Quantitative Models from Qualitative Data: Case Studies in Agent-Based Socio-political Modeling

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ABSTRACT

Many socio-economic policy, planning and assessment questions arise because not enough is known about their subjects. While inaccessibility and lack of hard data are the very challenges that may make a computer model invaluable, they are also reasons why many modeling and simulation applications are never undertaken. The authors have found that qualitative agent-based models that are appropriately focused can prove surprisingly rich in quantitative data. Such models, accompanied by a thorough delineation of the applicable scope and context, have provided important insights into otherwise inscrutable systems. Building on early lessons learned in qualitative modeling (Dixon & Reynolds 2003), broader issues of qualitative modeling are explored. Case studies include negotiations, historical research, and leadership succession.

1 Introduction

Policy-makers rely on analysts, and when a policy-maker refers to a *good analyst*, that typically means an analyst who is able to weave data into narrative without doing injustice to either. When supporting policy makers and analysts, modeling and simulation researchers often exceed the talents of even the best analysts. Useful models of complex systems are complex systems themselves, and those who promote their use must first master the skill of turning their models into narrative and vice versa.

The interplay of data and narrative is especially problematic when modeling data-poor systems. This is the case in most socio-economic policy issues that are outside of purely financial or demographic areas. It is certainly true of international arenas when considering closed governments, multi-national non-government organizations, or segments of populations or economies that are not well known even by their own governments. Often, notional models – on paper or in computers – may be the only way to assess these systems or plan for contingencies that involve them. Historically, lack of data has been seen as a limit to computer modeling, and analysts have made careers out of carrying trusted mental models of these systems around in their heads. These analysts have always been in shortage, are impossible to scale up, don't yet hook directly to the internet, and tend to retire from the workforce. Computer models are not likely to replace those analysts, but they could serve to replicate their stored knowledge and insights, solving the shortage, scalability and connectivity problems somewhat.

Addressing the first problem, communicating quantitative models to a narrative-based world, and the second, turning a narrative-based system into a quantitative model, lead to a possible conclusion: computer modeling and simulation must be embedded within a narrative context. That is a big, multi-disciplinary challenge, and the authors look forward to participating in it someday. The present paper, however, has a much more modest objective: to illustrate a few attempts to connect computer models with their narrative-based providers and consumers.

2 The goal of qualitative modeling

The goal in the analysis of complex systems is a change in thought process – a *discovery*. Also called insight, recognition or *eureka moment*, discovery is the central event in any analytic endeavor. Discovery is measurable: moments of discovery are often quite marked and can be revealed in a number of ways, including surveys and even physiological measurements of test subjects (Jung-Beeman 2004).

How is discovery defined in the context of a complex system? The classic definition of complexity was provided by Kolmogorov, among others, in the 1960s (Gammerman 1999). They defined the complexity of a set of numbers as the length of the shortest possible program that could produce that set of numbers. This technical notion of complexity has been extended by Gell-Mann, who defines the complexity of a system as the "length of the shortest message that will describe a system … employing language, knowledge and understanding that both parties share." (Gell-Mann 1994)

Naturally, this definition of complexity depends on the way the system is described. Clever selection of descriptive mechanisms can make seemingly intractable systems manageable. One can argue that most scientific endeavors consist of the discovery and development of descriptive mechanisms that allow one to reduce the complexity of a topic by reducing the length of its description. The difficulty, then, with Gell-Mann's definition is that it requires "…language, knowledge and understanding that both parties share". In the authors' experience, complex systems are always multidisciplinary. This means that concisely describing the many facets of the system necessitates communication among various disciplines, and there are no guarantees that experts in these different fields will understand each other. For example, consider the following domain-specific description:

$$F = ma.$$

This is Newton's famous relation between mass and acceleration, but it only has meaning to person with knowledge of elementary physics. In the context of physics, however, it is a clear and concise description of a physical phenomenon. Such descriptions can be thought of as forms of narrative, so that every narrative is composed within a different context, or paradigm. From this point of view, a discovery is the elucidation of a new narrative that describes a system. This definition is consistent with the ideas of narrative intelligence (Mateas 1999), which suggest that human cognition is intimately connected with narratives.

