# Chapter 9
# Crime and Corruption

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Like intergroup violence (Chap. 7) and insurgency (Chap. 8), crime and corruption are nearly inevitable companions of an international intervention. Both contribute to the reasons why the intervention occurs, and both may even grow and fester as side-effects of an intervention. Moreover, crime and corruption frequently serve as obstacles to a successful termination of an intervention.

High crime rates and frequent incidents of corruption are some of the main indicators and drivers of failed states, as well as some of the most important impediments to economic development (Frisch 1996, p. 68). A failed state cannot enforce laws against crime because the state itself is ridden with the crime of corruption, so much so that law enforcement is seen as unfair and illegitimate (The Fund for Peace 2008). Corruption is a particular type of crime that erodes the ability of the state to enforce the law or perform other functions. A widely cited definition of corruption is a "behavior which deviates from the formal duties of a public role because of private-regarding (personal, close family, private clique) pecuniary or status gains; or violates rules against the exercise of certain private-regarding influence." (Nye 1967). Because they are important drivers of state failure, both crime and corruption are among the most important phenomena to model for the purpose of international intervention.

## 1 Theories of Crime and Corruption

Most theories see crime and corruption as a breakdown of institutions. North (North 1990, p. 3) defines institutions as "the rules of the game in a society or, more formally, the humanly devised constraints that shape human interaction." Institutions "consist of both informal constraints (sanctions, taboos, customs, traditions, and codes of conduct) and formal rules (constitutions, laws, property rights)" (North 1991, p. 97).

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A. Kott and G. Citrenbaum (eds.), *Estimating Impact*,
DOI 10.1007/978-1-4419-6235-5_9, © Springer Science+Business Media, LLC 2010

In the case of crime and corruption, the rules that are breaking down are laws, but in the case of corruption, traditional cultural patron–client relations are also breaking down (Smith 2007). Adam Smith (1994) saw social institutions as the "invisible hand" through which a miracle can occur: individuals acting purely in their own interest create a society that is good for the whole. If the emergence of good social institutions out of utility-maximizing individual acts is a natural process, then crime and corruption are the breakdown of that process. In crime and corruption, individuals seeking their own benefit create dysfunctional social patterns.

Crime and corruption are social forces and are often not volitional at an individual level. The worst critics of corrupt practices are often those who feel compelled to engage in them. There are coercive forces that drive people into crime and corruption. In some failing states, crime and corruption are the only way of doing business (Smith 2007). A good model of crime or corruption will take into account coercive social forces that draw individuals into vicious cycles of mutually harmful behaviors instead of the virtuous cycles of Adam Smith's free market. The purpose of such a model would be to detect and guide intervening actions at tipping points, points at which actions make a difference as to whether social institutions enter and leave such vicious cycles. If no action is taken at these tipping points, then future corrective action could be far more difficult or impossible.

Sociological theories of crime generally fall into three categories: theories of strain, theories of social learning, and theories of control (Agnew 2009). Theories of strain blame crime on personal stressors. Theories of social learning blame crime on social rewards from involvement with other criminals and look at crime more as an institution in conflict with other institutions rather than as individual deviance from institutions. In contrast, theories of control look at crime as natural and rewarding and try to explain the formation of institutions, such as religion, that control crime.

Theorists of corruption generally agree that corruption is a vicious cycle and an expression of the patron–client relationship. In patron–client relationships, a person with access to resources trades resources with kin and members of the community in exchange for their loyalty. According to Smith (2007), corruption is a result of globalization. In his anthropological study of corruption in Nigeria, Smith studied traditional patron–client relationships based on mutual obligations. Nigerians of all social strata make use of patron–client ties for access to resources but feel that the elites have come to betray the people. The integration of the patronage system with bureaucracy has produced a postcolonial state that facilitates corruption, the betrayal of patronage obligations.

## 2 Methods of Modeling Crime and Corruption

We begin by introducing briefly several modeling approaches that do not involve an explicit simulation, particularly rule-based systems, Bayesian networks, and game-theoretical approaches. Later, in this chapter, we will discuss simulation-based approaches.

## 2.1 Rule-Based Systems

Rule-based systems describe relations between variables that are Boolean (either true or false) in traditional systems or scalar (using degrees of truth and falsehood) in fuzzy systems. For example, Situngkir and Siagian (2003) use a fuzzy rule set to model how corruption causes inefficiency in nongovernmental organization (NGO) aid distribution and its effect on future aid. For example, one simple rule is, if an NGO receives a large amount of aid from a donor, then the NGO accomplishes a large amount of support activities to the population it serves. Situngkir and Siagian include one simple feedback loop. The feedback loop reflects the fact that if an NGO is effective in utilizing the donor's funds for the intended purposes, the donor is more likely to support the NGO in the future. The model points out that the development of standards for the evaluation of NGO programs can reduce corruption.

## 2.2 Bayesian Networks

A Bayesian network is a group of propositions connected by links, each of which describes the probability that one proposition is true given that a set of others are true. These do not involve degrees of truth or falsehood as fuzzy sets do. Fuzzy set advocates argue that fuzzy sets are more general than Bayesian networks and subsume them (Kosko 1994). Bayesian networks can be created manually or learned automatically from a given set of data. In modeling crime, Bayesian networks are often used to find patterns in crimes for forensic purposes. Baumgartner et al. (2005) presents a Bayesian network model of offender behavior for the purposes of criminal profiling. Their network links the action of the offender on the scene of the crime to his psychological profile for the purposes of predicting the likely suspects when another crime occurs with similar attributes.

Bayesian networks are descriptive rather than causal. They tell us the event that we may expect to observe, without explaining why the event occurs. Unlike a simulation, they do not describe the process that leads to the event. However, a Bayesian network can be an excellent complement to an agent simulation, which addresses causal mechanisms. For example, in an agent-based simulation reported in Duong (2009), a Bayesian network is used to generate a simulated agent's attributes by deriving the probability that an agent has an attribute given its other attributes. Then, the model simulates interactions of such agents in order to generate society-level patterns, which can be used to assess intervention policies.

