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Incorporating Resilience into Dynamic Social Models

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Incorporating Resilience into Dynamic Social Models

PI: Eunice E. Santos

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1. Abstract

Social resilience has many definitions from different areas of study. It can be considered a measure of economic stability, environmental stability, or government stability, to name a few. Studying social resilience can also be concerned with the ability to recover from more dynamic impulses, such as economic recession, disasters, social upheaval, or political revolution. We propose an overarching framework designed to incorporate various aspects of social resilience, through the melding of independent resilience functions, each representing a definition or measure of resilience, into a comprehensive model. This framework generates a generic resilience function which integrates key aspects of resilience, such as stability and ability to recover. In this paper, we introduce a theoretical foundation, and then calibrate our model so that it matches reality with acceptable explanations using established social theories. The model also considers the dynamic properties of social resilience across cultures, geographical environments, economic developments, and other evolving factors, as well as resilience to the aforementioned dynamic impulses. As a demonstration of capability, we modeled the resilience of a fishing community along the coastal region of Somalia (1991 – 2012) during the waxing and waning of coastal piracy.

It may be noted that while the original performance period was 3 years, the project had a truncated performance period of less than 2 years (March 2013 to December 2014) due to the transfer of project personnel to a different institution.

2. Introduction

Social resilience has been studied by researchers in various research domains. For instance, economists keep an eye on economic resilience and its dependence on factors such as natural resources [1]; and ecologists concentrate on resilience in the face of climate change [2]. The challenge with modeling social resilience has been the myriad factors that need to be taken into account to provide a realistic model. Individual models, generated using a particular viewpoint, may give reasonable explanations. However, in many cases, such models fail to provide adequate explanation for all aspects of social resilience. Therefore it is both interesting and meaningful to generate a generic resilience function that combines different resilience models or functions while including key aspects of resilience such as stability and ability to recover. Due to non-linear interactions in social systems, it is evident that the simple combination of multiple resilience functions will not work. It is also noticeable that creating a monolithic complex resilience function from the ground up may not be feasible due to the absence of clarity on how all the different factors interact. Moreover, it is hard to identify all the key factors in a real world scenario without help from experts in different fields, not to mention the challenge to mathematically describe the interactions among some of these factors using measurements from observed phenomena. Therefore, it is critical to formulate a modeling framework that can combine multiple resilience functions, and generate an overarching resilience function without losing such interactions.

In order to design an overarching resilience function for complex scenarios, there is a need to combine multiple resilience functions generated by different experts or groups of experts under various assumptions. However, potential contradictions must be addressed in order for the resultant resilience function to work. Yet, these contradictions cannot be solved by simply using the information provided by the scenario. Instead, additional knowledge is required from relevant fields that study these interactions systematically. Social theories [3] are good at explaining interactions among factors in human behavior, and, as such, are promising candidates to close this research gap in modeling complex resilience functions. Resilience functions must match reality and give well-supported explanations. If several outcomes are possible in a given situation, the function should provide relevant probabilities or other weighting information. Without these underlying analyses, it is hard to explain why certain events happened during observation. For instance, take an incident from the Somali fishing community scenario that we modeling in this work, when illegal fishing and dumping occurred in Somali waters. One possible reaction of the local fishermen would be to ignore these events and continue fishing as before. Another possible reaction of the local fishermen might be to retaliate against the intruders. Are these two reactions equally likely? Without a fundamental understanding of individual and group behaviors, it is hard to answer this question. In short, we need a theoretical foundation to calibrate our model so that it matches reality with acceptable explanations. Social theories provide this foundation for our general model. Using established social theories such as conditional cooperation [4], we can deduce that retaliatory behavior of the local fisherman is much more likely.

In pursuit of our research goals, we made the following key research contributions in this project:

1. We formulated an overarching framework for modeling social resilience that captured key aspects of resilience behavior in complex systems, namely system stability and ability to recover in the face of perturbations in the environment. Our framework mathematically defines the resilience function by leveraging Bayesian Knowledge Bases (BKBs), a probabilistic reasoning network framework[5],[6]. BKBs allow for inferencing techniques that were used to generate quantitative measures of resilience in our validation experiments. We also leveraged our previous work in modeling complex real world social scenarios using social theories and social network models.

