Chapter 2
Causal Function for Rational Decision Making: Application to Militarized Interstate Dispute

This chapter describes and defines a causal function within the context of rational decision making. This is implemented using rough sets to build the causal machines. The rough sets were successfully used to identify the causal relationship between the militarized interstate dispute variables (causes) and conflict status effects.

2.1 Introduction

Rational decision decision making is the process of making decisions based on logic. In essence logic here refers to using relevant information and choosing a course of action which minimizes the energy required to execute a task. The concept of nature prefering the path of least resistance is a natural phenomenon which has been studied extensively throughout history. Examples of the applications of the principle of the path of least resistance are included in Calculus of Variation (Gelfand and Fomin 2000; van Brunt 2004; Ferguson 2004; Bertsekas 2005; Bellman 1954). Basically in rational decision making it does not matter what the objective is but rather that to make a decision rational, it matters how one arrives at the objective. In this regard some of the most atrocious events in histroy such as genocides and slavery might be classified as having being executed rationally as long as on reaching a goal relevant infomation was used and the process followed was logical including the observation of the principles of least resistance and the minimum energy.

There is a game where there are two parents with a daughter and son who need to cross a wide river (Anonymous 2012). They can only get to the other side by borrowing a boat from a fisherman. Nevertheless, the boat can only carry one adult or two children at a time. What is the rational way in which a family can cross the river and return the boat to the fisherman? The rational way of doing this is to cross from this side A to the other side B using the following steps:

1. First the children cross the river to side B.
2. Then the son returns to side A.
3. Then the father crosses to side B to join his daughter.

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4. Then the daughter returns to side A to pick her brother up and they both go to side B to join the father.
5. Then the son returns to side A to give the boat to the mother who crosses to side B to join the father and daughter.
6. Then the daughter gets into the boat and goes to her brother in side A and they both return to their parents in side B.
7. Then the daughter gets off in side B and the son returns to side A to give the boat to the fisherman.
8. Then the fisherman and the son go to side B to drop the son.
9. Then the fisherman returns to side A.

The boat crossed the river 13 times and this can be represented in the state space as in Table 2.1.

The process followed to achieve a goal was rational because it used relevant information that only the parents cannot be in the boat at the same time otherwise it will sink and that both children or a child and a fisherman can be on the boat at the same time. If this relevant information was not used (acting irrationally) then the boat could have sunk. Secondly, the whole process took 13 trips and could not have been done using shorter number of trips. If, however, this trip was done in more trips then this would have been irrational because the principle of minimum energy (path of least resistance) would have been violated. The process of decision making based on relevant information which maximizes the balance of utility is a rational decision. We use balance of utility because utility can be both positive and negative. Suppose we compare two ways of moving from A to B. The first action is to use a car and the second is to use a bicycle. The rational way is not just to choose a way

Table 2.1 State space of the distribution of the parents, children, fisherman and the boat. Here *bold* represents the location of the boat while *F* stands for the father, *M* for the mother, *S* for the son, *D* for the daughter and F_i for the fisherman

State	Side A	Side B
1	$FMSDF_i$	
2	$\mathrm{FMF_i}$	*SD*
3	$FMSF_i$	D
4	$\mathrm{MSF_i}$	*DF*
5	$MDSF_i$	F
6	$\mathrm{MF_i}$	*FDS*
7	MSF_i	FD
8	$\mathrm{SF_i}$	*MFD*
9	DSF_i	MF
10	$\mathrm{F_i}$	*DSMF*
11	F_iS	DMF
12		$FMSDF_i$
13	F_i	SDMF

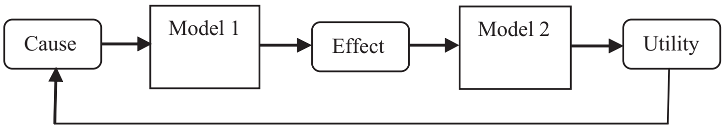

Fig. 2.1 Rational decision making process that uses causal functions

which minimizes time but to compare this with the cost of the choice made. In order to achieve maximum balance of utility the principle of minimum energy should be observed on reaching a decision and we term this a logical way of reaching a decision. In this chapter we introduce the causal machine for rational decision making (Marwala 2014).

