5.12
QS_Prev	−0.44	0.00	1.67

The specific classification results of each method in terms of conditional accuracies ($P(T = x \mid M = x)$, probability of true response given model response) are shown in Table 4. The conditional accuracies for QS3 (moderate quarantine) were roughly comparable across all models. However, MLSVM was much better than the other models in predicting QS1 (85.7%) and QS4 (66.7%). This observation suggests that there are more differentiated patterns of behavior for the divergent choices of no response (QS1) and more extreme response (QS4) decisions, which are identifiable by our multistage model. When making a moderate response

Table 4: Specific classification results of models.

Training Model	True Response QS1	QS3	QS4	Summary $P(T=x \mid M=x)$	Testing Model	True Response QS1	QS3	QS4	Summary $P(T=x \mid M=x)$
MLSVM									
QS1	27	2	1	90.0%	QS1	12	2	0	85.7%
QS3	5	29	3	78.4%	QS3	4	15	6	60.0%
QS4	0	5	18	78.3%	QS4	1	1	4	66.7%
Accuracy		82.22%			Accuracy		68.89%		
Linear SVM									
QS1	23	4	2	79.3%	QS1	12	4	0	75.0%
QS3	6	29	6	70.7%	QS3	3	12	6	57.1%
QS4	3	6	14	60.9%	QS4	2	2	4	50.0%
Accuracy		73.33%			Accuracy		62.22%		
Second-order POLY SVM									
QS1	31	1	0	96.9%	QS1	13	3	1	76.5%
QS3	1	32	0	97.0%	QS3	0	13	6	68.4%
QS4	0	3	22	88%	QS4	4	2	3	33.3%
Accuracy		94.44%			Accuracy		64.44%		
LDA									
QS1	25	4	2	80.6%	QS1	12	3	1	75.0%
QS3	6	27	3	75.0%	QS3	2	12	6	60.0%
QS4	1	5	17	73.9%	QS4	3	3	3	33.3%
Accuracy		71.1%			Accuracy		60.0%		
QDA									
QS1	32	4	0	88.9%	QS1	12	3	1	75.0%
QS3	0	28	0	100.0%	QS2	1	13	6	65.0%
QS4	0	4	22	84.6%	QS3	3	2	3	37.5%
Accuracy		86.7%			Accuracy		62.2%		

decision (QS3), responders appeared to differentiate less clearly as a whole; hence all models were equally less informative.

In Table 5, we depict the contribution of each model in making a correct to incorrect classification prediction in terms of a likelihood ratio (λ), given below:

$$\lambda = \frac{P(M = x|T = x)}{P(M = x|T \neq x)}$$

Table 5: Contribution of models in correct classification prediction.

	Likelihood ratio $\lambda = \frac{P(M=x\|T=x)}{P(M=x\|T^c=x)}$		
	$x = 1$ (QS1)	$x = 3$ (QS3)	$x = 4$ (QS4)
MLSVM	9.9	2.3	7.0
SLSVM	4.9	2.0	3.5
SPSVM	10.7	3.3	1.8
LDA	4.9	2.3	1.8
QDA	4.9	2.8	1.6

where

$$P(M = x|T = x) \equiv \text{probability model predicts response } x \text{ given true response is } x,$$

$$P(M = x|T \neq x) \equiv \text{probability model predicts response } x \text{ given true response is not } x.$$

With respect to predicting QS3, all models exhibited essentially comparable informativeness. MLSVM and SPSVM however were much more informative in predicting QS1. Moreover, MLSVM was much more informative in predicting QS4 than all other methods. The QS4 decision was the most difficult to predict because it is possible that the severity of the response made the responders more reticent and unsure of themselves in making such an extreme choice. In addition, the number of QS4 decisions in the training set (22) was considerably less than those of QS1 (32) and QS3 (36), and classifiers generally tend to bias in favor of the majority classes (QS1 and QS3) rather than the minority class (QS4).

In sum, our MLSVM algorithm was superior to all other available methods in predicting responders' choices—indicating the high potential value of MLSVM based real-time decision support tools. Although data limitation precluded us from doing so because of overfitting issues, further improvement of our approach may be possible by employing a multistage polynomial SVM, which could provide even better classification prediction accuracies.

MANAGERIAL INSIGHTS AND CONCLUDING COMMENTS

Since the 1990s we have seen the explosive growth of the use of IT to make massive amounts of data available for processing by an organization's decision makers. This growth in the application and use of IT spawned such improvements as Six Sigma, which was an effort to apply scientific and quantitative discipline and methodology (such as statistics) to manage and control processes more efficiently and effectively than via ad hoc decision making. This movement has been successful, but at a high cost in training and sustainability. Part of this effort centered on training humans to be good modelers and disciplined decision makers by exploiting the massive amounts of data made available by IT—a challenge indeed!