2. Our framework allows for the formulation of complex resilience functions by combining existing resilience functions and/or definitions. This was achieved in this work by leveraging social interaction rules provided by social theories.

3. We validated our framework by modeling a fishing community along the Somali coast during the 2006 Somali civil war and its aftermath. We focused on understanding the economic resilience of this community in the face of ecological damage and the spread of piracy in their neighborhood. Our model tracked the adaptive aspects of resilience in the fishing community and demonstrated causal links between events in the real world and the decision of some of the inhabitants to switch from fishing to piracy and vice versa.

In the following sections, we provide discussions of existing work in modeling resilience in complex systems before presenting our social resilience modeling framework. It may be noted that detailed discussions of the framework and the validation results are provide in Santos *et al*. [7] We will also provide the results in other future publications.

It may be noted that while the original performance period was 3 years, the project had a truncated performance period of less than 2 years (March 2013 to December 2014) due to the transfer of project personnel to a different institution.

3. Background

In this section we provide a discussion of existing research in resilience modeling from various fields. We will also introduce a probabilistic reasoning network framework based on Bayesian Knowledge Bases (BKBs). BKBs are central to our social resilience framework as they are used to represent socio-cultural information. Moreover, resilience functions can be designed using the inferencing algorithms that BKBs provide.

3.1. Resilience

The concept of resilience, albeit in very different contexts, has been used in a number of research areas [8]. In this section we will discuss a few of these research areas and see how resilience has been defined, represented, and modelled in these areas. In engineering systems, resilience has generally been defined as the measure of a system's ability to perform its tasks even after the failure of components or perturbations in the environment. The system is said to have a global equilibrium to which it tries to return. Resilience models in engineering fields measure the time taken for the system to recover to the global equilibrium. Francis et al. [8] proposes a measure that is based on the time taken to recover, recovery speed, and three resilience capacities, namely absorptive, adaptive, and restorative.

In the computer networks area, Rossow et al. [9] studied the resilience of peer to peer (P2P) botnets to various types of cyber-attacks. By categorizing the attacks and vulnerabilities that exist in a P2P system, they were able to study the resilience of the system for each of these attacks, and how it disturbed the system as a whole. In socio-ecological systems (SESs), resilience has been defined as a system's ability to maintain the core part of its features while undergoing changes [10], [11]. This represents the system's capacity to absorb a certain amount of disturbances and still be able to move to a stable state. Moreover, an SES is considered to have more than one stable state [12]. This has been represented using various mathematical representations such as basins of gravity wells and stability landscapes [13], [14].

On the other hand, community resilience considers the social and cultural aspects of the community, and how a community adapts during adverse situations like natural disasters [11], [15]. Analyzing community resilience requires complex modeling of the system which can be dynamic and can have multiple layers [15]. Keeping this in mind, Kirmayer *et al.* [15] represents community resilience as a multi-level resilience and study their resilience at individual, family and society levels. However, having more than one level on a system introduces multiple objective function whose interactions impact the system's resilience. There is a lack of work into modeling such complex system aspects of community resilience. A related work by Schwind *et al.* [16] models the evolution of integrated coastal systems resilience. They use dependency matrices to represent the relationships between multiple objective functions in the system. The values in this dependency matrix represent the probability of an objective's failure with respect to another failure. Since this requires data for all the objective functions involved in the system, they suggest using Bayesian networks as a better alternative.

3.2. Bayesian Knowledge Bases

A key challenge in modeling social resilience is the inherent uncertainty in social data. Moreover social data sets are usually incomplete. In order to overcome these challenges during modeling social resilience, we used Bayesian Knowledge Bases (BKBs) [5], [6]. BKBs form a rule-based probabilistic model, essentially a generalization of Bayesian Networks (BNs), but not requiring complete probability distributions for all the random variables. This feature of BKBs makes it very useful for modelling real world scenarios which have uncertain information. A BKB uses random variable to represent information and describe the state of the system. The relationships between random variables are given as conditional probability rules. BKBs are represented as a directed graph with instantiation nodes (I-Nodes) and support nodes (S-Nodes). I-Nodes represent the state of the random variable and S-Nodes represent the conditional probability rules between the random variables. **Figure 1** shows a basic BKB (fragment), with the rectangular box representing an I-Node and the circle representing an S-Node.