The rational decision making process that uses causal functions is illustrated in Fig. 2.1. Here the causal function (Model 1) which links the cause to the effect is identified. The effect is linked to a utility by another model (Model 2). Rational decision making means identifying the cause that maximizes the balance of utility. The framework in Fig. 2.1 is collectively known as a causal machine. This chapter deals with a causal function (Model 1) and several models are explored in this regard.

In this chapter the model which is implemented uses the neuro-rough set to identify the causal relationship between demographic characteristics and HIV risk (Simiński 2012; Marwala and Crossingham 2008; Marwala and Crossingham 2009; Shamsuddin et al. 2009; Sabzevari and Montazer 2008; Choudhari et al. 2005; Czyzewski and Królikowski 2001).

The next section defines causality which is the basis of a causal machine.

2.2 Defining Causality

In this book it is proposed that causality is one of the elements that can be used for rational decision making. An example of causality is illustrated in Fig. 2.2. This figure illustrates three states of two balls. In State 1 a white ball is pushed to move towards a black ball. In State 2, the white ball hits the black ball. In State 3, both the white and the black balls are moving. It is clear here that the cause of the black

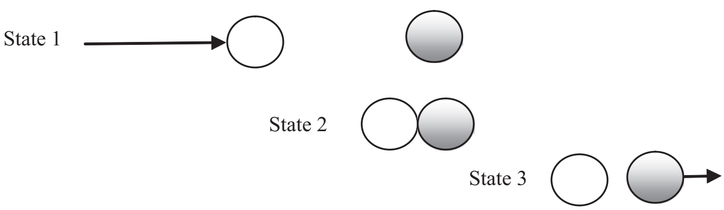

Fig. 2.2 Illustration of causality using two balls

ball moving is it being struck by the white ball. It is also clear that there was a transmission of information from the white ball to the black ball and that information is energy. As explained in Chap. 1 for event A to cause event B, there should be a flow of information from A to B, and A should happen before B. It is clear that events in Fig. 2.2 illustrate causality i.e. exchange of information (energy in this case) and that the cause happened before the effect. The relationship between the cause and the effect can be quantified easily using Newtonian Mechanics and the principle conservation of energy.

2.3 Models of Causality

In order to create a causal machine it is important to study different theories that have been proposed to explain causality. This section studies different models of causality as have previously been conceptualized and these are the transmission, probability, projectile, causal calculus, manipulation, process, counterfactual and structural theories of causality (Marwala 2014).

2.3.1 Transmission Theory of Causality

The transmission theory of causality is a model where causal information is transmitted from the cause to the effect (Sokolovski and Akhmatskaya 2012; Liu et al. 2012; Hubbard 2012; Ehring 1986; Kistler 1998; Salmon 1984; Dowe 1992). The information which is transmitted depends on the specific case being analyzed and in Fig. 2.2 it is energy.

2.3.2 Probability Theory of Causality

The probability theory of causality is based on the fact that some classes of causality are probabilistic (Mitroff and Silvers 2013; Ramsahai 2013; Kim 2013). For example, there is a conventional statement that *smoking causes lung cancer* (Yan et al. 2014; Park et al. 2014). There is a correlation between Smoking and Lung Cancer, but not all people who smoke get lung cancer. In the deterministic world smoking does not cause cancer. Nevertheless, in the probabilistic world smoking most definitely does cause lung cancer. To be specific, the phrase should be expressed as follows: the probability of lung cancer being present given that the subject smokes is high but is not necessarily definite. Consequently, a generalized causal model is necessarily probabilistic with the deterministic version being a special case.

2.3.3 Projectile Theory of Causality

The projectile theory of causality is a generalized version of the transmission theory of causality (Marwala 2014). The projectile theory of causality assumes that some information is transmitted from the cause to the effect in a form of a projectile with a specific intensity and configuration. The information that is transmitted from the cause to the effect can leave the point of cause with a certain velocity and sometimes reach the point of effect or sometimes falls short of the target and from this it is possible to build a probability distribution of causation.