IT plays a key role in supporting and facilitating rapid response multi-organizational collaborative decision making via real-time modeling and information sharing by providing new tools to support group decision making. Such tools allow dispersed and eclectic decision makers to address multiple strategic and tactical problems. Testing and evaluation of these tools in simulated environments (such as we have done in this study) provides an initial platform and opportunity to assess their value under such conditions (Harrison, Lin, Carroll, & Carley, 2007; Chaturvedi et al., in press). As machine learning algorithms such as SVMs mature, modeling could be done automatically by machines with minimal human intervention. Such a modeling approach has several key advantages. First, the process owner is largely removed from the modeling task, resulting in unbiased model identification. Second, automated modeling saves time and improves information sharing among decision entities, which is particularly crucial in rapid response situations. This automation also removes the bias of what is being done versus what is being articulated by the decision makers.

In this article, we explored SVMs, which given the dynamic nature of incoming data, have the capability to dynamically model and analyze decision processes to support real-time decision making. Although SVMs have achieved good predictive and explanatory power in general management applications (Chi et al., 2007a) they had not been applied or tested in rapid response multi-organizational collaborative decision-making contexts. Therefore, a central objective of this study was to use a design science approach (e.g., Hevner et al., 2004; Holmstrom et al., 2009) to explore the viability and effectiveness of using automated SVMs for real-time decision support tools.

We explored the ability of SVMs to model, explain, and anticipate multi-organizational decision-making behavior and responses with data from an exercise involving a high-magnitude crisis situation. We utilized an intelligent agent-based simulation environment to generate the data to train and test our solution approach, and then used SVMs to model and examine collaborative response strategies. When dealing with human behaviors, particularly in a multi-echelon decision-making situation, standard single stage SVMs did not adequately capture behaviors within and across organizational settings. To overcome this deficiency, we employed SVM to model, understand, and anticipate multi-agency response strategies to a high-magnitude crisis situation. In the exercise, decision makers exhibited different patterns of behavior requiring the development, application, and evaluation of a sequential MLSVM algorithm that permitted partitioning decision maker responses into behavioral subsets. We then used these subsets to individually model and examine the diverse patterns of response behavior with a MLSVM algorithm that sequentially permitted modeling of different patterns of behavior among decision makers within and across organizations and levels.

The use of SVMs in the physical and physiological sciences is rapidly increasing in popularity. This research note assesses and extends their use and value in the decision and management sciences by deploying the algorithm as part of a DSS to support real-time multi-organizational, collaborative decision making in a crisis situation. Part of this study involved modeling decision-making behavior, which is a novel approach. Our results show that the MLSVM we developed is clearly superior to single stage SVMs in anticipating and understanding behavior because one model does not fit all patterns of behaviors. Such machine learning algorithms show promise as tools that can be used in rapidly evolving crisis situations to quickly assess response strategy behavior and provide the capability to share information with decision makers in a multi-organizational collaborative environment, thus lending to more effective decisions. Our results indicate that there is considerable promise in applying SVMs to improve and optimize multi-organizational, collaborative decision making in particular, and decision making in general through rapid modeling in data-rich environments. We envision that the use of SVMs to support IT-based DSS will grow as the management community learns more about such machine learning tools.

The contributions of this research note include a validation of the effectiveness of SVMs as an automated generic IT–based decision support tool to model and improve the effectiveness of multi-organizational, collaborative decision making in high-magnitude crisis situations. Further, the anticipatory and explanatory effectiveness of our MLSVM algorithm indicates that it would effectively capture different patterns of behavior across decision makers in such an environment. Thus, given that it is technically feasible to automate an MLSVM so that it could dynamically model real-time behavior and share this information, we feel it is likely that there is promise that this type of algorithm could form the core of a set of IT-based DSS tools to provide real time, rapid, coordinated decision support. We hope this note will serve to motivate further research on such IT-based decision support tools as well as to improve decision-making effectiveness in practice.

REFERENCES

Carley, K., Altman, N., Kaminsky, B., Nave, D., & Yahja, A. (2004). *Biowar: A city-scale multi-agent network model of weaponized biological attacks*. Technical Report (CMU-SRI-04–101). Carnegie Mellon University, Pittsburgh, PA: CASOS.

Chaturvedi, A., Dolk, D., & Drnevich, P. (in press). Design principles for virtual worlds. *MIS Quarterly*.