The study of a complex system consists of identifying (or inventing) a set of narrative paradigms that is sufficient to fully describe the system. Gell-Mann's definition can be extended to include an active sharing of information between domain experts so that each can understand narratives from the others' narrative paradigms. Alternatively, we extend the definition of description to include both the narrative and a specification of the encompassing narrative paradigm.

3 Discovery and narrative

The scientific method (Wilson 1990) is the systematic use of experimentation to confirm or refute a hypothesis. Sherman Kent, an intelligence analysis pioneer, made a connection between the scientific method and intelligence analysis (Kent 1949). Narrative paradigms – which take on many forms in science, art, mathematics, creative writing, analysis, insight, synthesis, etc. – are implicit in the scientific method. A hypothesis, for example, is a form of narrative with an associated narrative paradigm. In using the scientific method in any field, it is vital to make explicit the associated narrative paradigm (*e.g.* organic chemistry, quantum mechanics, social psychology, *etc.*) Although it follows that hypotheses typically speak to a specific narrative paradigm, it is the authors' experience that novel discoveries often arise from a narrative paradigm shift, suggesting that qualitative modeling should support multiple narrative paradigms.

The scientific method provides a means for confirming hypotheses, but not a way to generate hypotheses. Finding a good narrative paradigm and creating a compelling narrative are the *art* of science. This is the process of discovery, insight and recognition – the eureka moment.

The eureka moment itself is an emotional state (Jung-Beeman 2004). But how is such an emotional state described? How do discoveries happen? What spring in the human psyche is the source of insight? This remains the central question for scholars of the history and philosophy of science (Crease 1993a). The elusive answer lies not only in the study of science and scientists, but also within science itself – in, for example, the disciplines of psychology, cognitive science, management science and engineering process.

The philosopher Robert Crease (Crease 1993b) suggests that an essential element to discovery is *puttering*, an undirected experimentation with a system to determine its behavior. Such familiarization increases the investigators' recognition of events in the system and increases confidence in assessments of those events. Improved recognition and confidence enable the investigator to move to more formalized, directed experiments with the system. As a consequence the investigator is better able to formulate novel hypotheses. The study of complex systems is filled with anecdotes of surprising behavior that was not so surprising in retrospect. Examples of surprise events that were obvious in hindsight include the fall of the Soviet Union

(Weschler 1984), the 2003 power outage in the northeastern United States (Wald 2004) and the terrorist attacks on the U. S. on September 11, 2001. Recognition and confidence might have allowed analysts of these systems to synthesize the many warning signs and make the crucial discoveries that pointed to the possibility of these events.

What leads an analyst to putter with a system? In the first chapter of his book *An Introduction to Scientific Research*, E. Bright Wilson says that a topic “should interest the investigator strongly” (Wilson 1990). Intelligence analysts must be curious people. Clearly, no software system can engender these qualities in a user – finding such a user is a problem beyond the scope of the current study. However, assuming the presence of a curious, interested user, a modeling environment must be able to indulge the investigator’s curiosity.

A related notion is that there is a well-focused mode of study called *flow* (Csikszentmihalyi 1990) when the investigator is *in the groove* or *in the zone*. Interest, curiosity and puttering may be necessary – though generally not sufficient – predicates to flow.

It can be argued that flow is a necessary condition for discovery, and puttering a necessary condition for flow. Researchers and analysts must be able to putter with their systems to understand them and to achieve flow in order to make discoveries. For wide-open, unstructured problems it is difficult to start this process when a strategy for puttering is not obvious. This is the *bootstrap problem*; solving it or at least overcoming it will be crucial to establishing a contextual framework to support discovery.