2.3.4 Causal Calculus

Causal calculus is a model of inferring interventional probabilities from conditional probabilities (Rebane and Pearl 1987; Verma and Pearl 1990; Pearl 2000). Suppose we would like to estimate the hypothesis that HIV causes AIDS then causal calculus permits us to estimate the interventional probability that a person who is forced to have HIV (obviously illegal) develops AIDS $P(AIDS|forced(HIV))$ from the conditional probability that a person develops AIDS given the fact that he/she has HIV $P(AIDS|HIV)$. Causal calculus assumes that the structure that connects variables is in existence and where the structure does not exist it can be identified from the observed data using Bayesian networks.

2.3.5 Manipulation Theory of Causality

The manipulation theory of causality considers causal relationships between a causal variable x and an effect variable y and considers changes in x called Δx and assesses whether it leads to changes in y (Δy) in the model $y=f(x)$ (Baedke 2012; Annus et al. 2008; Hausman and Woodward 2004). If it does, then there is a causal relationship between x and y. If this is not the case then there is another variable which both x and y depend on.

2.3.6 Process Theory of Causality

Process theory of causality considers the causal relationship between variable x and y and identifies the actual process of causality not its mirror (Dowe 1992; Salmon 1998). The difficulty with this model lies in differentiating between the actual cause and effect from its mirror.

2.3.7 Counterfactual Theory

In counterfactual thinking, given a factual with an antecedent (cause) and a consequence (effect), the antecedent is altered and the new consequence is derived (Maudlin 2004). Suppose one would like to test what happens to the sugar level in a patient when insulin is administered. Then one would observe what happens to the sugar level when nothing is administered and compare this to when insulin is administered. In this instance not administering insulin is called a factual while administering insulin is called a counterfactual. Ideally for the efficacy of insulin to be observed then not administering insulin (factual) and administering insulin (counterfactual) should happen at the same time which is physically impossible. The compromise is for the factual and counterfactual to happen at nearly identical conditions (Collins et al. 2004; Loewer 2007).

2.3.8 Structural Learning

Structural learning identifies connections between a set of variables. In structural learning there are three causal substructures that define relationships between variables (Wright 1921) and these are direct and indirect causation ($X \rightarrow Z \rightarrow Y$), common cause confounding ($X \leftarrow Z \rightarrow Y$) and a collider ($X > \rightarrow Z > \leftarrow Y$). In structural learning relationships between variables are identified using heuristic optimization techniques. Now that we have discussed different causal models, the next section describes the causal function.

2.4 Causal Function

In this section we define a causal function which is a function that takes an input vector (x) and propagate it into the effect (y) where y happens after x and there is a flow of information between x and y. This function can be appropriately represented mathematically as follows:

$$y = f(x) \tag{2.1}$$

Here f is the functional mapping. This equation strictly implies that y is directly obtained from x. Of course this elegant equation is not strictly only applicable to the cause and effect but can still be valid if x and y are correlated and thus become a correlation function if either or both of the conditions (1) y happens after x, and (2) there is a flow of information from x to y are violated.

To illustrate the concept of a causal function we will use a classical problem in Physics of a ball colliding with a stationary ball which is illustrated in Fig. 2.2. To derive the causal function which relates the character of the cause to the character of the effect we apply the principles of conservation of energy and momentum assuming that the collision is perfectly elastic. The conservation of energy can be written as follows:

$$\frac{1}{2}m_1u_1^2 = \frac{1}{2}m_1v_1^2 + \frac{1}{2}m_2v_2^2 \Rightarrow m_1u_1^2 = m_1v_1^2 + m_2v_2^2 \tag{2.2}$$

