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DISTORTION OF "MENTAL MAPS" AS AN EXEMPLAR OF IMPERFECT SITUATION AWARENESS

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ABSTRACT

This paper provides the first results of dissertation research that seeks to develop and apply an experimental milieu for the study of imperfect Situation Awareness/Situation Understanding (SA/SU) and of decision-making based on that SA/SU. It describes an agent-based simulation and initial results of simulation experiments conducted with that framework. The simulation experiments explore a specific, easily understood, and quantifiable example of human behavior: intelligent agents being spatially "lost" while trying to navigate in a simulation world. The paper concludes with a discussion of on-going and planned research based on modifications to that simulation and conduct of additional experiments.

1 INTRODUCTION

This paper provides the first results of dissertation research that seeks to develop and apply an experimental milieu for the study of imperfect Situation Awareness/Situation Understanding (SA/SU) and of decision-making based on that SA/SU.

I am investigating decision-making under imperfect SA/SU by conducting a series of simulation experiments that explore a specific, easily understood, and quantifiable example of human behavior: intelligent agents being spatially "lost" while trying to navigate in a simulation world.

As a means to that end I am implementing an agent-based simulation framework that supports those experiments. My research is structured as an iterative cycle of experiments and simulation enhancements. The objective of the experiments is to provide insight into multiple aspects of decision-making as affected by problem complexity, information quality, risk tolerance, and decision strategies.

1.1 Background

In my research in general, I choose to blur any distinctions between Situation Awareness and Situation Understanding into a single over-arching concept in keeping with the pragmatic definition of (Adam 1993)"knowing what is going on so I can figure out what to do." In this paper I begin with exploration of how to define "imperfect" SA/SU.

Following Endsley's view (Endsley 1995a; Endsley 1995b) imperfect SA/SU may be caused by imperfect perception of one's environment, imperfect understanding of what is perceived, and/or imperfect projection of that understanding to predict the consequence of one's decisions on future events. Imperfect SA/SU is characterized by information that is incomplete, uncertain, and/or erroneous.

To date, most technological approaches to improving SA/SU have looked to improve the availability, organization, and visualization of the data provided to decision makers. In so doing they have focused on providing more information while avoiding data overload. While incomplete information is a large problem for SA/SU, I believe the role of erroneous information is equally important, especially as it relates to correcting the decision-maker acting on a worldview that is wrong.

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Handling erroneous and other forms of imperfect information is particularly problematic in modeling and simulation. Computer simulations generally strive for accuracy, resolution and fidelity, trying to represent " ground truth", rather than an individual's imperfect understanding of what that truth may be. While error and uncertainty are certainly critical factors in representing the real world, they are not easily captured by the physics-based mathematical models upon which most military simulations are based. Computer simulations do not do well in representing the "fog of war". One of the first challenges in exploring imperfect SA/SU in a computer model is simply how to generate realistic "bad" information for use by simulated decision-makers.

1.2 Fundamental Concept: Multiple Worldviews

My approach is based on Monte Carlo experiments with an agent-based simulation. As I have implemented the agent-based approach, the simulation must maintain multiple descriptions of the simulation environment. The first of these is ground truth, which is the true state of all the objects in the environment. Ground truth is common to all entities in the simulation. It represents the environment that affects and is affected by an entity's physical behaviors.

Additional descriptions of the environment are required to capture an individual entity's worldview, which defines the state of objects as each simulated entity perceives that state to be. This worldview is the basis for the agent's cognitive behaviors, how the agent decides what to do next. The problem of generating "bad" information is thus the question of how to make this worldview differ from ground truth in a realistic way. This paper discusses a set of simulation experiments that systematically vary aspects of an agent's worldview and explore how a mistaken understanding of ground truth might affect achievement of the agent's goals.

1.3 Scope

I am looking for understanding of more complicated problems of human decision-making by exploring a restricted decision space. I am focusing on a single but highly representative type of decision: the fundamental question at each stage in a simulated agent's movement: "where to go next?" The question can be at a global or local level depending on the degree of precision needed to represent the agent's options. The decision elements that must be represented include:

- a goal – an endpoint or location towards which the entity's movement is directed;
- the geo-spatial environment and the entity's interaction with that environment
- environmental feature characteristics – landmarks, identifying qualitative and quantitative attributes;
- the entity's perception of the environment – its view of those factors in its world that might influence its movement;
- ground truth constraints – those factors in the world that restrict or otherwise affect the entity's physical movement;
- inference procedures – the algorithms and/or heuristic methods by which the entity selects that next position, given its goal, its understanding of the environment and its capabilities to move within that environment
- uncertainty and errors – the sources and extent of the entity's potentially imperfect understanding of its environment.