## 2.3 Game-Theory Approaches

Rational-choice theory posits that humans are goal-driven and act to achieve their goals specifically to maximize their "utility," their measure of how well they have reached their goals. Game-theoretical approaches and neoclassical economic models of general equilibrium theory (Arrow 1951) are both based on the assumption of rational choice. Both approaches use mathematical techniques to find equilibria, points in the game at which no player can make a move that would improve the player's situation (utility value). Since agents in these models are rational, the agents gravitate toward these equilibria and stay there because no further move can improve their utility. The equilibria are thought to describe human behaviors such as whether a prisoner will testify against his accomplices in the prisoner's dilemma game (Axelrod 1984), or what the market prices of goods in the general equilibrium theory model will be.

Game-theoretical approaches analyze a criminal act in terms of the benefits and costs to each player in the act. For example, Eide (1999) uses a one-stage game to identify the conditions necessary for a behavior, such as crime and corruption, to occur by analyzing the cost and benefit of possible behaviors. Regression analysis of the effect of income on crime is used to support the rational-choice theory of crime in a game theory-based analysis.

Game theory is also used in the modeling of corruption. A common game-theoretical formulation for modeling of corruption involves a principal and an agent, in which the principal, seeking to maximize its utility, delegates decision-making power to an agent who may choose to maximize his own utility or that of a hidden principal (Farida and Ahmadi-Esfahani 2007). Corrupt acts are moves in the game.

### *2.4 Neoclassical Econometrics*

Neoclassical econometrics is another tool based on rational-choice theory, suitable for modeling crime and corruption. Farida and Ahmadi-Esfahani (2007) present a study of the negative effect that corruption has on the production function important to economic growth, using a mathematical analysis within neoclassical theory called the Solow growth model. The Solow growth model includes several determinants of productivity such as capital and labor. Using the corruption index data (Transparency International 2009) and adding corruption to the productivity determinants, the study shows that economic data from Lebanon is consistent with a Solow model, and corruption acts as a detriment to production.

## 3 Simulation-Based Modeling of Crime and Corruption

Unlike the modeling techniques we discussed up to this point, simulation-based approaches are able to take into account greater complexities of interacting parts of social phenomena. In particular, fuzzy cognitive maps (FCM) and system-dynamics models are effective in describing complex systems, and agent-based models are well suited to modeling how systems become complex.

### 3.1 Fuzzy Cognitive Maps and System Dynamics

FCMs are fuzzy rule sets that incorporate representation of feedback loops. Feedback occurs when the output of a series of rules is input back into the same series of rules. The result is recomputed until it converges to either a steady state (called a fixed point in dynamical systems theory) or a repetitive state (called a limit cycle in dynamical systems theory). This state is then taken as an answer to the question the system was asked to compute. FCMs are well suited to modeling institutions such as commonly accepted forms of corruption, which a society learns when people perform acts that mutually reinforce each other.

Calais (2008) presents an FCM that models drug addiction, crime, economic productivity, international police interdictions, and America's image abroad (Fig. 1). In Calais's model, drug availability and drug usage are in a positive feedback loop. That means the more drugs are available, the more they are used, and the more they are used, the more they are available. There is also a positive feedback loop between American Image and tourism. Analysis of the model shows that international interdiction improves America's image abroad and economic productivity and decreases the prevalence of drug addiction. Calais also presents a guide for modeling crime with an FCM.

Like an FCM, a system-dynamics model describes relationships between variables but makes use of time-based differential equations to indicate the scalar value of a variable rather than Gaussian distributions to indicate "degree of membership" as in FCMs. Since feedback is involved, higher order effects can be observed. Dudley presents a system-dynamics model of corruption (Dudley 2006). The model (Fig. 2) includes positive feedback between corruption, bureaucracy, a weak legal system, lack of transparency, and resource rents (theft of resource revenues through corruption). Negative feedback occurs when more corruption leads to an improved legal system and decreased resource rents. In terms of individual

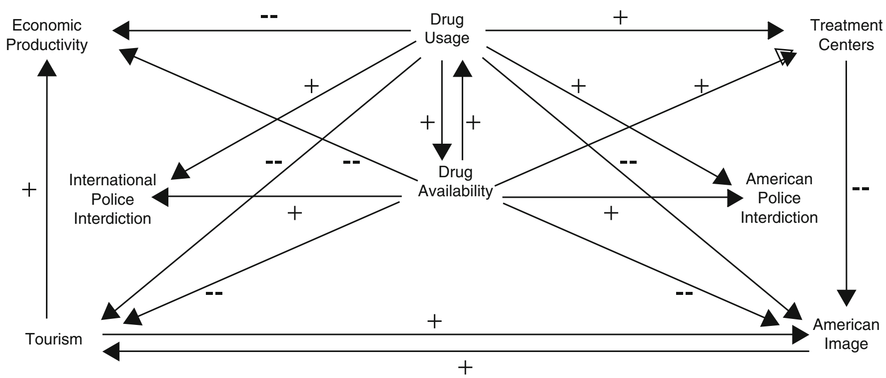


**Fig. 1** Fuzzy cognitive map of the impact of drug addiction (figure reprinted with permission from Dr. William Allan Kritsonis, Editor-in-Chief, National FORUM Journals, Houston, Texas)