Based on the above observations, these appear to be basic requirements for qualitative modeling to support analysis of complex systems:

1) To address complex systems – which are complex because they cannot be encompassed by narratives within a single narrative paradigm – the model or models must be able to support multiple narrative paradigms. This implies a modeling framework that encourages the synthesis of different narrative paradigms and facilitates the formation of hybrid narratives required by the complex system.

2) The modeling process must address the bootstrap problem. While the psychology of motivation is beyond the scope of modeling specifications, a good modeling environment should provide some support for the *where-to-start* aspect of the bootstrap problem. One way to implement this requirement would be to suggest entry-point narrative paradigms to use for a particular analytical task. That is, given a narrative paradigm, there could be a library of basic narrative building blocks, or some prototypical narratives appropriate to the problem. For example, within the narrative paradigm of political science, there are many political theories that attempt to explain broad classes of recurring political behavior, such as insurrection and factionalism. A modeler tasked with analyzing a political problem might select from a political science narrative paradigm library that includes suggestions for a number of theoretical frameworks for addressing the problem. Similarly, modelers can help address the bootstrap problem by building up libraries of narratives developed for previous problems into a searchable knowledge base. Modelers, analysts, and even policy-makers could then bring up similar previous problems to use as a starting point for analyzing new problems.

3) The modeling environment should be *affective* in that it should create in the user an emotional state that facilitates discovery. To this end, the environment should support and encourage puttering: the construction of multiple (hybrid) narratives to explain the system, or aspects of the system. As puttering leads to a concrete hypothesis, the environment could provide an investigative framework based upon the scientific method – supporting the formal specification of hypothesis, the design and execution of experiment, the analysis of experimental data and any resulting changes needed to either experiment or hypothesis. Throughout this process, the system should endeavor to hold its user in a state of flow for the analysis of the problem. The environment should, under no circumstances, distract from this flow state. As an example of a bad environment, consider the *Clippy* assistant from the Microsoft Office Suite of products. This cybernetic assistant intrudes on the thought process of the user, distracting from the core task with information about features of the software. This self-absorption on the part of the environment interrupts the user's flow, and is probably the reason the *Clippy* is so universally loathed (Smart Computing 2001).

4 Lessens learned in qualitative modeling

Much of the effort toward systemizing analysis has been applied to what is properly the *evidence gathering* phase of the scientific method. The rest of the process (aside from some automation in experiment control) is left to scientists and their indentured graduate students. Technologies for data mining, text searching, and correlation analysis are important tools for the systematic management of data, but systematic analysis of those data is addressed by only a few technologies.

Agent-based modeling (ABM) is a natural framework for describing a broad variety of complex systems (Shalizi 2004). The goal of ABM is to link data with their *causal narrative*, telling the story behind the data in some cases, highlighting where important data are missing in others. The authors have found that ABM is a powerful narrative paradigm for generating novel discoveries about complex systems and since 1999 have been developing the behavior-action simulation platform (BASP) ABM framework (Reynolds & Dixon 2000).

BASP is able to incorporate multiple narrative paradigms within the context of software agents. In addition to agent-based models, a BASP model may take advantage of other suitable representations such as game theory or artificial neural networks. Supporting the interaction of ABM with other analytical narrative paradigms, such as data mining and concept mapping (Hoffman 1995) is a future thrust for the authors' research.

BASP supports multiple modeling narrative paradigms within the same model. In this way, for example, ground combat can be combined with game theory and fuzzy logic in the same simulation. BASP integrates these different narrative paradigms using a muscle-and-nerve narrative paradigm of simulation, with state variables as nerves and software modules called *aspects* as muscles. Elucidating and extending this simulation narrative paradigm to make it more transparent is an ongoing goal of BASP research.