Chi, H., Ersoy, O., Moskowitz, H., & Altinkemer, K. (2007a). Toward automated intelligent manufacturing systems (AIMS). *INFORMS Journal of Computing*, *19*(2), 302–312.

Chu, P., & Spires, E. (2000). The joint effects of effort and quality on decision strategy choice with computerized decision aids. *Decision Sciences*, *31*(2), 259–292.

Drnevich, P., Mehta, S., & Dietz, E. (2006). Coordinating effective government response to bio-terrorism. In S. Amass, A. Chaturvedi, & S. Peeta (Eds.), *Advances in Homeland Security, Volume II: Guiding Future Homeland Security Policy—Directions for Scientific Inquiry*. West Lafayette, IN: Purdue University Press, 55–78.

Drnevich, P., Ramanujam, R., Mehta, S., & Chaturvedi, A. (2009). Affiliation or situation: What drives strategic decision making in crisis response? *Journal of Managerial Issues*, *21*(2), 216–231.

Drnevich, P., Brush, T., & Chaturvedi, A. (2010). Examining the implications of process and choice for strategic decision making effectiveness. *International Journal of Decision Support System Technology*, *2*(3), 1–15.

Goes, P., Pino, J., & Vakharia, A. (2008). Call for papers: Special topic forum new frontiers in collaborative decision making. *Decision Sciences*, *39*(3), 595–597.

Green, L., & Kolesar, P. (2004). Improving Emergency Responsiveness with Management Science. *Management Science*, *50*(8), 1001–1014.

Guide, V., & Van Wassenhove, L. (2007). Dancing with the devil: Partnering with industry but publishing in academia, *Decision Sciences*, *38*(4), 531–546.

Hardy, C., & Phillips, N. (1998). Strategies of engagement: Lessons from the critical examination of collaboration and conflict in an interorganizational domain. *Organization Science*, *9*(2), 217–230.

Harrison, J., Lin, Z., Carroll, G. & Carley, K. (2007). Simulation modeling in organizational and management research. *Academy of Management Review*, *32*(4), 1229–1245.

Hevner, A., March, S., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly*, *28*(1), 75–105.

Holmstrom, J., Ketokivi, M., & Hameri, A. (2009). Bridging practice and theory: A design science approach. *Decision Sciences*, 40(1), 65–87.

Joachims, T. (1998). Text categorization with support vector machines: Learning with many relevant features. *Proceedings of ECML-98, 10th European Conference on Machine Learning*, 137–142.

Joachims, T. (2002). *Learning to classify text using support vector machines*. Boston: Kluwer Academic.

Kumar, K., & Niti, K. (1998). Differential learning and interaction in alliance dynamics: A process and outcome discrepancy model. *Organization Science*, *9*(3), 356–367.

Kumar, K., & Van Dissel, H. (1996). Sustainable collaboration: Managing conflict and cooperation in interorganizational systems. *MIS Quarterly*, *20*(3), 279–300.

Lin, Z., & Carley, K. (1993). Proactive or reactive: An analysis of the effect of agent style on organizational decision making performance. *International Journal of Intelligent Systems in Accounting, Finance, and Management*, *2*(4), 271–287.

Lin, Z., & Carley, K. (1997). Organizational response: The cost performance tradeoff. *Management Science*, *43*(2), 217–234.

McKay, S. C., Chaturvedi, A., & Adams, D. E. (2011). A process for anticipating and shaping adversarial behavior. *Naval Research Logistics*, doi: 10.1002/nav.20440.

Osborn, R., & Hagedoorn, J. (1997). The institutionalization and evolutionary dynamics of interorganizational alliances and networks. *Academy of Management Journal*, *40*(2), 261–278.

Ross, A., Buffa, F., Droge, C., & Carrington, D. (2009). Using buyer-supplier performance frontiers to manage relationship performance. *Decision Sciences*, *40*(1), 37–64.

Schwaighofer, A. (2005). MATLAB interface to SVM light. Institute for Theoretical Computer Science at Graz University of Technology, accessed October 23, 2007 available at www.cis.tugraz.at/igi/aschwaig/software.html

Sexton, R., Sriram, R., & Etheridge, H. (2003). Improving decision effectiveness of artificial neural networks: A modified genetic algorithm approach. *Decision Sciences 34*(3), 421–442.

Venkatesh, V. (2006). Where to go from here? Thoughts on future directions for research on individual-level technology adoption with a focus on decision making. *Decision Sciences 37*(4), 497–518.