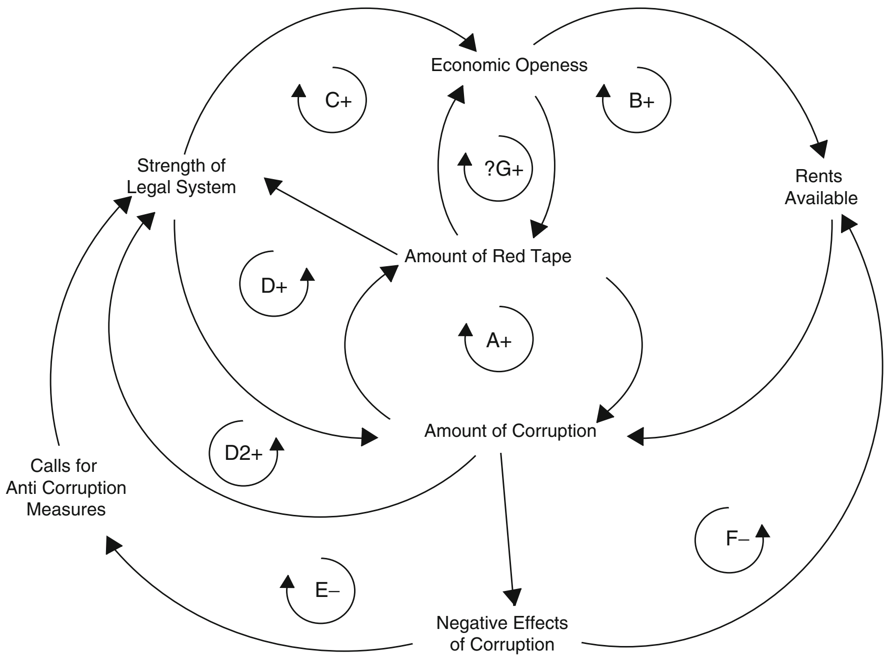


**Fig. 2** A portion of Dudley's system-dynamics model of corruption

corrupt behaviors, the size of a bribe, the likelihood of payment, the value of service, and the effect of individual punishment are all factors in whether an individual takes a bribe. The need to keep a job, power, and loyalty can increase corrupt workplace behaviors. Analysis of the model leads to the conclusion that corruption is positively influenced by resource rents and negatively influenced by an improved legal system.

Both FCMs and system-dynamics models allow visualizations (e.g., Figs. 1 and 2) that appeal to nonspecialists. Practitioners often cite the appeal of presenting multiple factors of a system in a single visualization, which includes the direction in which the factors influence each other. Model users often value this visualization for encouraging insight into the system as much as they value the numerical answers obtained by these systems.

## *3.2 Agent-Based Simulations*

Agent-based simulation can go a step farther by computing new social structures not previously identified in theory. FCMs and system dynamics are appropriate when the modeler knows all significant relations between entities. In contrast, agent-based simulation is suitable to those problems in which the modeler knows only a few relations and wishes to explore their implications. In effect, the implications are computed from these few relations as from first principles.

Agent-based models simulate the processes by which agents perceive their situation and make choices. Agents in such simulations come in two flavors: reactive and cognitive. Reactive agents have a few static rules that determine their behavior, with different macrolevel patterns emerging from different starting conditions. For example, an agent may have a static rule: avoid being close to another type of agent who is suspected of being likely to commit a crime. When the model simulates reactions of agents to each other, they may separate themselves from each other according to type, thus exhibiting a new macrolevel pattern not explicitly encoded in the model.

Unlike reactive agents who operate with a fixed set of predefined rules, cognitive agents can learn and change the rules by which they behave. Learning is important for the simulation of the emergence of institutions because it allows feedback from macro (society-level) rules down to micro (individual level) behaviors, a phenomenon known as "immergence." For example, a macrolevel rule could be the society's enforcement of a transparency program for reduction of corruption, while the microlevel rule could be the individual decision to avoid corrupt acts. Upper-to-lower feedback is essential for the emergence of new practices that are computed from the simulation's assumptions rather than being predetermined by the modeler beforehand (Andrighetto et al. 2007).

## *3.3 Reactive Agent Models*

Reactive simulations, while less capable than cognitive-agent simulation, are adequate for testing a policy's effects with existing societal structures. For example, Dray et al. (2008) present a reactive agent model of drug enforcement policy, in which three law-enforcement strategies – standard patrol, hot-spot policing, and problem-oriented policing – are tested on a street-based drug market. Data from the urban environment of Melbourne, Australia, is used, and complex interactions between wholesalers, dealers, users, outreach workers, and police are modeled. Indicators include number of overdoses, fatalities, cash in dealers' hands, and numbers of committed crimes. The results show that problem-oriented policing is more effective in this environment than other strategies. Emergence of new structures is not required in a simulation in which the reactions of agents to policies are known and stay the same during the simulation.

In some models, reactive agents include limited elements of cognition, such as a simple memory based on past interactions. Makowsky (2006) presents a reactive agent model, CAMSIM, which uses a rational-choice approach to explain why people become criminals. In CAMSIM, agents have an age and choose a career based on maximum lifetime utility, from three possible careers – professional, labor, and crime. They infer the outcome of their own life from the lives of those around them. By simulation design, those around them are mainly their relatives.

The difference between the three possible careers is the amount of investment required, crime having a negative investment. Location and reproduction are also modeled. Changes in life expectancy matter to the career choice in this model. One conclusion of this model is that the effects of career choices extend over multiple generations. In effect, children "learn" from their ancestors' life experiences, even though the model does not include an explicit learning mechanism.

Another approximation of cognition occurs when agents operate within a genetic algorithm and learn new social structures as a group (Axelrod 1984). They do not learn through their individual experiences as an autonomous agent would. Instead, they learn through the experience of the "species," the group of agents within which they reproduce. Agents with better strategies reproduce in greater proportion so that the entire species evolves strategies that are more fit to their environment. In computational social science, these social strategies are mutually recognized rules of social interaction and social institutions (Axelrod 1984).

Much research in the field of computational social science models the social evolution of institutions by iterative game-playing and genetic algorithms. Axelrod's iterated prisoner's dilemma (IPD) was a pioneering study in which the strategy of cooperation emerged among agents even though they could have received an immediate benefit by cheating (Axelrod 1984). The IPD models the emergence of social behavior, which is relevant to the study of the breakdown of institutions through corruption and crime.

Situngkir (2003) applies a similar genetic algorithm and iterated game-theory approach to study corruption. The payoff matrix includes the cost of going to jail and the benefits of both corrupt and honest acts. As agents learn the best behaviors, they converge upon the strategy that is best for them given the strategies of other agents. Each agent reaches equilibrium and remains there because it can do nothing to better its situation. Situngkir shows that the behavior with the highest payoff is often corruption.