When there is more information, it is convenient to represent it in multiple BKB fragments. However, the information across these BKBs have to be preserved. The BKB fusion [17] algorithm helps in fusing multiple BKBs to one single BKB which gives a whole view of the model. Also, the fusion algorithm considers the reliability of each fragment while fusing, thereby assigning more importance to more reliable BKB fragments. Various algorithms have been developed for BKBs to do different analysis such as belief updating, belief revision, and contribution analysis [5], [18], [19]. These algorithms help in reasoning on the system as a whole and to predict its outcome. In this work on modeling social resilience, we used belief updating [5] to calculate the probability of each random variable.

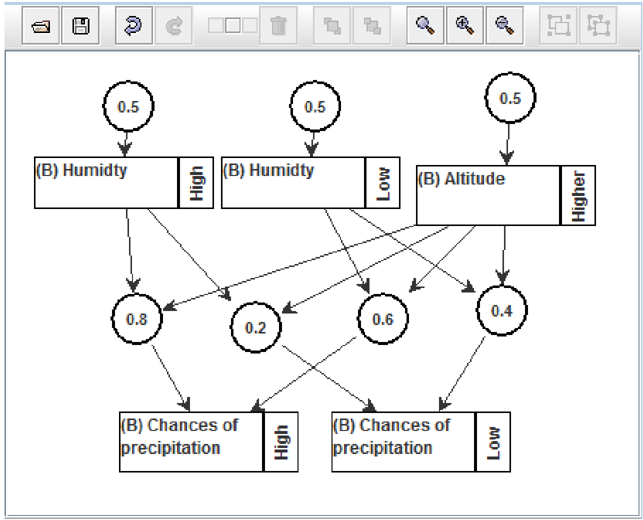

Figure 1 Basic Bayesian Knowledge Base (BKB) fragment

4. Resilience Modeling Framework

Resilience is subjective, and is dependent on a myriad of different factors which may vary in importance based on the community being modeled, and even vary with the Subject Matter Experts (SMEs) involved in the modeling.

SMEs are uniquely positioned to identify factors of importance because they have already been studying the major factors within the community of interest and have some insight into why certain factors are critical to understanding resilience. All experts are not the same, some are more reliable than others, and they may model scenarios at different granularities. As the number of factors grows, it becomes increasingly difficult for a single SME to model a community. This leads to larger scenarios modeled in part by different SMEs. The experts modeling communities can still work with the experts modeling scenario dynamics to achieve a more comprehensive model of both resiliency and dynamics. Differences of opinion can be readily handled computationally based on a rating of the trustworthiness or expertise of each SME. In an effort to remove subjectivity and also to make the process more auditable, a computational model is desirable.

In order to represent critical social information, it is desirable that scenario modelers build their models using a probabilistic knowledge base. There are various choices available for probabilistic knowledge bases such as Bayesian Networks or Markov Logic Networks. For a proof of concept, we use Bayesian Knowledge Bases (BKBs) because they do not require full specification of the probability distributions and handle uncertainty very well.

The criterion for measuring resilience can be a function of the probabilities that the underlying model can estimate. Since the work pursued in this project is initial work and a proof of concept, we used simple thresholds on the conditional probabilities of a target variable (an SME-specified factor of interest for resilience) given evidence (factors not of interest for resilience). These thresholds define an N-dimensional surface in an M-dimensional space. Using the terminology from the field of dynamical systems, we refer to this surface as a fitness “well”.

The resilience of a community in a scenario can now be defined by how hard (easy) it is to move the scenario outside of the well. Since we have defined the well in terms of constraints on the conditional probabilities of the target given the evidence, in order to compute the resiliency, we would like to know the relative mass of probability within the well versus the mass outside of the well. With respect to the scenario, we are computing the total percentage of scenarios where the constraints are satisfied versus the percentage of scenarios where the constraints are not satisfied. Therefore the resilience is not just the probability of the constraints being satisfied, but rather on the probability of the circumstances that lead to the constraints being satisfied.