Here m_1 and m_2 are masses of the white and black balls, respectively while u_1 and u_2 (here u_2 is equal to zero) are the velocities of white and black balls respectively before collision whereas v_1 and v_2 are the velocities of white and black balls respectively after collision. Using the principle conservation of momentum we obtain the following equation:

$$m_1u_1 = m_1v_1 + m_2v_2 \Rightarrow m_1u_1 = m_1v_1 + m_2v_2 \tag{2.3}$$

Solving Eq. 2.1 and 2.2 gives the values of v_2 and v_3 as follows:

$$v_1 = \frac{(m_1 - m_2)u_1}{m_1 + m_2} \tag{2.4}$$

$$v_2 = \frac{2m_1u_1}{m_1 + m_2} \tag{2.5}$$

Equation 2.4 and 2.5 quantify the functional mapping (causal function) between the velocity of the cause (u_1) and the velocity of the effect (v_1 and v_2) and this relaionship can be elegantly expressed in matrix form as follows:

$$\begin{Bmatrix} v_1 \\ v_2 \end{Bmatrix} = \begin{bmatrix} \frac{(m_1 - m_2)}{m_1 + m_2} & 0 \\ \frac{2m_1}{m_1 + m_2} & 0 \end{bmatrix} \begin{Bmatrix} u_1 \\ u_2 \end{Bmatrix} \tag{2.6}$$

Now that we have described what a causal function is, the next step is to describe what a causal machine is and its relations to rational decision making.

2.5 Causal Machine for Rational Decision Making

A causal machine which was described in Fig. 2.1 is a combination of a causal function and a utility function. Basically a causal function gives an effect for a given cause and each effect has a utility associated with it. Here utility is the value that is derived from an object. A rational decision making process in this context will be a process of identifying the appropriate cause that will maximize the balance of utility. In this chapter we apply rough sets to build a causal function and from this a causal machine and apply this to interstate conflict modeling.

2.6 Interstate Conflict

In this book we illustrate the causal function and machine using the concept of modelling interstate conflict using rough sets technique. The concept of modelling interstate concept is best illustrated in Fig. 2.3.

In Fig. 2.3, there are a number of variables that are used to predict interstate conflict and these include *Allies*, which is a binary measure coded 1 if the members of a dyad are linked by any form of military alliance and 0 if they are not. Another variable is the *contingency* which is also binary, and is coded 1 if both states are geographically contiguous meaning they share a border and 0 if they do not share a border and *Distance* is an interval measure of the distance between the two states' capitals. *Major power* is a binary variable coded 1 if either or both states in the dyad are a major power. A dyad here means each variable is manifestation of relationships between two countries. The variable *Democracy* is measured on a scale where 10 is an extreme democracy and −10 is an extreme autocracy, and we identify the country with the lowest level of democracy as the weakest link, in this chapter the value of the less democratic country in the dyad is used for our analyses. The variable *Dependency* is the sum of the countries import and export with its partner divided by the Gross Domestic Product of the stronger country and this is a continuous variable measuring the level of economic interdependence (dyadic trade as a portion of a state's gross domestic product) of the less economically dependent state in the dyad. *Capability* is the logarithm, to the base 10, of the ratio of the sum of the total population, the number of people in urban areas, industrial energy consumption, iron and steel production, the number of military personnel in active duty as well as military expenditure in dollars in the last 5 years measured on stronger country to a weaker country. The details of this can be found in a seminal book by Marwala and Lagazio (2011).

The next pertinent question is under what conditions does the model in Fig. 2.3 becomes a causal function. The first condition is that the input should have hap-

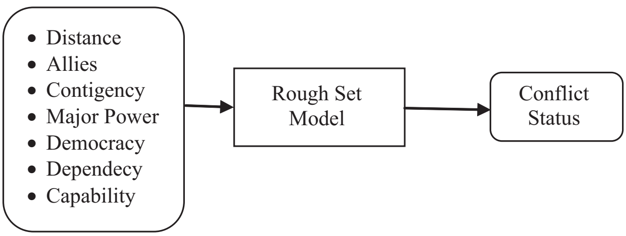

Fig. 2.3 A rough sets based model for conflict prediction

pened or been known before the effect. The second condition is that there has to be a flow of information from the cause to the effect. Taking for an example variable *Distance*, the rational decision maker would have taken into account of the distance from his capital before engaging in militarized conflict. Again with the variable *Allies* the rational decision maker would have taken into account of whether there are any strategic alliances between the countries before engaging in militarized conflict. Likewise, the rational decision maker would have also looked at variables Contingency, Major Power, Dependency, Capability and perhaps Democracy before engaging in militarized conflict. The model in Fig. 2.3 does meet the two criteria for a causal machine.