### *3.4 Cognitive Agent Models*

In models that use cognitive agents, the agents learn how to perceive their environment and act upon the perceptions of their individual experiences. For example, Singh (2002) presents a cognitive agent model of urban crime patterns, in which agents with a common autonomous agent cognitive architecture called Belief, Desires, Intentions (BDI) use an artificial-intelligence technique called case-based reasoning. In BDI, agents deliberate over their beliefs and desires and commit to them as intentions. Using case-based reasoning, agents formulate a plan to achieve their goals by inferring from previous similar cases to which they have been individually exposed (Singh 2002). Singh's model includes variables of the law, the offender, the time, and the place. Criminal agents use their cognitive architectures to determine if a target of crime is a good target and to learn physical paths to their goals. The model yields a pattern of crime in a particular urban landscape.

## 4 Case Study: Cognitive Agents and Corruption

Nexus Network Learner (NNL), created with the Repast Simphony agent-based simulation tool kit (North et al. 2007), models the learning of social institutions of social network choice and role-based behaviors (Duong 2009).

NNL's model of corruption is based on Smith (2007). In the model, corruption is the result of conflict between the roles and role relations of the kin network and the bureaucratic network, two separate social structures with their own institutions forced into conflict by globalization. The model includes the kin network, the bureaucratic network, role behaviors that result in corruption, and the capacity of agents to learn new behaviors based on their cultural motivations.

The U.S. government used the NNL corruption model in the large simulation-based study described by Messer (2009). This study of hypothetical events in an African country examined the effects of international interventions on corruption, among other effects.

### 4.1 *Overview of the Nexus Network Learner*

The analyst initializes the NNL with data about individual behaviors and transactions, which are adjusted over time by the agents in the simulation, according to their goals. Agents use an artificial-intelligence technique to learn what traits to look for in the choice of network partners and in resource allocation behaviors. They base their choice on goals that are specific to their culture. Individual agents converge upon common practices and situations. When agents learn new behavior sets, a new social institution emerges.

Behaviors and goals that are input to the NNL corruption model include, for example, bribing, stealing, or whether to accept an offer of employment from an agent who has been rumored to steal from his employees. Behaviors such as stealing are input through a small rule set that implements a change in the flow of funds to role relations based on whether the agent or a network relation has learned to perform a behavior.

In sociology, the theoretical basis of NNL is in Symbolic Interactionism (Blumer 1986), in which roles and role relations are learned and created through the display and interpretation of signs (Duong and Grefenstette 2005). In the NNL corruption model, examples of roles include "Consumer," "Vendor," and "Maternal Uncle." An example of a role-relation rule is that the husband may choose up to three wives. The roles "Husband" and "Wife" belong to the Kin role network, while the roles "Vendor" and "Consumer" belong to the Trade role network. Examples of signs are social markers such as "Gender" and "Ethnicity."

NNL models the institution–individual linkage simultaneously with the individual–institution links. In this case, institutions are emergent social and legal norms that underlie collective activity and influence individual interaction. Figure 3 illustrates this process.

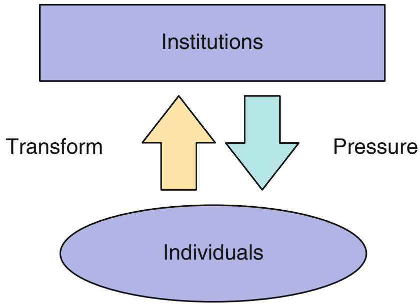


**Fig. 3** Emergence with cross-scale dynamics

## 4.2 *Networks of Agents*

The NNL corruption model comprises three social networks: a network of bureaucratic relations, a network of trade relations, and a network of family relations. Each of these networks consists of a set of agents connected to other agents through a role relation. Agents may have active roles, in which they have the job of initiating a role relationship with a preferred partner, and passive roles, in which they may accept the relationship. For every active role, there is one corresponding role, and vice versa. All other roles are derived from these active–passive pairs.

The roles are described in an input file that includes a distribution for the typical number of persons in each role relation (for example, a man has on average six children and a standard deviation of 2). It also includes the demographic characteristics of those eligible to choose role relations (such as a husband must be a male of working age), the accounts that a role is responsible for (such as family support or employee salaries), the flow of money to the accounts as expected by the proper implementation of each role (for example, a person's dependents should get three-fourths of his salary), and the conditional utility in a transaction (for example, if a service providee has a plan to bribe and a service provider has a plan to accept a bribe, the transaction has less direct utility). There are 65 different roles in the three networks of the NNL corruption model, partly listed in Table 1.

The criteria for entering an active role are deterministic rules that are defined in the role input file. In contrast, the criteria for choosing or accepting a role partner are expressed in the probabilities of a Bayesian network. These probabilities may be changed by learning; thus the name, "Nexus Network Learner." The NNL uses a Bayesian network to characterize the demographic data of a country and to generate the initial agent characteristics. The Bayesian network describes certain characteristics that agents cannot change, for example, ethnicity or gender. It also describes other characteristics that agents can change on an individual basis during the simulation, for example, behavioral characteristics, such as bribing or stealing, and preferences for choices of others in social networks (based on social markers or behavioral characteristics).

Finally, the Bayesian network describes demographic characteristics that individual agents do not learn but are rather the output of the computations made

**Table 1** Roles, network associations, and types (active, passive, derived) for the Nexus Network Learner corruption model