2 SIMULATION EXPERIMENTS

The first set of experiments completed as part of this research incorporate elementary representations of three basic modes of dynamic decision-making: formulation of a plan of action (route planning); attempted implementation of that plan (route following), and adjustment or abandonment of the plan as events fail to match expectations (way finding).

2.1 Model Basics

The experimental simulation is implemented in the simulation package AnyLogic®. AnyLogic® is a Java platform and model development with AnyLogic® consists of building the appropriate graphical structures and customizing their function with Java code.

The model is designed to represent simulated entities finding their way on an arc/node network. The minimal model considers a single entity whose basic goal is to move from a given start node in the network to a designated end node. The entity can attempt to generate a route plan, a sequence of nodes and arcs from the start point to the end goal, or it can employ a variety of search techniques to try and find its way to the goal. Should an entity attempting to follow a route become "lost", i.e., diverge from its chosen route, it can switch to search tactics to either attempt to rejoin its route or to otherwise achieve the end goal.

Being "lost" carries with it the idea of some kind of failure in the entity's mental map. The types and degrees of such failure are examples of poor SA/SU, and the extent to which they affect the entity's ability to achieve its end goal provides a measure of the value of SA/SU. Actual humans can find their way from one point to another with very rudimentary, ambiguous, unclear and/or inaccurate maps or directions. An effective simulation of getting or being "lost" should take into account this human resilience in assessing the effects of imperfect SA/SU.

Minimal model requirements for simulation of being "**lost**" include:

- The capability for an entity's view of where it is and where it is going to be different from ground truth.
- An error taxonomy that reflects both types of being lost and degrees of "lostness";
- The mechanisms by which an individual achieves different states of being lost; and
- The mechanisms by which an individual recognizes and attempts to correct being lost.

In the model a single entity is represented by two agents: the **ground truth (GT) agent**, who operates in the world of physical reality, and the **the voice-in-head (VIH) agent**, who makes decisions and directs the movement of the GT agent based on the entity's perceived world view.

An arc/node network constitutes the entity's world, but the GT agent operates on the arc/node network that represents the "real" world of the entity, while the VIH agent uses an idiosyncratic view of that network, a "**mental map**" that represents its own particular, generally distorted, view of ground truth geography.

Route planning and route following decisions are made with respect to the VIH mental map, while actual movement takes place on the ground truth network. The GT agent moves through the GT network, and reporting to the VIH agent the characteristics of the GT network as the GT agent experiences them. The VIH agent monitors the GT agent's progress, and compares the state of the VIH mental map to the GT network characteristics reported by the VIH agent. The VIH agent can use these data to update the mental map, but that map remains subject to misperception and/or misinterpretation of the GT data, both of which may influenced by biases induced by previous states of the mental map.

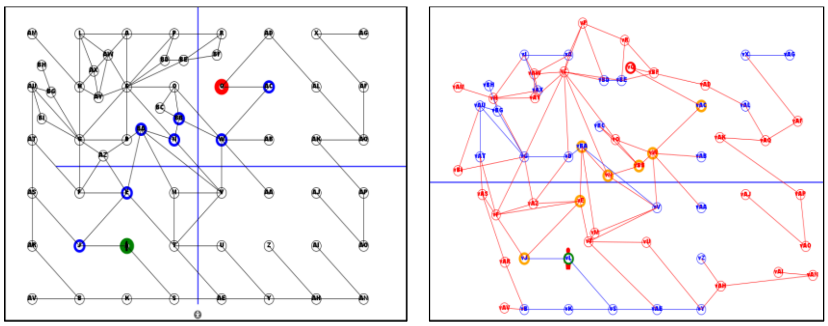
2.2 Initial Objectives:

The first set of experiments:

- quantify the influence of different degrees of mental map distortion with respect to the success or failure of the entity in achieving its goal;
- define initial measures of task performance and look for correlations between these measures and different success/failure modes;
- identify potential heuristics that define the entity's "lost level", measuring whether the entity is making acceptable progress towards its goal; and
- investigate the effects of updating the mental map to match observed ground truth as the entity moves along the ground truth network.