To mitigate the bootstrap problem, the authors have developed the issue-player matrix (IPM) process, which elicits expert knowledge, expresses it as an ABM, and supports the narrative discovery process. The process is iterative and puttering-oriented, encouraging flow during both elicitation and model building. The latter parts of the process are currently supported in software. Addressing the earlier knowledge elicitation phase, however, will require an interface and methodology to support various modes of thinking and styles of flow. Finding suitable approaches for knowledge elicitation and developing software to support those processes in a flow/puttering-oriented framework is another area of research. Both current and future processes are inherently collaborative, so supporting framework should have a strong collaborative component.

Having rendered expert knowledge into an agent-based model, BASP supports the iterated refinement and exploration of the model through simulation. BASP provides an extremely flexible interface that allows models to be copied and modified at will. Research is continuing to make this interface more affective to encourage modeling flow in the user.

The authors are quick to point out that, as a candidate narrative-embedded modeling technology, BASP is in its infancy. Indeed, although BASP is a powerful modeling and simulation tool (Dixon & Reynolds 2003), its greatest value has been as an experimental platform for the exploration of flow/puttering-oriented methodologies and technologies for data gathering, manipulation, and presentation.

For the authors, the most striking discovery of both research and case studies is that supporting the *process* – of modeling, of analysis, or of policy-making – is the area of greatest potential payback and yet currently least expenditure of effort. The importance of process, discovered by the authors after more than two years of developing qualitative models for analysts, is evident in Heuer (1999). This realization has been cause for a close reevaluation of how BASP fits into the processes of the analysts it is intended to support.

For BASP case studies, the first step in the process has been to identify appropriate experts in the field of interest. Subject matter experts (SMEs), often analysts in the field, tend to be fact finders and archivists, with tremendous capabilities for research and retrieval. Their capacity for synthesis, retrospection and abstraction are often underutilized, and stimulating these talents is vital to the modeling process. This stimulation can be accomplished by providing the appropriate focus and context in terms of the questions asked. Secondly, the SMEs identify key players and high-priority topics. They should agree on these at some level – if not, the problem may have insufficient focus or unclear context. It is typical for SMEs to have differing perspectives on how to define groups as key players, but there should be a consistent way to reconcile those differences (*e.g.* one definition is at a higher level of detail than the other.) It is common – and appropriate – to find considerable disagreement among SMEs on how each key player may rank each issue. The modeler should always be prepared to explain any differences in terms of the respective SMEs' points of view (or *biases*).

It sometimes happens that the most important insights arise during this initial definition phase. This appears to be a synergy between the narrative paradigms of modeling and the domain of the SME. Certainly, it is clear that no technology will capture these events unless it is process-centric. This has resulted in a shift of BASP research toward support of the analytical process and away from the technology of modeling and simulation.

5 Case studies

While BASP is an ABM narrative paradigm, the authors remain steadfastly narrative paradigm agnostic – no single narrative paradigm is appropriate to all problems and there is seldom a single appropriate narrative paradigm for a given problem. The case studies that follow are included because they were influential in developing the authors' awareness of narrative paradigm.

5.1 Amnesty

Some problems come to analysis with volumes of data and no clue how they interrelate. Epidemiological studies early in an outbreak are often of this class, with vast minutiae regarding the infected individuals, their situations, behaviors, communities and so on. The epidemiologist then searches for a narrative that tells how an infectious agent connects a house painter in Cincinnati to a lawyer in Edinburgh. Most narratives come together as soon as the right data have been correlated, but in some cases the narrative is the product of an inspired guess, which then leads to the collection of crucial data.

A variation on this problem – where the unexplained data were model-generated – was a model developed by the authors in 2003. It is a model of a government contending with multiple rebel groups. The initial model was intended to explore what factors would promote negotiations between the rebels and the government and what factors might prevent them. Unfortunately, no values for the input parameters led to negotiations. Exploration of the space of all parameters lead to the realization that there was a hidden parameter – the government took so long to forgive past transgressions that the rebels had no incentive to improve their behavior. Once the government's *memory* was parameterized, an exploration revealed that this one factor was the key driver to bringing the rebels into negotiations. Some thought on this lead to the following narrative (see Figure 1):

> For infinite memory (nothing is ever forgiven) the rebels had no incentive to change their behavior. For no memory (all is forgiven) the rebels had no incentive to change today, for there is always tomorrow. For some intermediate values of memory, the rebels did, eventually, come to the bargaining table. Finally, for some values between zero and intermediate, there were long periods of volatility, with many false starts but little or no progress toward negotiations. These reflected episodes of costly social turmoil, possibly worse than no negotiations at all.