| No. | Role name | Role network | Type | No. | Role name (continued) | Role network | Type |
|---|---|---|---|---|---|---|---|
| 1 | Wife (P) | Kin | p | 33 | Government purchaser | Trade | a |
| 2 | Child | Kin | p | 34 | Vendor | Trade | p |
| 3 | Government employee | Bureaucratic | p | 35 | Government vendor | Trade | p |
| 4 | Husband | Kin | a | 36 | Corporate receiver | Trade | a |
| 5 | Father | Kin | a | 37 | Head of government | Bureaucratic | d |
| 6 | Government employer | Bureaucratic | a | 38 | Government receiver | Bureaucratic | a |
| 7 | Retailer | Trade | p | 39 | Service provider | Bureaucratic | p |
| 8 | Employer | Trade | a | 40 | Home receiver | Kin | a |
| 9 | Sister | Kin | d | 41 | Head of corporation | Trade | d |
| 10 | Brother | Kin | d | 42 | Employee | Trade | p |
| 11 | Maternal aunt | Kin | d | 43 | Customer | Trade | a |
| 12 | Paternal uncle | Kin | d | 44 | Purchaser | Trade | a |
| 13 | Maternal cousin | Kin | d | 45 | Service providee | Bureaucratic | a |
| 14 | Paternal cousin | Kin | d | 46 | Head of household | Kin | d |
| 15 | Coworker | Bureaucratic | d | 47 | Provider | Kin | d |
| 16 | Mother | Kin | d | 48 | Corporate taxman | Bureaucratic | p |
| 17 | Sibling | Kin | d | 49 | Corporate taxpayer | Bureaucratic | a |
| 18 | Paternal grand parent | Kin | d | 50 | Income1 | Trade | d |
| 19 | Maternal grand parent | Kin | d | 51 | Income2 | Trade | d |
| 20 | Dependent | Kin | d | 52 | Income3 | Trade | d |
| 21 | Spouse | Kin | d | 53 | Income4 | Trade | d |
| 22 | Parent | Kin | d | 54 | Income5 | Trade | d |
| 23 | Grade1 | Bureaucratic | d | 55 | Income6 | Trade | d |
| 24 | Grade2 | Bureaucratic | d | 56 | Income7 | Trade | d |
| 25 | Grade3 | Bureaucratic | d | 57 | Income8 | Trade | d |
| 26 | Grade4 | Bureaucratic | d | 58 | Income9 | Trade | d |
| 27 | Grade5 | Bureaucratic | d | 59 | Income10 | Trade | d |
| 28 | Grade6 | Bureaucratic | d | 60 | Government pay distributer | Bureaucratic | d |
| 29 | Grade7 | Bureaucratic | d | 61 | Pay distributer | Trade | d |
| 30 | Grade8 | Bureaucratic | d | 62 | Government payee | Bureaucratic | d |
| 31 | Grade9 | Bureaucratic | d | 63 | Household taxpayer | Bureaucratic | d |
| 32 | Grade10 | Bureaucratic | d | 64 | Income taxman | Bureaucratic | p |

during the simulation, such as unemployment statistics. The conditional probability that one agent property is related to another is used to generate agents with sets of properties similar to those of a population. The notional data could say, for example, that a working-age male of a given ethnic group is three times more likely to choose a person of his own ethnic group for his wife than he is likely to choose a wife of another ethnic group. Table 2 lists a set of nodes for the Bayesian network of the NNL corruption model, including their possible variables. Figure 4 illustrates a small portion of the Bayesian network.

In each of the three networks, there are eight types of corruption relations:

- Stealing/Trade Network (Scam)
- Bribing/Trade Network (Gratuity)
- Hiring Kin/Trade Network (Nepotism)
- Bribing to Be Hired/Trade Network (Misappropriation)
- Stealing/Government Network (Levy, Toll, Sidelining)
- Bribing/Government Network (Unwarranted Payment)
- Hiring Kin/Government Network (Nepotism)
- Bribing to Be Hired/Government Network (Misappropriation)

## 4.3 Agent Learning and Adaptation

In the simulation loop, agents perform two basic tasks. One is seeking and accepting role partners based on their traits and behavioral tendencies. The other is distributing money between financial accounts based on traits and behavioral tendencies of network partners. Agents also have the ability to observe and report behaviors based on their role, which may result in a penalty for some behaviors. Agents learn to keep the strategies that seem to increase the utility of their kin. Figure 5 illustrates the interaction between an individual's traits, his role interactions, and the institutions that result when these are combined with external government interventions such as penalties, foreign aid, or changes in resource pricing.

NNL's agents use genetic algorithms to learn and adapt to new role behaviors. Which behaviors are to be learned is an input to the simulation. NNL uses the genetic algorithm technique called the Bayesian Optimization Algorithm (BOA). Every agent includes an entire BOA that encodes a list of behaviors from which an agent may accept a subset. An agent tries each set of behaviors for a number of simulation cycles and then switches to another set. Table 3 illustrates the fit strategies of a single agent and how they change over time. The first seven learned behaviors are an agent's personal behaviors that determine the distribution of funds along networks. The last five behaviors determine the criteria for network choices. This particular agent learned behavior to employ his kin. The behaviors of accepting a bribe for employment, bribing for services, and stealing from a customer were tried and rejected early in the simulation run. The agent also learned not to choose employees who would offer him bribes but relearned the behavior later in the simulation run.

**Table 2** Selectable characteristics of agents

| No. | Agent properties | Options | Possible values/description |
|---|---|---|---|
| 1 | Role | 4 | Service providee, a service provider, employer, employee (can be many) |
| 2 | Hidden behavior | 5 | Steal from customer; Bribe for services; Accept bribe for services; Bribe employer; Accept bribe employer (can be many) |
| 3 | Know about behavior | 2 | Does or does not |
| 4 | Gender | 2 | Male or female |
| 5 | Ethnic preference | 6 | Four tribes, foreign, other (can be many) choice for spouse and employee |
| 6 | Corrupt | 2 | Is corrupt or is not corrupt |
| 7 | Ethnicity | 6 | Four tribes, foreign, other (can be many) |
| 8 | Zone | 4 | Region1, (can be many) |
| 9 | Age | 3 | Under 15, working age, over 60 (can be many) |
| 10 | Sector | 3 | Government, industry, agriculture (can be many) |
| 11 | Income | 10 | Low to high (can be many) |
| 12 | Reside (type of family) | 3 | Nuclear family, matrilocal, patrilocal |
| 13 | Wife age | 3 | Under 15, working age, over 60 (can be many) |
| 14 | Wife gender | 2 | Relative to the agent, if the agent is the wife then the selection is male |
| 15 | Wife ethnicity | 6 | Four tribes, foreign, other (can be many) |
| 16 | Child ethnicity | 6 | Four tribes, foreign, other (can be many) depends on the societal "Reside" |
| 17 | Child age | 2 | Working age, under 15 |
| 18 | Employee income | 10 | Ten levels, could be many |
| 19 | Employee ethnicity | 6 | Four tribes, foreign, other (can be many) |
| 20 | Employee is kin | 2 (Y/N) | Employer corruption |
| 21 | Accept bribe for services | 2 (Y/N) | Employee corruption |
| 22 | Penalized | 2 (Y/N) | Is or is not penalized |
| 23 | Employer steal from organization | 2 (Y/N) | Employer corruption |
| 24 | Bribe employer | 2 (Y/N) | Employee corruption |
| 25 | Bribe for services | 2 (Y/N) | Employee corruption |
| 26 | Steal from customer | 2 (Y/N) | Employee corruption |
| 27 | Steal from organization | 2 (Y/N) | Employer corruption |
| 28 | Accept bribe employer | 2 (Y/N) | Employer corruption |
| 29 | Rig election | 2 (Y/N) | Government corruption |
| 30 | Commission for illicit services | 2 (Y/N) | Government corruption |
| 31 | Unwarranted payment | 2 (Y/N) | Government corruption |
| 32 | Gratuity | 2 (Y/N) | Private sector corruption |
| 33 | Levies, tolls, sidelining | 22 (Y/N) | Government corruption (could be many) |
| 34 | Misappropriation | 2 (Y/N) | Government corruption |
| 35 | String pulling | 2 (Y/N) | Employer corruption (employee is kin) |
| 36 | Productive | 2 | Is or is not productive |