2.3 Simulation Components Explored

As shown in figure 1 these initial experiments use two versions of a network with a variety of node connectivity and node distance relationships. The simulation considers a single entity whose goal is to move from a randomly selected network start node to a randomly designated end node. The thick green and red circles indicate randomly chosen start and end goal nodes respectively. The thick blue circles represent the optimal path between the two, as determined by an A* algorithm based on arc distance.



Ground Truth Network **Random Distortion of Ground Truth Network**

Figure 1: Simulation Arc/Node Networks

For each experiment, the entity's mental map is created by distorting the ground truth map either deforming spatial relationship between nodes, i.e., changing the distance and angles of connecting arcs, and/or changing the topological nature of the network by removing ground truth nodes from the mental map. Again, as shown in figure 1, the red circles and arcs represent the distorted elements of the ground truth network, the blue elements the unchanged elements. The start and end goal nodes remain unchanged, but now the path the agent believes to be optimal is based on the distorted distances and is indicated by the thick orange circles on the map. In this particular instance, the sequence of nodes in the perceived shortest distance path remain the same, but the perceived distance is different from the actual ground truth distance, as are the headings of the arcs that must be chosen by the agent, leading to the potential to stray from the optimal path.

The entity can attempt to use the A* algorithm to generate a route plan according to its mental map, or it can employ a variety of search techniques to try and find its way to the goal. Should an agent attempting to follow a route become "lost", i.e., diverge from its chosen route, it can switch to search tactics to either attempt to rejoin its route or to achieve the end goal.

Each experiment is deemed a success if the entity finds its way to the goal and a failure otherwise. There are three ways an entity can fail the experiment:

- dead end – the entity finds itself in a node from which it has tried all possible exit paths;
- lost no node – the entity travels on an arc without finding a node before reaching a user-set threshold parameter; or
- lost no goal – the entity has been off its planned path and visited a number of nodes that exceeds a user-set threshold parameter.

Entity movement requires of a sequence of decisions: each time the entity reaches a node, it must decide which arc to take next, or, if it travels along an arc without reaching an expected node, it must decide whether to continue on that arc or quit. These decisions are a function of the entity's current decision-making mode, the amount of distortion in the entity's mental map, and the threshold parameters set by the user to persist in the face of ground truth deviation from the conditions anticipated according to that mental map. Later experiments will introduce a number of additional mental map features and entity decision options based on those features.

2.4 Types of Experiments

Two types of experiments are used to analyze the decisions made by the agents and the effects of those decisions on goal achievement. Interactive simulations provide detailed insight into agent behavior for specific model input values; parametric experiments provide a more thorough basis for statistical assessment of that behavior over a wide range of possible input values. Both are Monte Carlo simulations, which provide random sampling by selection of numerical results from known or hypothesized statistical distributions.

When the simulation is executed interactively the GT agent's movement can be tracked visually and updates to the VIH agent's mental map can be seen as the entity moves. The simulation can be paused at any time and the internal values of model variables examined. This form of simulation execution provides the most complete view of the entity's behavior. It is useful for verifying and debugging model code, but more importantly it supports exploration of the causes and effects of specific entity decisions.

When the simulation is executed in parametric mode, specific combinations of parameter values define the each set of experimental conditions that comprise different experimental cases. Each of these cases is executed for a number of Monte Carlo trials and output statistics are kept.

2.4.1 Interactive simulations

Figure 2 shows a snapshot of the interactive simulation output for the ground truth and mental map networks of Section 2.3. It provides the path of the entity highlighted in yellow on the ground truth map and the entity's perceived position on the mental map. The figure again shows the entity's optimum path – the blue circles from the green initial node to the red goal node displayed on the ground truth map, and the entity's perceived best path – the orange circles on the mental map. The figure also shows gauges that track the distance traveled and the distance to the goal, the number of choices available at each node, and the difference in the true (ground truth) and the perceived (mental map) bearing of the next target node from the current node. This is shown here as having updated its mental map to correspond to the ground truth conditions experienced during its movement, the nodes and arcs shown in green representing corrections to the mental map. Future experiments may explore other map update criteria, including errors in perceiving ground truth and/or uncertainty with respect to recognition of ground truth features. Dealing with such uncertainty will provide one avenue for exploration of risk tolerance strategies.