The data set used in this chapter is the population of politically relevant dyads from 1885 to 2001 which is described in detail and used by Oneal and Russett (2005). The politically relevant population which are contiguous dyads as well as all dyads containing a major power, are selected because they set a hard test for prediction. By neglecting all distant dyads composed of weak states means we ignore much of the influence that variables not very amenable to policy intervention, distance and national power, would exert in the full data set and make the task harder by reducing the predictive power of such variables. Concentrating only on dyads that either include major powers or are contiguous, we test the discriminative power of the predictive models on a difficult situations.

The dependent variable of the models consisted of a binary variable which indicated the onset of a militarized interstate dispute (MID) of any severity after the independent variables have been observed (Maoz 1999). Merely dyads with no dispute or with only the initial year of the militarized conflict, ranging from any severity to war, are included in the analysis.

The next section describes the rough set causal function which is used to model the framework in Fig. 2.3.

2.7 Rough Sets Causal Function

Rough sets technique is a computational intelligence method which is intended to estimate concepts from the observed data. Unlike other computational intelligence methods that are applied to handle uncertainty and imprecision, rough set theory does not require any additional information about the experimental training data such as the statistical probability (Pawlak 1991; Pawlak and Munakata 1996; Crossingham 2007; Crossingham and Marwala 2007; Nelwamondo 2008; Marwala and Lagazio 2011). Rough set theory handles the estimation of sets that are hard to explain with the available information (Ohrn 1999; Ohrn and Rowland 2000; Marwala and Lagazio 2011). It is used mainly to classify uncertainty and uses the upper and lower estimation to handle inconsistent information.

Rough set theory is based on a set of rules, which are described in terms of linguistic variables. Rough sets have been applied to decision analysis, particularly in the analysis of decisions in which there are contradictions (Marwala 2012). Because they are rule-based, rough sets are highly transparent but they are not as accurate. However, they are not good universal estimators and other machine learning techniques such as neural networks are better in their predictions. Thus, in machine learning, there is always a trade-off between prediction accuracy and transparency.

Rough set theory offers a method of reasoning from vague and imprecise data (Goh and Law 2003). The method is based on the assumption that some observed information is in some way associated with some information in the universe of the discourse (Komorowski et al. 1999; Kondo 2006). Objects with the same information are indiscernible in the view of the available information. An elementary set consisting of indiscernible objects forms a basic granule of knowledge. A union of an elementary set is referred to as a *crisp set*, or else, the set is considered to be *rough*. In the next sub-sections, rough set theory is described.

2.7.1 Information System

An information system (Λ), is described as a pair (U, A) where U is a finite set of objects known as the universe and A is a non-empty finite set of attributes as described as follows (Crossingham 2007; Nelwamondo 2008; Marwala 2012; Marwala and Lagazio 2011).

$$\Lambda = (U, A) \tag{2.7}$$

All attributes $a \in A$ have values, which are elements of a set V_a of the attributes a (Dubois 1990; Crossingham 2007; Marwala and Lagazio 2011):

$$a : U \to V_a \tag{2.8}$$

A rough set is described with a set of attributes and the indiscernibility relation between them. Indiscernibility is explained in the next subsection.

2.7.2 The Indiscernibility Relation

The *indiscernibility relation* is one of the central ideas of rough set theory (Grzymala-Busse and Siddhaye 2004; Pawlak and Skowron 2007; Marwala and Lagazio 2011; Marwala 2012). *Indiscernibility* basically suggests similarity (Goh and Law 2003) and, consequently, these sets of objects are indistinguishable. Given an information system Λ and subset $B \subseteq A$, B the indiscernibility defines a binary relation $I(B)$ on U such that (Pawlak et al. 1988; Ohrn 1999; Ohrn and Rowland 2000; Nelwamondo 2008; Marwala and Lagazio 2011):

$$\begin{aligned} &(x, y) \in I(B) \\ &\textit{if and only if} \\ &a(x) = a(y) \end{aligned} \tag{2.9}$$

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