[Figure 1 about here]

5.2 Small Group Decision-Making

The other side of the modeling and simulation question comes up in cases where the narrative comes together first, resulting in a *collection requirement* – a place to look for missing data. The authors developed an historical recreation model in 2003 depicting the decision by Nazi Germany to invade Czechoslovakia in 1938 (See Figure 2). A notional model was outlined as the domain expert, Klaus Fischer, recounted the events leading up to the invasion. In this case, that outline became the narrative paradigm for this problem, because it provided the following narrative:

> In the years leading to the invasion, Hitler was a consensus builder, which he accomplished by carrot or stick, as appropriate. The evidence trail was there for every event except one: the military, which had opposed Hitler on the timing of the invasion, suddenly capitulated in August 1938, following the resignation of Army Chief of Staff General Ludwig Beck. What stick did Hitler use?

[Figure 2 about here]

Further research by Dr. Fischer uncovered that a secret proclamation in August 1938 diverted most of the military budget to the Nazi paramilitary wing, the *Waffen SS*, undermining the Army and General Beck.

5.3 Succession

This is another small group decision-making problem, but in this case the powerful central leader has left and the remaining members are deciding on a successor. Very little is known about members of the group aside from the three considered most likely successors, each of whom is associated with one of the three major functions of the organization. In a session with a domain expert, circles and arrows were drawn and tables were constructed to describe, numerically, the interactions decision makers and the three candidates. An ABM was constructed in the end, but the intermediate product – a linear, table-driven model – proved even more useful. In fact, when the group did finally choose a successor, a visit back to the model confirmed the choice.

Figure 3 shows the three-dimensional outcome space. The three dimensions correspond to the three major functions mentioned above or, rather, to how well those functions are being performed. Each dimension is divided into eleven categories, resulting in the cube of cells shown in the figure. The color of a cell indicates the most likely successor under those circumstances.

[Figure 3 about here]

As regards the real-world outcome: the model was constructed well before the succession occurred, and at that time, the state of the three organizational functions was left unspecified. The model could have been used at any time simply by providing the best estimates of the status at that time, and yet the actual succession came as a surprise. Before referring back to the model, the modelers each guessed the outcome, and all guesses were wrong. A return to the model showed that the correct outcome was there all along – why was its lesson lost on the modelers?

Figure 4 shows the outcome space sliced along the Function 3 dimension. Part of the problem in interpretation came from *conventional wisdom* bias, and part with failing to believe the model. The latter came from the fact that Function 3 was known to be doing well, corresponding to the lower slices in Figure 4 where blue cells predominate. Blue was the first-guess candidate, but just a little further examination would have pointed to a very different outcome.

[Figure 4 about here]

The reality was that Function 1 and Function 2 had not been going well, and this information *was* known throughout the project. That puts the result in the lower-left quadrant of each of the slices in Figure 4. If we assume no knowledge whatsoever about Function 3 and take the mean, the result is shown in Figure 5.

[Figure 5 about here]

That is, for this subset of outcome space, there is an eight out of nine, or 0.89, probability that green will be the successor. Green was, in fact, the successor.

Initially, this model was intended to be descriptive only: its predictive potential was realized only after the fact. The similarity to a *phase diagram* of the three dimensional outcome representation in Figure 3 introduced an entirely new narrative paradigm and new ways to analyze the model, such as focusing on subsections of *phase space*, as in Figure 5.