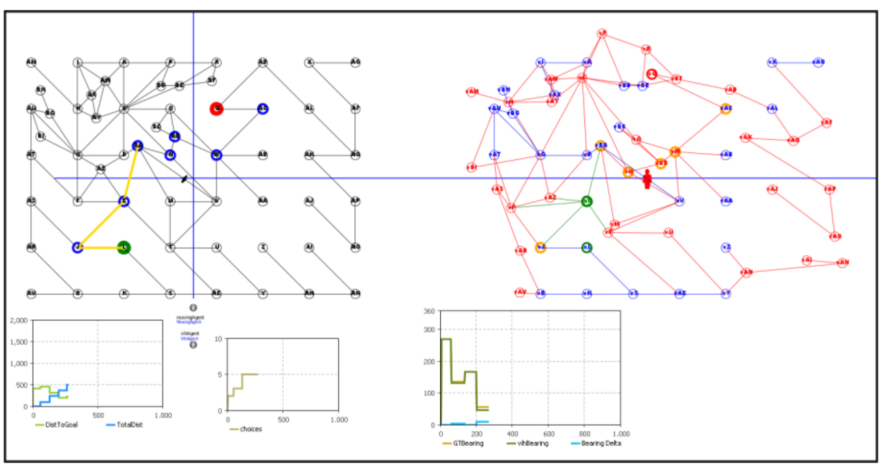


Figure 2: Interactive Simulation Experiment

In the figure shown the entity fails to find the node for which it was searching within the distance threshold, resulting in a lost no node failure mode. The cause of its wrong decision was the distorted perception of the target node's position, resulting in the entity selecting the wrong arc connection.

2.4.2 Parametric experiments

The model was run for fifty replications of each combination of the values shown in table 1 resulting in more than 30 thousand separate simulation runs.

Table 1: Parametric Simulation Variants

Parameter	Values
X and Y error limit: Amount a VIH node can vary from its Ground Truth position in either X or Y	50, 100, 150, 200, 250, 300, 350, 400
Probability of Node Error: Probability that a VIH node varies from its Ground Truth Position	0.25, 0.5, 0.75, 1.0
Nodes Without a Goal Limit: Number of nodes that will be searched without finding an intermediate or terminal goal – exceeding this value results in Lost No Goal termination mode	3, 7, 10, 15, 20
Distance Error Threshold: Distance that will be searched along an arc if an expected node is not found at the VIH distance from the last node – exceeding this value results in Lost Nod Node termination mode	50, 125, 200, 275

During each run model output statistics were collected and stored in a comma separated variable (CSV) file suitable for analysis in spreadsheet programs such as Excel® and JMP®.

3 RESULTS

Monte Carlo simulation experiments have long been used to support hypothesis testing, exploring the effects of specific input variables on model outputs. One popular approach applies ANOVA techniques to test for significance in simulation output means, accompanied by linear regression to establish a numerical relationship between input values and outputs. These techniques, however, assume the underlying model to have properties, such as homoscedastic normal distributions, that may not be warranted, especially in the case of dichotomous output variables. Of more interest to my research is the application of data farming and data mining techniques to look for exploratory data analysis. These techniques rely heavily on data visualization and include partitioning, regression tree analysis, and logistic regression on maximum likelihood parameters.

3.1 Analysis of Termination Condition by Input Parameters

Analysis of the experimental results begins with exploring the effects of the parameter values on the success or failure of each experiment, i.e. whether the entity achieved the desired goal, Normal Termination, or failed in one of the three failure modes described above. Since this result is a categorical variable it is not well suited for traditional ANOVA techniques, but is better handled with a variety of maximum likelihood approaches.

3.1.1 Fit y by x

The first step in analyzing the results of the parametric case matrix of table 1 is simply to look at the results by termination condition as shown in figure 3.

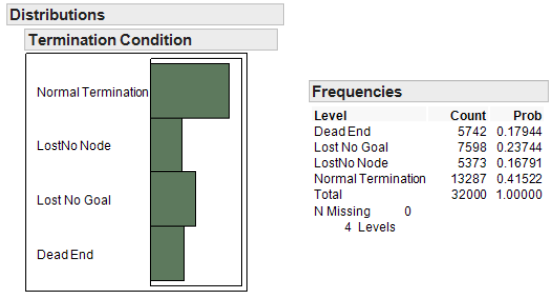


Figure 3: Frequency of Termination Condition

These results can be broken down by the various parameter values as shown in figure 4.