(continued)

**Table 2** (continued)

| No. | Agent properties | Options | Possible values/description |
|---|---|---|---|
| 37 | Employee productive | 2 | Is or is not productive (system related) |
| 38 | Scam | 2 (Y/N) | Private sector corruption |
| 39 | Employed | 2 (Y/N) | Government or private sector |
| 40 | Employee sector | 3 | Sector of employment (government, agriculture, or industry) |
| 41 | Employee: bribe employer | 2 (Y/N) | Employee corruption (system related) |
| 42 | Service provider :steal from customer | 2 (Y/N) | Private sector corruption (system related) |
| 43 | Service provider income | 10 | Low to high (can be many) used to relate corruption to income level |
| 44 | Taxman sector | 1 | Government |
| 45 | Service providee Bribe for services | 2 (Y/N) | Government corruption |
| 46 | Factionalization | 2 (Y/N) | More factionalization, less inter racial marriage and employment |
| 47 | Service provider age | 3 | Under 15, working age, over 60 (can be many) |
| 48 | Service provider employed | 1 | Employed (system related) |
| 49 | Taxman employed | 1 | Employed (system related) |

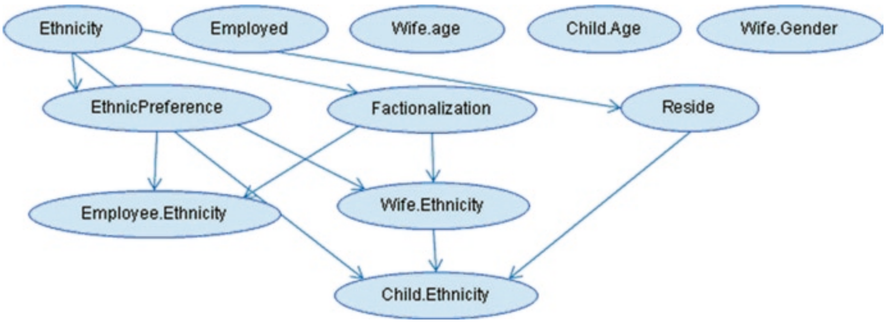


**Fig. 4** A small portion of the Bayesian network that illustrates dependencies

The fitness of a strategy is measured with a utility, or "happiness," function. In the NNL corruption model, an agent's utility derives from the advantageous trade interactions of the dependent kin. The question as to which kin are dependent is defined in the role file. For example, agents of matrilocal tribes consider their mother's side to be their responsibility. Agents of patrilocal tribes consider relatives on their father's side to be their responsibility. Finally, modern urban neolocal families consider only their children to be their responsibility. However, agents are "happy" (in other words, they find utility) not when their kin receive funds but

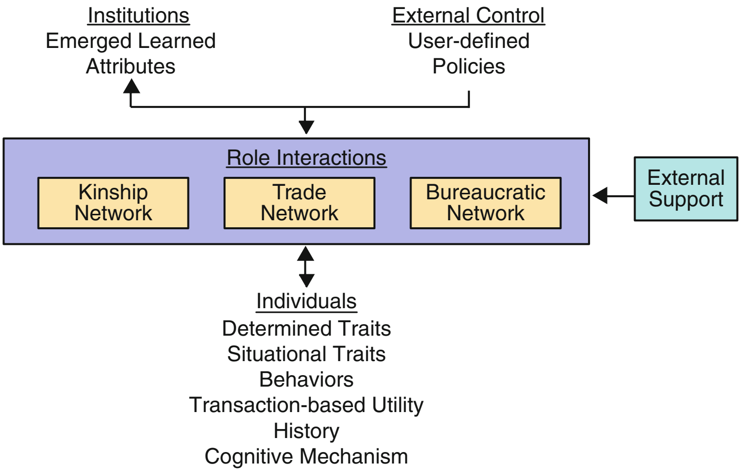


**Fig. 5** Nexus Network Learner conceptual model

rather when they receive proper care, e.g., receive services and buy goods. Stealing and bribing can lessen the amount of happiness.

"Coevolution" occurs when two or more agents simultaneously learn from and adapt to each other. For example, one agent learns that choosing an employee who bribes his employer is an advantageous behavior. Simultaneously, another agent learns that offering bribes to his employer is advantageous. Such agents that learn from and adjust to each other create social structure: institutionally accepted corruption that exists throughout a society.

NNL agents learn to make fund allocation choices and network partner choices according to their individual incentives to support their kin. As they change each other's incentives, for example, by hiring employees who offer bribes, the choices they make become new social structures through the coevolutionary process. In some contexts, bribes flourish, and in others, they do not. For example, in the NNL corruption model, agents learn from their genetic algorithms the types of persons to include in their social network, based on criteria, including kinship, ethnicity, and bribing behavior. Their genetic algorithms also lead them to decide whether they divert funds across networks through bribing and stealing.