Westley, F., & Vrendenburg, H. (1997). Interorganizational collaboration and the preservation of global biodiversity. *Organization Science*, *8*(4), 381–403.

Yi, M., & Davis, F. (2001). Improving computer training effectiveness for decision technologies: Behavior modeling and retention enhancement. *Decision Sciences*, *32*(3), 521–544.

APPENDIX A: HIGH-MAGNITUDE CRISIS DECISION MODEL DEVELOPMENT

Machine learning algorithms are a subset of data-mining tools. They include artificial neural networks, decision trees, and more recently, SVM. Prior research has successfully applied SVM with excellent results in many different areas, but to the best of our knowledge none have been applied to modeling behavior in general and decision-making response strategies for crisis response in particular. In the simulation experiment in our case, although participants could observe the overall impacts of the decisions made following each decision-making round, they did not receive any information regarding the decisions made or the factors and variables used to make the decisions (model) by participants from the other various governmental levels and agencies. We focused on developing and applying an MLSVM algorithm to model and predict what decision makers in organizations would do in response to a simulated high-magnitude crisis. Intuitively, we expected that the underlying behavioral model-structure would be a mixture of response sub-patterns because: (i) different people within and across agencies may focus on different decision-making criteria, in part, contingent on the degree of coordination and communication occurring; (ii) even the same individual may use different decision-making criteria under different circumstances and they have different decision-making capabilities and training. Contrary to single stage models, which generally yield one aggregate model of response behavior, the purpose of MLSVM is to identify and model any mixture of behavioral sub-patterns that exist in the dataset.

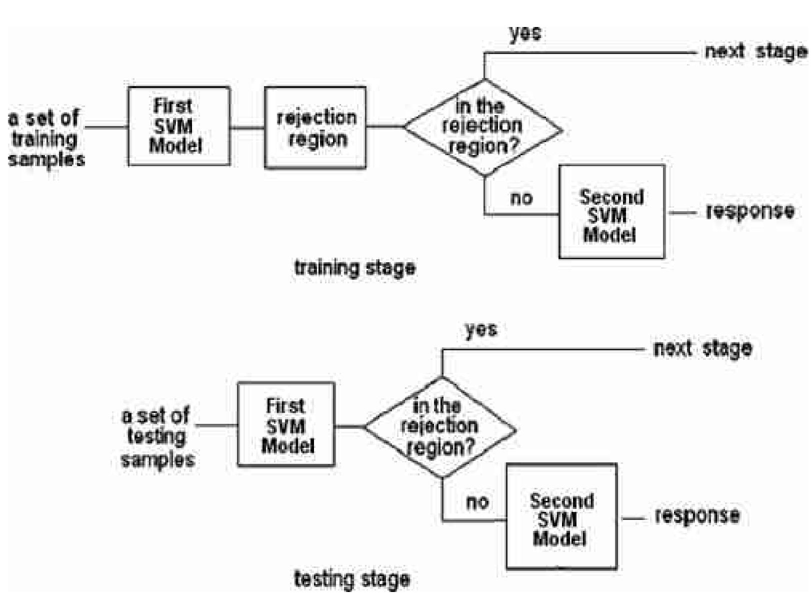
Conceptually, multistage SVMs extend the original single stage SVM algorithm to a multistage structure. The original SVM is a margin-based learning algorithm. During construction, the algorithm automatically selects a subset of samples, known as support vectors, and builds the decision boundary with maximum margin and minimum training errors based on them. The distance between the response of a sample and the decision boundaries induced by a SVM model measures the confidence of the model in predicting the sample response. Namely, misclassifications are more likely for the samples whose responses are closer to the decision boundaries than are those that are farther away. Furthermore, the set of samples that are well represented or approximated by a given SVM model should share a similar underlying model-structure. Thus, using the sample-margin information, we select the subset of samples that are homogeneous for the underlying model-structure and we can "train" a SVM model, based on this "sanitized" subset, to better capture the common underlying model-structure of the subset. We can iterate the process on the remaining samples until no further partition is necessary. Upon termination, we obtain an aggregation of sub-models, which provides insight into the sub-patterns in the dataset. The multistage SVM algorithm does not have restrictions on the type of SVM models used per se, although models with a more simple parametric form are preferred. In the remainder of this appendix we discuss the training and testing procedures of the model.