6 Conclusion

Qualitative modeling and simulation have an important role in the analysis of complex policy issues. The goal of qualitative modeling is to promote discovery, and therefore must support both puttering (undirected experimentation) and flow (well-focused, in-depth study). A useful modeling and simulation framework should be capable of expressing problems, hypotheses and outcomes using multiple distinct narrative paradigms, or *narrative paradigms*. Agent-based modeling is an effective and intuitive modeling methodology for problems that are readily approached in terms of policies and issues. BASP is a prototype platform for supporting multiple narrative paradigms within an agent-based framework. Features of BASP – particularly IPM – are specifically intended to facilitate puttering and flow. Continuing research is expected to incorporate additional puttering/flow capabilities into the BASP framework.

The authors' experiences in developing and applying BASP have led to the conclusion that process trumps any technology. The process of framing, researching and structuring a problem is the most fertile regime of complex policy analysis, a fact brought to light as long ago as 1949 by Sherman Kent and further explored by Richards Heuer between 1978 and 1986 – an old but seldom trodden path.

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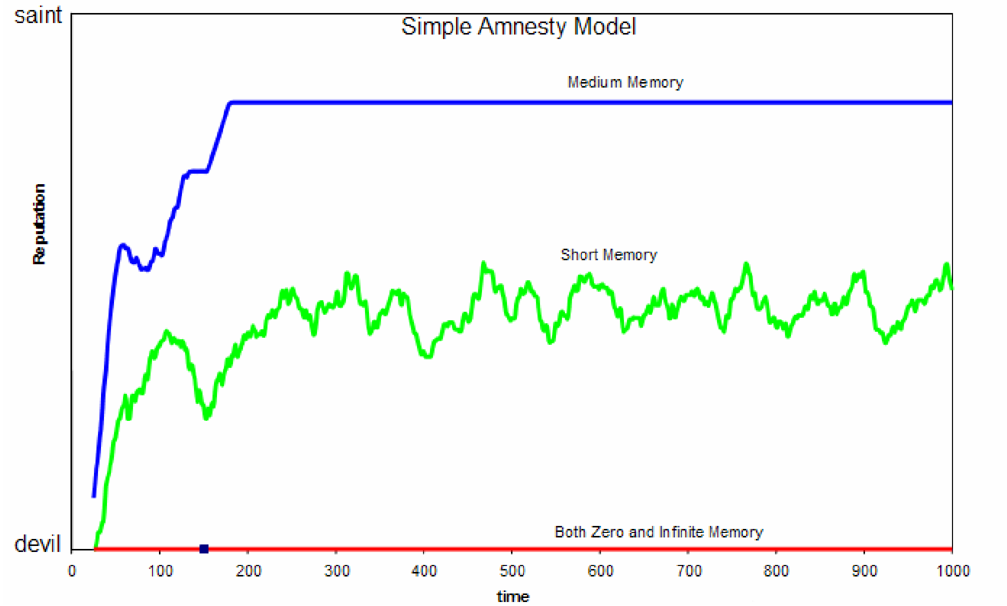