Because incentives are modeled as culturally-based, the effects of different interventions, such as increased penalties for stealing, foreign aid, and resource rents, can be studied in a particular cultural setting. Corruption is changed institutionally through synchronous changes in the habits of individuals, for example, groups of employees who decide not to accept employment from employers who steal, as well as groups of employees who tolerate abuse because no other employment is available. Agents are driven by new incentive structures that come both from intervening actions and from other agents' reactions to those actions.

For example, a run of the NNL corruption model that tested incarceration penalties for corrupt behavior displayed cyclical behavior at relatively low levels

**Table 3** Example of an individual agent selection of top strategy over multiple learning cycles

| Learning cycle | Utility result | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 66 | N | Y | N | Y | N | N | N | N | N | Y | N | Y |
| 2 | 85 | N | N | N | N | N | N | N | Y | N | N | N | Y |
| 3 | 633 | N | N | N | N | Y | N | N | N | N | N | N | N |
| 4 | 755 | N | N | N | N | N | N | N | Y | N | Y | N | N |
| 5 | 902 | N | N | N | N | N | N | N | Y | Y | N | N | Y |
| 6 | 925 | N | N | N | N | N | Y | N | Y | N | N | N | Y |
| 7 | 575 | N | N | N | N | Y | N | N | N | N | Y | N | Y |
| 8 | 748 | N | N | N | N | N | Y | N | Y | N | N | N | Y |
| 9 | 1,873 | N | N | N | N | N | N | N | Y | N | N | N | Y |
| 10 | 2,545 | N | N | N | N | N | N | N | Y | N | N | Y | Y |
| 11 | 105 | N | N | N | N | N | N | N | Y | Y | Y | N | Y |
| 12 | 1,743 | N | N | N | N | N | N | N | Y | N | N | N | Y |
| 13 | 2,747 | N | N | N | N | N | N | N | Y | N | N | N | Y |
| 14 | 2,803 | N | N | N | N | N | N | N | Y | N | N | N | Y |
| 64 | 18,275 | N | N | N | N | N | N | N | Y | N | N | N | Y |
| 70 | 20,459 | N | N | N | N | N | N | N | Y | N | N | N | Y |
| 74 | 23,011 | N | N | N | N | N | N | N | Y | N | Y | N | Y |
| 79 | 12,797 | N | N | N | N | N | N | N | Y | N | Y | N | Y |

| Strategy component | Description |
|---|---|
| 1 | Bribe employer (Y/N) |
| 2 | Accept bribe employer (Y/N) |
| 3 | Steal from organization (Y/N) |
| 4 | Bribe for services (Y/N) |
| 5 | Accept bribe for services (Y/N) |
| 6 | Steal from customer (Y/N) |
| 7 | Factionalization (Y/N) |
| 8 | Employee: is kin (Y/N) |
| 9 | Employer: steal from organization (Y/N) |
| 10 | Employee: bribe employer (Y/N) |
| 11 | Service provider: steal from customer (Y/N) |
| 12 | Service providee: bribe for services (Y/N) |

of bribing and stealing. In each cycle, bribing or stealing goes up, then the number of penalized agents goes up, and then bribery or stealing goes down again. In this example, agents reacted to each other in a path-dependent way typical of coevolutionary systems: at one point in the run, the cycle became very large so that a large proportion of agents learned to bribe. Bribing nearly became institutionalized; however, the penalty succeeded in damping the newly accepted behavior early on. The intervention was successful in keeping the bribing level constrained, but the social forces made the bribing persist, so much so that about a third of all agents in this 100-agent simulation were incarcerated at some point. Table 4 lists the properties of the penalized agents at a single time late in the simulation run.

**Table 4** Properties of penalized agents

| Properties for 31 "Penalized" agents | Values |
|---|---|
| Gender male/female | 18/13 |
| Ethnicity A/L/K/M/Frn/other | 7/4/3/6/2/9 |
| Region R1/R2/R3/R4 | 2/9/15/5 |
| Age under15/working age/ over 64 | 9/22/0 |
| Sector Govt/Ind | 18/13 |
| Family organization p/m/n | 19/11/1 |
| Income I1/I2/I3/I4/I5/I6/I7 | 0/2/3/6/12/7/1 |
| Penalized | 31 |
| Employed (y/n) | 29/2 |
| Bribe employer (y/n) | 0/31 |
| Accept bribe employer (y/n) | 0/31 |
| Steal from organization (y/n) | 0/31 |
| Bribe for services (y/n) | 24/7 |
| Accept bribe for services (y/n) | 20/11 |
| Steal from customer (y/n) | 0/31 |
| Factionalization (y/n) | 16/15 |
| Employee: is kin (y/n) | 4/27 |
| Employer: steal from organization (y/n) | 2/29 |
| Employee: bribe employer (y/n) | 0/31 |
| Service provider: steal from customer (y/n) | 1/30 |
| Service providee: bribe for services (y/n) | 20/11 |

### *4.4 Using the Nexus Network Learner*

When using the NNL, the analyst or modeler typically follows these steps:

- Determine the social role networks that are relevant to the problem, and determine how the incentives for breaking the law can be represented by shifting resources from one network to the other; define rules that describe resource flows in transactions.
- Define roles with different powers of observing a law-breaking behavior, behaviors with different chances of being convicted in a justice system, and penalties with different incarceration lengths.
- Describe the demography of the population under study, accounting for demographic characteristics such as employment, education, and ethnicity.
- Assign notional but ultimately measurable probabilities to the Bayesian network, with the intent of replacing the notional data with real ones as the model matures.
- Execute the simulation; a single run of a model with 100 agents will take about 2 h on a typical laptop computer.
- Examine the output files, which are lists of the agents and their attributes, all defined in the Bayesian network. One output file lists the attributes that an agent actually displays in its simulated actions. Another output file lists the learned

strategies that encode the desired behaviors of each agent (but not necessarily the ones that the agent had an opportunity to perform) and how much an agent's kin actually benefits from the agent's behavior.
- Repeat the simulation multiple times to explore the possible outcomes; take note of the classes or characteristics of persons penalized in each simulation; consider the pattern of relations emerging between the intervention, such as a change in penalty policy, and the behavioral strategies that the agents evolve.