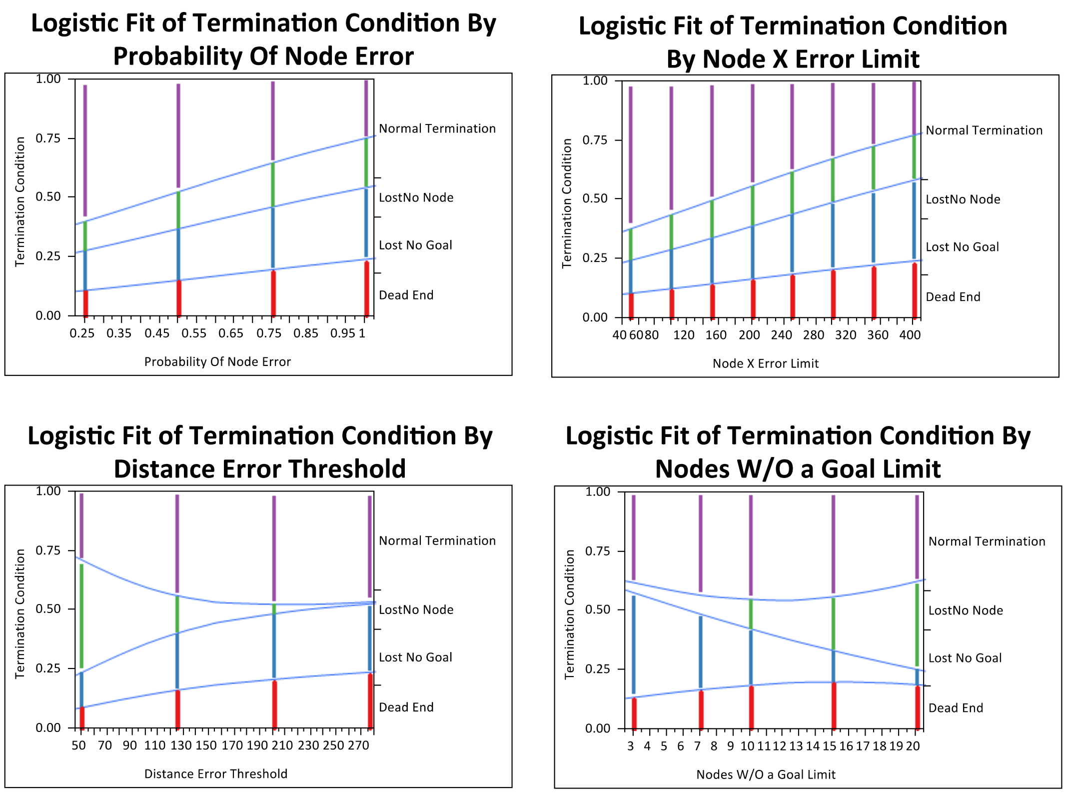


Figure 4: Logistic Fit of Termination Condition as a Function of Input Parameter Values

Each of the input parameters shows a statistically significant correlation with Termination Condition, p> 0.001, but a model based on any of them individually provides a poor fit to the data.

The relationship between node error limit – the extent of spatial distortion in node placement in the mental map, and probability of error in node placement show basically the same trend. Both of these parameters contribute to the level of distortion in the mental map and can be expected to interact with each other.

As could be expected, terminations due to inability to find a node along an arc (lost no node) decrease as the distance error threshold increases, while they increase as the nodes without a goal limit increases. Similarly the terminations resulting from inability to find the goal after visiting the number of nodes that exceeds the user-set threshold parameter decreases as this parameter increases, and increases somewhat as the distance threshold parameter increases.

3.1.2 Partition Analysis

I applied two JMP® methods to fit a model of the termination results as a function of the input parameters. The first of these is a partitioning analysis in which classes of the dependent variable, termination mode, are divided according to the their probability of occurrence given different values of the independent variables expressing the parameter values in table 1.