Figure 1 - Amnesty Model

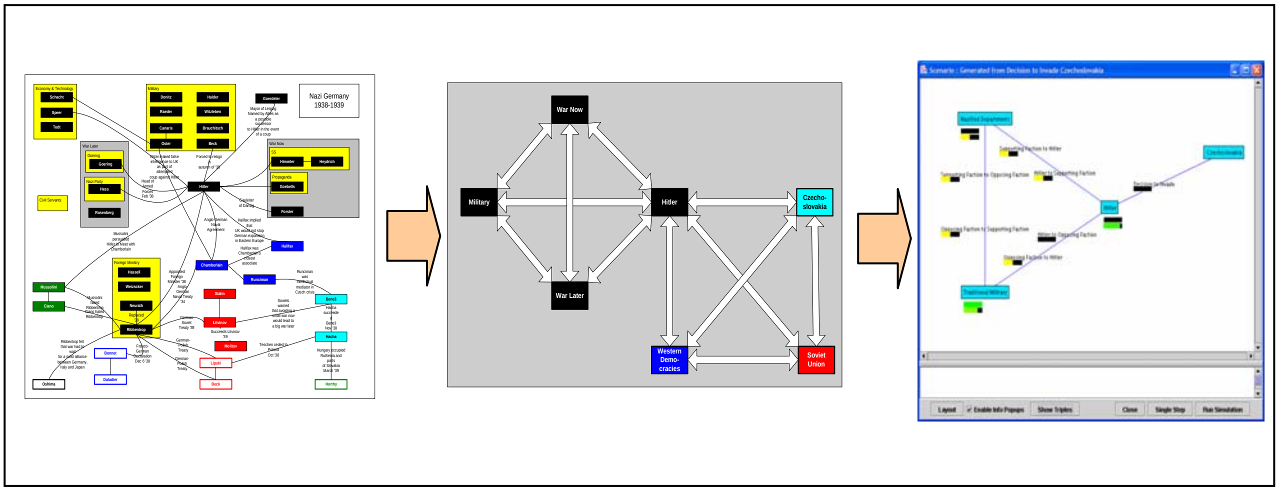

Figure 2 – (a) Detailed model included every significant player in 1938. (b) First abstraction – *Hitler*, *War Now*, *War Later*, *Military*, and the external parties; *Western Democracies*, *Soviet Union* and *Czechoslovakia*. (c) Final model – *Hitler*, *War Now*, *War Later*, and *Czechoslovakia*.