## 5 Practical Tips

- Recognize that computational modeling of crime and corruption is a young, immature field, and that current models are far from reliable. Make sure that model users understand this and that they apply modeling results with an appropriate degree of caution.
- Include in the modeling team a social scientist with a strong background in crime and corruption. This social scientist should collaborate directly and continuously with the modelers.
- When possible, use a recognized social theory of crime and corruption, or a consistent combination of several social theories. Often, a social theory postulates that certain foundational behaviors of individuals cause the emergence of social behavioral patterns. In such cases, first "hard-code" the underlying behaviors, and then develop the computational model until it demonstrates the emergence of theoretically asserted societal patterns.
- In modeling effects of interventions on crime and corruption, include representations of social institutions that control crime and corruption. Then, examine how interventions affect these institutions.
- Employ, when possible, well-accepted modeling tools. For instance: when implementing system-dynamics simulations, consider tools such as Vensim, Powersim, and iThink; for reactive-agent models, consider open-source tool kits such as NetLogo, Repast Simphony, MASON, or Swarm; and, for cognitive-agent models, consider Repast Simphony or MASON.
- Strive for a computer simulation that is causal in nature. Give preference to a model that involves few assumptions but demonstrates multiple real-world phenomena of crime and corruption.
- Maximize the number of variables in a model that are measurable in the real world. In the case of system dynamics models, for instance, recognize that stocks are more likely to reflect measurable quantities than flows, and attempt to maintain a ratio of stocks to flows of at least three to one.
- Usually, it is more efficient to begin the development of a model using a set of notional data. As the model matures and data requirements become better defined, notional data can be gradually replaced with real-world data.

# 6 Summary

Sociological theories of crime include: theories of strain blame crime on personal stressors; theories of social learning blame crime on its social rewards, and see crime more as an institution in conflict with other institutions rather than as individual deviance; and theories of control look at crime as natural and rewarding, and explore the formation of institutions that control crime. Theorists of corruption generally agree that corruption is an expression of the Patron–Client relationship in which a person with access to resources trades resources with kin and members of the community in exchange for loyalty. Some approaches to modeling crime and corruption do not involve an explicit simulation: rule based systems; Bayesian networks; game theoretic approaches, often based on rational choice theory; and Neoclassical Econometrics, a rational choice-based approach. Simulation-based approaches take into account greater complexities of interacting parts of social phenomena. These include fuzzy cognitive maps and fuzzy rule sets that may incorporate feedback; and agent-based simulation, which can go a step farther by computing new social structures not previously identified in theory. The latter include cognitive agent models, in which agents learn how to perceive their environment and act upon the perceptions of their individual experiences; and reactive agent simulation, which, while less capable than cognitive-agent simulation, is adequate for testing a policy's effects with existing societal structures. For example, NNL is a cognitive agent model based on the REPAST Simphony toolkit. NNL's Corruption Model structures corruption as arising from conflict between the roles and role relations of kin and bureaucratic networks. The NNL model includes three overlapping social networks each with roles: bureaucratic, trade, and kin or family networks. As agents make choices (e.g., whether to accept bribes), other agents with whom they interact observe the choices and draw conclusions about their utility. Different cultures are modeled by increasing the social or economic penalties attached to various behaviors.

# 7 Resources

The following is a list of links to data and software resources that aid in the study of crime and corruption, and the software that runs the models, mentioned in the text.

1. Open Source Software
   Weka Data Mining Software
   http://www.cs.waikato.ac.nz/ml/weka/
   Assortment of machine learning algorithms for analyzing data R
   http://www.r-project.org/
   Environment for statistical computing and graphics
   Sage
   http://www.sagemath.org/

Mathematics software system
Jess
http://www.jessrules.com/
Rule engine and scripting environment
FuzzyJess
http://ai.iit.nrc.ca/IR_public/fuzzy/fuzzyJToolkit.html
NetLogo
http://ccl.northwestern.edu/netlogo/
Environment for multiagent simulation
Repast Simphony
http://repast.sourceforge.net/
Environment for multiagent simulation
Mason
http://cs.gmu.edu/~eclab/projects/mason/
Discrete-event multiagent simulation library core in Java
Swarm
http://www.swarm.org/
Environment for multiagent simulation

2. Commercial Software
Vensim
http://www.vensim.com/
Environment for system dynamics modeling and simulation
IThink
http://www.iseesystems.com/
Environment for system dynamics modeling and simulation
Powersim
http://www.powersim.com/
Environment for developing many types of simulations

3. Corruption
Transparency International
http://www.transparency.org/
Datasets on numerous corruption indicators, such as the corruption perceptions index, the global
corruption index, and the bribe payers index
The Global Integrity Report
http://report.globalintegrity.org/
Resources and indicators on governance and corruption trends around the globe
Internet Center for Corruption Research
http://www.icgg.org/corruption.research.html
Links to academic research on corruption
World Bank Governance Data
www.worldbank.org/wbi/governance/data
Dataset on governance dimensions including *control of corruption*
Organized Crime and Corruption Bibliographic Database
http://www.osgoode.yorku.ca/NathansonBackUp/search.htm
Repository of articles and links concerning transnational corruption, human rights, and security
The Terrorism, Transnational Crime and Corruption Center
George Mason University
http://policy-traccc.gmu.edu/transcrime/corruption.shtml
Academic resources on the links among terrorism, transnational crime and corruption

4. Crime
Law Moose World Legal Resource Center

http://www.lawmoose.com/internetlawlib/1.htm
Legal reference materials
FBI Uniform Crime Statistics
http://www.fbi.gov/ucr/ucr.htm
US crime data and reports
National Criminal Justice Reference Service
http://www.ncjrs.gov/
Listings and/or repositories of justice and substance abuse information
National Archive of Criminal Justice Data
http://www.icpsr.umich.edu/NACJD/index.html
Listings and/or repositories of crime and justice data
Bureau of Justice Statistics
http://www.ojp.usdoj.gov/bjs/
Listings and/or repositories criminal justice statistics

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