In the remaining portion of this section, we provide brief discussions on BKBs and its inferencing methods before providing a mathematical definition of our resilience measure. A more detailed discussion on BKBs and BKB inferencing methods can be found in Santos et al [20].

4.1. BKB Definition and Inferencing

A BKB is a directed, bipartite graph consisting of instantiation nodes (I-nodes) and support nodes (S-nodes). Each I-node is an instantiation of a component random variable, written as $R = v$, where R is the random variable and v is the value of the random variable in that instantiation.

A correlation-graph over a set I of I-nodes is a directed graph $G = (I \cup S, E)$, in which S is a set of S-nodes such that $\{I \cap S\} = \emptyset$. The set of edges E is a subset of $\{I \times S\} \cup \{S \times I\}$, and for each $q \in S$ there exists precisely one $\alpha \in I$ such that $(q, \alpha) \in E$. If there is a link from an S-node $q \in S$ to an I-node α then we say that q *supports* α. For each S-node q in a correlation-graph G, we denote $Tail_G(q)$ as the set of all incoming I-nodes (parent nodes) of q, i.e., $Tail_G(q) = \{\alpha \in I | \alpha \to q \in E\}$, and $Head_G(q)$ as the I-node supported by q in G (aka child node), i.e., $Head_G(q)$ is the I-node α where $q \to \alpha \in E$. We use $a \to b$ instead of (a, b) to represent an edge from a to b in graphs.

The parameters of a BKB are given by the conditional probability values associated with its S-nodes. Each S-node q in the correlation graph G is assigned a number $w(q)$ which serves as a weight of q and represents the conditional probability $P(Head_G(q)|Tail_G(q))$. BKBs exclude conditional probabilities of the form $P(A = a|B = b, B = b', \ldots)$ where $b \neq b'$, since the conditioning event becomes empty. BKBs also disallow conditional probabilities of the form $P(A = a|I_1)$ and $P(A = a|I_2)$ where I_1 and I_2 are not *mutually exclusive*. Two sets of I-nodes I_1 and I_2 are said to be mutually exclusive if there is an I-node $R = v_1$ in I_1 and an I-node $R = v_2$ in I_2 for which $v_1 \neq v_2$. I-node sets that are not mutually exclusive are said to be *compatible*. Any set of S-nodes $\{q_1, q_2, \ldots, q_n\}$ where $Head_G(q_i) = \{R = i\}$ that has compatible tails must have a sum of weights less than or equal to one.

A BKB K is a tuple (G, w), where $G = (I \cup S, E)$ is a correlation-graph and w is a function from S to $[0,1]$ such that the following conditions hold:

1. For any S-node $q \in S$, at most one instantiation of each random variable can appear in $Tail_G(q)$.
2. For any two distinct S-nodes $q_1, q_2 \in S$ that support the same I-node, $Tail_G(q_1)$ and $Tail_G(q_2)$ are mutually exclusive, and furthermore q_1 and q_2 are also said to be mutually exclusive
3. For any $Q \subseteq S$ such that (*i*) $Head_G(q_1)$ and $Head_G(q_2)$ are mutually exclusive, and (*ii*) $Tail_G(q_1)$ and $Tail_G(q_2)$ are not mutually exclusive for all q_1 and q_2 in Q,

$$\sum_{q \in Q} w(q) \leq 1.$$

BKBs can also be represented as "if-then" rules. In this representation each S-node q in a BKB $K = (G, w)$ corresponds to a conditional probability rule (CPR) of the form $l_G(q) \overset{w(q)}{\Longrightarrow} Head_G(q)$, which has the meaning if $Tail_G(q)$ then $Head_G(q)$ with probability $w(q)$. For brevity when discussing structure, we leave off the weights, specifying rules as $\{Tail_G(q) \Longrightarrow Head_G(q) | q \in S\}$.