Model Training Procedure

The training procedure for the high magnitude, crisis response decision model is as follows:

In step 1: Set $k = 1$ for the first stage. Let $S(0)$ represent the entire dataset, and $S(k-1)$ the subset forwarded from the previous stage; namely, the rejected subset at the $(k-1)$th stage. In step 2: Train a first linear SVM model based on $S(k-1)$ for the kth stage. Partition $S(k-1)$ into two parts based on the ± 1SVM margin. The

Figure A1: Internal structure of multistage SVM.



points falling outside this region are the accepted subset, and the points inside the rejection region are the rejected subset. Then we train a second linear SVM model on the accepted subset and save it as the appropriate model for that stage. In step 3: Check the termination conditions. If either of the two conditions are satisfied, then stop; otherwise, let $k = k + 1$, $S(k)$ be the rejected subset of samples and proceed to step 2.

Model Testing Procedure

The testing procedure for the high magnitude crisis response decision model is as follows:

In step 1: Set $k = 1$ for the first stage and let $f_k(x)$ represent the first linear SVM model and $g_k(x)$ represent the second linear SVM model for the kth stage. In step 2: Calculate the value of $f_k(x)$ for the testing sample; if the value is outside the rejection region, then interpret $g_k(x)$ as the final classification label and stop. If the value falls within the rejection region, then let $k = k + 1$ and do step 2 again. We provide an overview of the internal structure of our multistage SVM in Figure A1.

Herbert M. Moskowitz is professor emeritus and held the Lewis B. Cullman Distinguished Professorship of Manufacturing Management at the Krannert Graduate School of Management, Purdue University. His areas of specialization are management science, applied statistics, and data mining with emphasis on manufacturing and technology, Six Sigma, and health care. His recent research has focused on developing and applying machine learning algorithms and applying Six Sigma and Factory Physics Concepts to pharmaceutical development and manufacturing and health care management and engineering. He joined Purdue in 1970 and has also held visiting appointments at the University of Mannheim, University of British Columbia, London Business School, Wharton School, Instituto Technologico Costa Rica, University of Rouen, Helsinki University, Technical University in Finland, and the Monterrey Institute of Technology in Mexico. He holds a BS degree in mechanical engineering, and an MBA and PhD in management from UCLA.

Paul L. Drnevich is an assistant professor of strategic management at the Culverhouse College of Commerce and Business Administration at the University of Alabama. His research interests include: firm value creation/appropriation and the effects of environmental uncertainty on performance; the implications of capabilities and environmental factors for innovation and performance in entrepreneurial ventures and small business; and the use of virtual environments and agent-based simulations to study strategic decision making in interorganizational networks. He has authored research for outlets such as the *Strategic Management Journal, MIS Quarterly, Academy of Management Learning & Education,* and *Journal of Small Business Management,* among other venues.

Okan K. Ersoy is a professor of electrical and computer engineering at Purdue University. His current research interests include statistical and computational machine learning, decision analytics, digital signal/image processing and recognition, transform and time-frequency methods, diffraction theory, and their applications in remote sensing, imaging, diffractive optics, nanotechnology, finance, management, and distant learning. He has published approximately 250 papers and two books and several book chapters in his areas of research. He also holds four patents. He is a fellow of IEEE, and a fellow of the Optical Society of America.

Kemal Altinkemer is an associate professor at the Krannert Graduate School of Management, Purdue University. He was a guest editor for *Telecommunication Systems, Information Technology and Management, ECRA* and *IsEB*. He is an associate editor in seven journals related with telecommunications, E-commerce and management information systems (MIS). His research interests are in design and analysis of computer networks, infrastructure development, distribution of priorities by using pricing as a tool, infrastructure for e-commerce and pricing of information goods, new emerging marketplaces, and strategy from brick-and-mortar to click-and-mortar business models. He has more than 40 publications in prominent journals such as *Operations Research, Operations Research Letters, Management Science, INFORMS Journal on Computing, Transportation Science, EJOR, Computers and OR, Annals of Operations Research,* and more than 40 publications in various conference proceedings. He is a member of INFORMS, AIS, and ACM.

Alok R. Chaturvedi is a professor at the Krannert Graduate School of Management, Purdue University and the Chairman and CEO of Simulex, Inc., a modeling and simulation company where he led the development of the Synthetic Environment for Analysis and Simulation (SEAS), a platform for large-scale multi-agent simulations, used by the US Department of Defense. He is also the founding director of the Purdue Homeland Security Institute and previously served at the Institute for Defense Analyses (IDA) and has been involved with several government task forces on important public policy and national security matters. He is also the principal investigator and project director for several major grants from the National Science Foundation, Indiana 21st Century Research and Technology Fund, Office of Naval Research, Defense Acquisition University, and several Fortune 500 companies. He received his PhD in management information systems and computer science from the University of Wisconsin-Milwaukee.