This process begins with the construction of contingency tables based on the observed frequency of dependent variable responses compared to the expected frequency under the null hypothesis that response rates are independent of the various parameter values. JMP® software implements this process by iteratively exploring all of the possible two factor contingency tables for combinations of the parameter levels and response possibilities. For each possible contingency table JMP® calculates the G^2 statistic:

$$G^2 = 2\sum_{i=1}^{I}\sum_{j=1}^{J} n_{ij}\log\left(\frac{n_{ij}}{\mu_{ij}}\right)$$

where μ_{ij} is approximated by $\widetilde{\mu_{ij}} = \frac{row\ sum * col\ sum}{total} = [(\sum_i n_{ij})(\sum_j n_{ij})]/[\sum_i \sum_j n_{ij}]$. The formula finds the expected number in each cell by multiplying the proportion of the col contributions to the overall sum times the row size. When partitioning data, the G^2 is exploring evidence for the null hypothesis that the row and col variables are statistically independent, the larger the statistic, the greater the evidence they are dependent. The ideal situation would be to partition the data so that the column data, which represent the response variables or different experimental outcomes, are completely determined by the values of the row data, which are the factors of the experimental design. The degrees of freedom in a test of independence are equal to (number of rows)−1 × (number of columns)−1.

The largest resultant G^2 value in each iteration defines the partition split for that iteration. Figure 5 shows the improvement in the R^2 value (also referred to as U, the uncertainty value) for a series of 11 splits. This R^2 value is meant to serve an analogous function to the R^2 value derived from classical correlation coefficients, but is not as easily interpreted as that value. This R^2 is the ratio of the **Difference** to the **Reduced** negative log-likelihood values, where:

- **Difference** is the difference between the **Reduced** and **Full** models. It measures the significance of the regressors as a whole to the fit.
- **Full** describes the negative log-likelihood for the complete model, and
- **Reduced** describes the negative log-likelihood that results from a model with only intercept parameters.

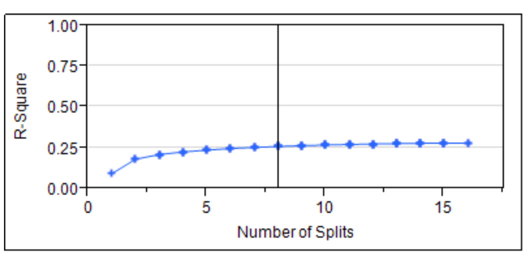


Figure 5: Partition Split History

Figure 5 shows little change in the R^2 value after five splits. Figure 6 shows a view of the partition with five splits. The results are shown as colored points in partition columns; JMP® also supports a hierarchal view of the splits. The initial split is on the value for the nodes without a goal limit, which is then broken in one case by a distance error threshold and the other by node error limit. In the first case, where the nodes without a goal limit is relatively small, < 10, the successive splits are dominated by the parameters that control the amount of distortion in the network, the probability and amount of node placement error. In the case where the distance error threshold becomes more significant, smaller distance cases show the dominance of the lost no node termination condition, while this condition occurs rarely in the larger distance error threshold cases. As the probability of node errors and their magnitude increase, the data show an increase in the other abnormal termination cases, lost no node and dead end. The normal termination condition is greatest for small values of node error variables coupled with large distance error threshold tolerances.