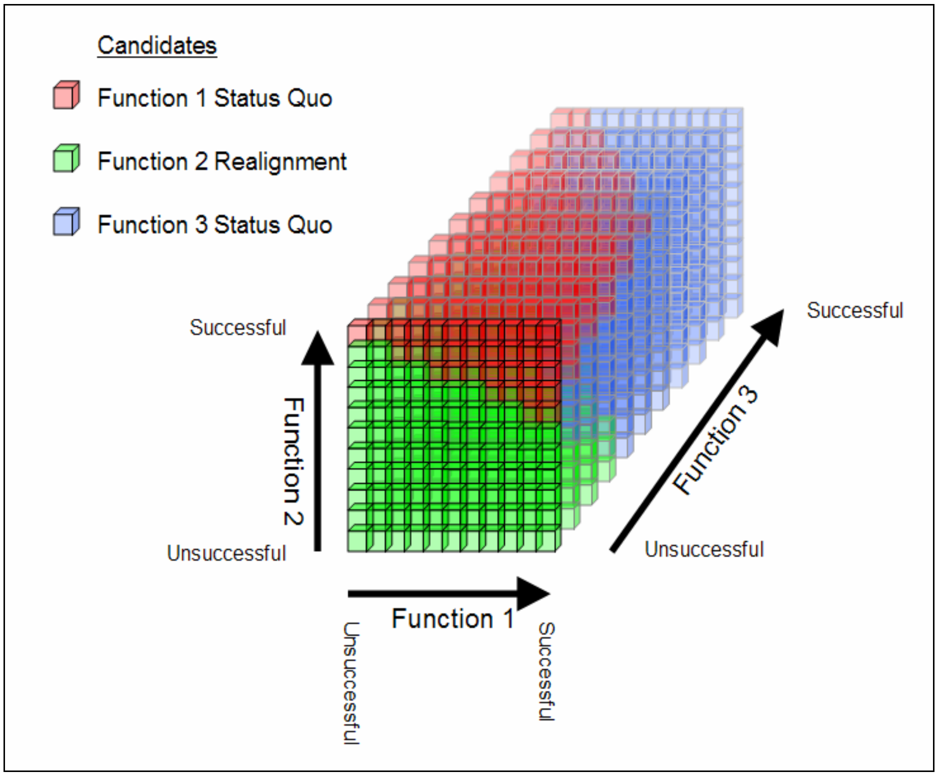

Figure 3 - Three-dimensional Outcome Space for the Succession Model

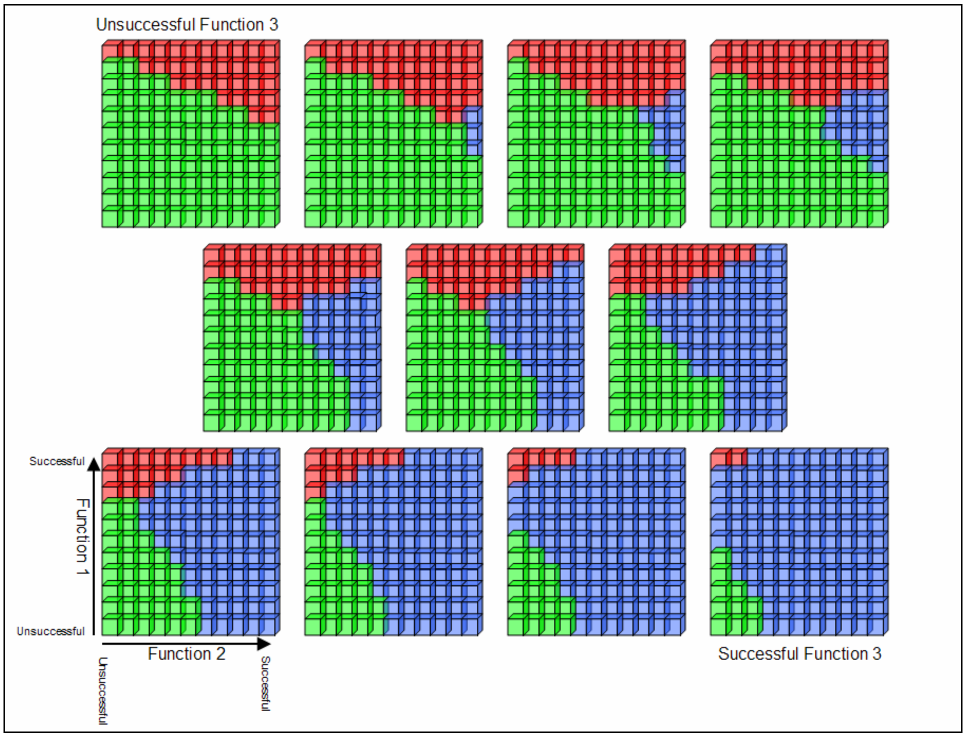

Figure 4 - Slices of Outcome Space for the Succession Model

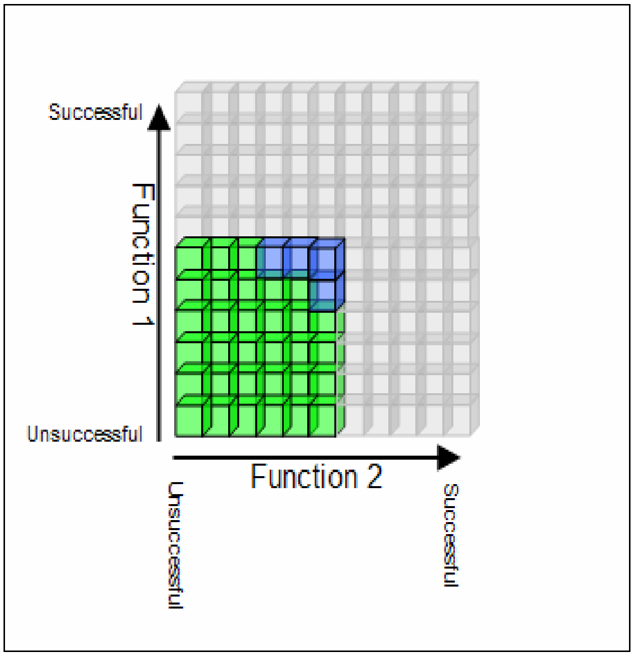

Figure 5 - Mean over Function 3

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