Let $K = (G, w)$ be a BKB with correlation-graph $G = (I \cup S, E)$. A subgraph $\tau = (I' \cup S', E')$ is called an inference over K if:

1. τ is acyclic
2. (Well-supported) $\forall \alpha I', \exists q \in S', q \rightarrow \alpha \in E'$, or equivalently, every I-node in τ must have a supporting S-node in τ.
3. (Well-founded) $\forall q \in S', Tail_\tau(q) = Tail_G(q)$
4. (Well-defined) $\forall q \in S, Head_\tau(q) = Head_G(q)$
5. I' is a state. Thus I' is referred to as the state of the inference. Furthermore if I' is a complete state then τ is said to be a complete inference over K.

The joint probability of an inference τ, denoted by $P(\tau)$, is calculated by multiplying all of the weights of all S-nodes in the inference, equivalently $P(\tau) = \prod_{q \in S_\tau} w(q)$ where S_τ is the set of all S-nodes in τ. We call a state θ *well-represented* in a BKB K if there exists an inference over K whose I-node set coincides with θ.

We call two inferences $\tau_1 = (I_1' \cup S_1', E_1')$ and $\tau_2 = (I_2' \cup S_2', E_2')$ compatible if for all $q_1 \in S_1', q_2 \in S_2'$ such that $d_{\tau_1}(q_1) = Head_{\tau_2}(q_2)$, we have $Tail_{\tau_1}(q_1) = Tail_{\tau_2}(q_2)$. For a BKB $K = (G, w)$ and correlation-graph $G = (I \cup S, E)$, define evidence Ev as a set of random variable instantiations $Ev \subset I$ such that for all random variables $A_j, A_k \in Ev$, $A_j \neq A_k$ for $j \neq k$. Let $T \subset I$ be a set of random variable instantiations such that $T \cap Ev = \emptyset$ and for each random variable $A_j \in T$, $A_j \notin Ev$.

4.2. Resilience Definition

Mathematically, a measure of resilience, denoted by $\mathfrak{R}: (K, \mathbb{E}, T, C) \rightarrow [0,1]$ defines a mapping from a BKB K, a superset of complete evidence variable instantiations $\mathbb{E}$, a set of target variable instantiations T, and a set of constraint functions C where $c_t: (Ev, K, W_t) \rightarrow \{0,1\}$ for $c \in C, t \in T$ onto $[0,1]$. We call C *satisfied* if, for all $c_t \in C, c_t \rightarrow 1$, and represent this with $C(Ev, T, K) = 1$

A detailed description on our methodology for formulating multiple resilience functions and using social theories to combine them to generate overarching resilience functions and measures are described in Santos *et al* [7].

5. Experimental Validation

We modeled the resilience of the fishing community along the coastal region of Somalia (1991 – 2012) to validate our resilience framework. Table 1 lists some of the events that we used in our scenario. From the fall of the Barre regime in 1991, the situation in Somalia became unstable and the strife between their clans continues today [21]–[25]. Lack of law enforcement from local government or any foreign entity left around 2000 miles of vast coastal region open to illegal fishing for many big fishing companies. This deprived the coastal Somalian fishing communities of their resources. Due to this illegal fishing, some of the fishermen started guarding their sea by attacking, capturing, and looting illegal fishing vessels. However, these attacks which began as a means to safeguard their coast turned this region into a profitable piracy environment. This was made worse by the 2004 Tsunami which affected most of the coastal region, destroying fishing boats, nets, and other fishing infrastructure. During the 2006 rule of the Islamic Courts Union (ICU), piracy dropped considerably due to their strict enforcement of Sharia law. After the decline of the ICU, the high profile hijackings of two ships, MV Faina and MV Sirius Star, led to an almost 600 percent [21] increase in piracy activities during the years 2008-2009. At the end of our timeline, there were many anti-piracy measures in place. International ships were using onboard security forces, and land-based anti-piracy forces were deployed. These measures reduced piracy during 2010-2012 [24]. These complex factors, and also our previous work on Somalia [26], [27], provided convincing reasons to use this scenario for our model.

We defined resilience functions for two communities, a fishing community resilience, $\mathfrak{R}_f: \left(K, C_f, \mathbb{E}_f, T_f\right) \rightarrow [0,1]$, and a pirate community resilience, $\mathfrak{R}_p: \left(K, C_p, \mathbb{E}_p, T_p\right) \rightarrow [0,1]$, where the functional form is identical but the evidence, targets, and constraints vary. Now we compute the probability of the target given the evidence by marginalizing over all evidence sets, and then compute the resilience for each community as $\mathfrak{R}_{r\in\{p,f\}} = \sum_{Ev\in\mathbb{E}_r} p(X_{Ev}) C(T_r, Ev, K)$.