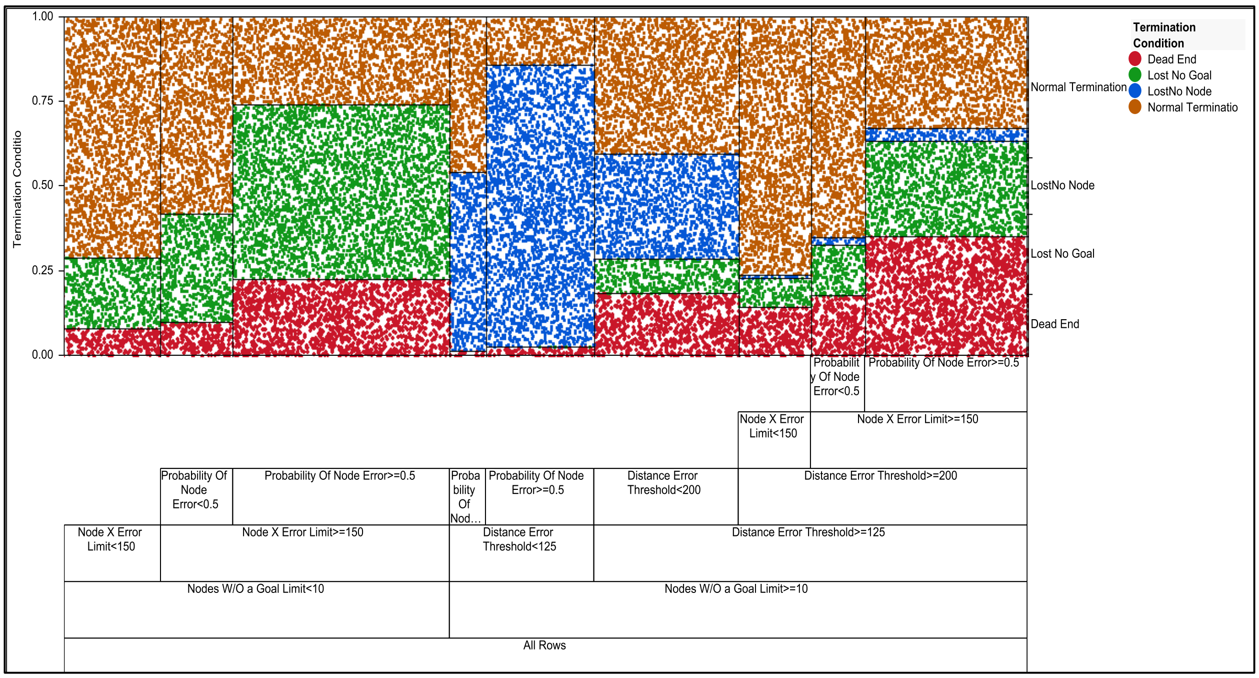


Figure 6: Partition By Termination Condition

Figure 7 shows the relative contributions of the parameters to the split decisions. The probability of node error is used into the greatest number of split decisions, but interestingly accounts for the least contribution to overall G^2 values.

Term	Number of Splits	G^2	G^2
Probability Of Node Error	3	1867.2963	
Node X Error Limit	2	2289.8351	
Distance Error Threshold	2	9899.6150	
Nodes W/O a Goal Limit	1	7862.9744	

Figure 7: Parameter Contributions to Partition Splits

The partitioning process does provide an estimate of the probability of the termination mode outcomes as a function of the input parameter values, but, as mentioned above, the R^2 value is not necessarily a good indicator of the goodness of fit of that function. Another way to judge the value of the partition process is to look at the confusion matrix, a comparison of the actual and predicted values of the classification process used. In this case, the confusion matrix, shown in table 2, provides a misclassification rate of 0.443, or in other words predicts correctly at a rate of 0.557.

Table 2: Partition Confusion Matrix

Actual Predicted

	Dead End	Lost No Goal	Lost No Node	Normal Termination
Dead End	1914	1642	117	2069
Lost No Goal	1502	3697	6	2393
Lost No Node	205	0	3621	1547
Normal Termination	1779	1861	1056	8591

3.1.3 Regression Fit

JMP® also supports a logistic regression fit, which is similar to ordinary least squares regression, but which uses the logistic function to provide linear transforms of non-linear functions describing the relationship between continuous input variables and categorical outputs. The logistic regression fit to the data above converged in gradient after 7 iterations with an R2 value of 0.2442. The confusion matrix for the logistic regression fit is shown in table 3.

Table 3: Logistic Regression Fit Confusion Matrix

	Dead End	Lost No Goal	Lost No Node	Normal Termination
Dead End	723	1736	386	2897
Lost No Goal	485	3672	136	3305
Lost No Node	157	72	3762	1382
Normal Termination	485	1770	1016	10016

4 FUTURE WORK

As stated above, my research plan is comprised of a series of linked experimental cycles and simulation enhancements. Each of these cycles expands and/or refines exploration of a spectrum of decision-making behaviors associated with:

- varying the factors make decisions “hard”, from problem complexity to criticality of potential outcomes;
- the effect of different degrees of uncertainty and/or error on the decision-maker;
- the potential for different strategies to mitigate or exacerbate risk and other concerns; and
- the view of decision-making as a dynamic process, with recurrent evaluation of progress towards goals and associated adjustment of behavior choices.

Simulation enhancements will reflect the understanding gained through analysis of experimental results. The enhanced model will then be applied to further investigation of decision processes and the factors affecting those processes.

Ultimately, the ability represent different worldviews for multiple simulation entities can support exploration of cognitive theories in simulation experiments.

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