For our constraint functions we used simple thresholds on the probability of the target given the evidence, $W_t \otimes \epsilon_t$, where ϵ_t was our threshold for target t and $\otimes$ was our comparison operation.

Time Step	Time Period	Description
t_0	1991	With the fall of the Barre regime in 1991, Somalia entered into a civil strife among its clans that continues even till today. The absence of a central government led to collapse of infrastructure (storage facilities, credit markets, etc.) of the fishermen.
t_1	1990-2004	The absence of coastal patrolling encouraged foreign fishing companies to indiscriminate illegal fishing in Somali waters leading to reduction of fish stocks.
t_2	1990-2004	Taking advantage of lawlessness, foreign companies dump hazardous waste in Somali waters further decimating fish stocks. Fishermen start to take matters into their own hands
t_3	Dec. 26, 2004	The Tsunami that caused havoc in South East Asia, affected the coastal regions of Somalia badly. The boats of the fisherman were swept away depriving them of their only livelihood. Hence it led to reduced fishing and a surge in piracy.

Table 1 Selected events from the Somali fishing community scenario

.

For the Fishing community, we used the following three key random variables as resilience targets:

Target Variable	Target State
(B) Fish supply is sufficient	Yes
(B) Has (access to) a (fishing) boat	Yes
(B) Has fishing equipment	Yes

For the Pirate community, we also had three resilience targets:

Target Variable	Target State
(B) Attitude towards piracy	Positive
(B) Piracy benefit is ok	Yes
(B) Piracy cost is ok	Yes

We generated quantitative measures of the resilience of the two communities for all the events in the scenario. We were able to see that the resilience of the fishing and piracy communities changed as we expected over the course of the scenario. A detailed description of the validation experiments and the results analysis are provided in Santos *et al* [7].

6. Conclusion and Future Directions

Considering the challenging research objectives of this project, namely producing an overarching framework for modeling and combining numerous types of resilience, our initial results have been tremendously encouraging. Representing the complexity of a Somali fishing village during a period of dramatic upheaval is a challenge in itself. Selecting the pertinent details to include, while excluding those that would only add complexity without providing additional resolution and clarity, remains a formidable obstacle. Matching the trends of our results to actual events indicates that we were able to develop an effective model that provided insightful explanations for the trends seen with the shift of individuals in the community from fishing to piracy and vice versa. Modeling such a complex scenario, while also identifying and incorporating multiple resilience measures into a comprehensive whole, represent great strides towards identifying the overall resilience of a social entity.

However, much work remains to refine the resilience integration method, and to better genericize the framework to readily accommodate a wide variety of situations. With additional application to diverse scenarios, the framework can be greatly strengthened into a robust tool for measuring social resilience in general. Moreover, our research highlighted issues with computational complexity that go hand-in-hand with complex social modeling. It would be ideal to be able to include more random variables related to the scenario to increase the resolution and sensitivity of the model to more types of resilience. We continue to explore alternative algorithms and architectures to allow for such improvements. Additionally, computational improvements would allow for the utilization of more social theories, which could then be evaluated and validated, as well potentially improve the calculation of a comprehensive social resilience measure. The team will further investigate social theories for inclusion in future efforts.

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Abstract

We propose an overarching framework designed to incorporate various aspects of social resilience, through the melding of independent resilience functions, each representing a definition or measure of resilience, into a comprehensive model. This framework generates a generic resilience function which integrates key aspects of resilience, such as stability and ability to recover. In this paper, we introduce a theoretical foundation, and then calibrate our model so that it matches reality with acceptable explanations using established social theories. The model also considers the dynamic properties of social resilience across cultures, geographical environments, economic developments, and other evolving factors, as well as resilience to the aforementioned dynamic impulses. As a demonstration of capability, we modeled the resilience of a fishing community along the coastal region of Somalia (1991 – 2012) during the waxing and waning of coastal piracy.

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