AGENT-BASED SIMULATION OF SOCIAL LEARNING IN CRIMINOLOGY

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Abstract: Criminal behaviour exists in many variations, each with its own cause. A large group of offenders only shows criminal behaviour during adolescence. This kind of behaviour is largely influenced by the interaction with others, through social learning. This paper contributes a dynamical agent-based approach to simulate social learning of adolescence-limited criminal behaviour, illustrated for a small school class. The model is designed in such a way that it can be compared with data resulting from a large scale empirical study.

1 INTRODUCTION

Within Criminology, the analysis of the emergence of criminal behaviour is one of the main challenges (Gottfredson and Hirschi, 1990). An important mechanism behind the emergence of criminal behaviour is social learning (Burgess and Akers, 1966). To analyse this mechanism, this paper presents an agent-based approach to simulate social learning, which specifically addresses the mutual influence of peers, parents and school, with respect to delinquent behaviour.

To formalise and analyse the emergence of criminal behaviour through social learning, an artificial society has been modelled to represent a small school class. The models for the agents have been formally specified by executable temporal/causal logical relationships, using the modelling language TTL (Bosse et al., 2006) and its executable sublanguage LEADSTO (Bosse et al, 2007). This language allows the modeller to integrate both qualitative, logical aspects as quantitative, numerical aspects. Moreover, since the language has a formal logical semantics, simulation models created in TTL and LEADSTO can be formally analysed by means of logical analysis techniques.

In the field of Criminology, it is often quite difficult to perform experiments that involve changes in the real world. A model as the one presented in this paper can be used to study general patterns in the development of criminal behaviour.

Simulation can help to answer what-if questions and to verify theories about the relation between different processes. Discussions with a team of criminologists taught us that the evidence provided by simulation models is already considered as useful knowledge about the relevance of criminological theories such as the *differential association theory,* which will be discussed below.

In a next step of the research, we plan to validate the model using data of an existing empirical study e.g. (Weerman and Bijleveld, 2007). In that study, the social networks of 1730 non-delinquent, minor delinquent and serious delinquent pupils at lower-level secondary schools in the Netherlands were analysed. This paper only reports about the first step, the model and simulations.

In Section 2 a summary from the literature on social learning is presented. Section 3 discusses the chosen modelling approach. The simulation model is presented in Section 4, and Section 5 discusses simulation results. In Section 6, these results are analysed using formal techniques. Section 7 presents related work. Finally, Section 8 concludes the paper.

2 SOCIAL LEARNING

According to (Moffitt, 1993), two types of delinquents can be distinguished: *life-course-persistent* offenders, who stay criminal throughout their entire life and *adolescence-limited* offenders, who only show antisocial behaviour during

adolescence. Life-course-persistent anti-social behaviour is caused by neuropsychological problems during childhood that interact cumulatively with their criminogenic environments across development, which leads to a pathological personality. Adolescence-limited antisocial behaviour is caused by the gap between biological maturity and social maturity. It is learned from antisocial models that are easily mimicked, and it is sustained according to the reinforcement principles of learning theory. They peak sharply at about age 17 and drop fast in young adulthood. In the current paper, we explicitly focus on the adolescence-limited offenders.

An influential theory on the emergence of adolescence-limited criminal behaviour is the *differential association theory*, which was first proposed by Sutherland and Cressey (1966) and later expanded by Burgess and Akers (1966). In short, this (informal) theory states that behaviour is learned through interaction with others. We learn most from the people we are in close contact with, like parents and peers. There are two basic elements to understanding the differential association theory. First, the content of what is learned is important (e.g., motives, attitudes and evaluations by others of the meaningful significance of each of these elements). Second, the process by which learning takes place is important, including the intimate informal groups and the collective and situational context where it occurs. Criminal behaviour itself is learned through assigning meaning to behaviour, experiences, and events during interaction with others.

According to Sutherland and Cressey (1966), the extent to which delinquent behaviour is imitated is influenced by the *frequency*, *duration*, and *intensity* of the contact. Frequent, long and important or prestigious contacts have a larger influence. In addition, the *priority of learning* influences the social learning process: the earlier behaviour is learned, the more influential it is.

3 MODELLING APPROACH

To formalise and analyse the emergence of criminal behaviour through social learning from an agent perspective, an expressive modelling language is needed. On the one hand, qualitative aspects have to be addressed, such as certain characteristics about the agents (e.g., their age), their social relationships (e.g., who are their parents and friends). On the other hand, quantitative aspects have to be addressed. For example, an agent's level of delinquency, which is

the extent to which an agent exhibits delinquent behaviour, can best be described by a real number. The change of this delinquency can best be described by a mathematical formula. Another requirement of the chosen modelling language is its suitability to express on the one hand the basic mechanisms of social learning (for the purpose of simulation), and on the other hand more global properties of social learning (for the purpose of logical analysis and verification). For example, basic mechanisms of social learning involve decisions of individual agents to attach to their peers, whereas global properties are statements that consider the learning process over a longer period, like "eventually the delinquent pupils become less delinquent".

The predicate-logical Temporal Trace Language (TTL) (Bosse et al., 2006) fulfils all of these desiderata. It integrates qualitative, logical aspects and quantitative, numerical aspects. This integration allows the modeller to exploit both logical and numerical methods for analysis and simulation. Moreover it can be used to express dynamic properties at different levels of aggregation, which makes it well suited both for simulation and logical analysis.

TTL is based on the assumption that dynamics can be described as an evolution of states over time. The notion of state as used here is characterised on the basis of an ontology defining a set of physical and/or mental (state) properties that do or do not hold at a certain point in time. These properties are often called *state properties* to distinguish them from dynamic properties that relate different states over time. A specific state is characterised by dividing the set of state properties into those that hold, and those that do not hold in the state. Examples of state properties are *'agent 1 has a delinquency level of 0.35'*, or *'agent 2 has an attachment to agent 3 of 0.5'*.

To formalise state properties, ontologies are specified in a (many-sorted) first order logical format: an *ontology* is specified as a finite set of sorts, constants within these sorts, and relations and functions over these sorts (sometimes also called signatures). The examples mentioned above then can be formalised by n-ary predicates (or proposition symbols), such as, for example, has_delinquency(agent1,0.35) or has_attachment_to(agent2, agent3, 0.5). Such predicates are called *state ground atoms* (or *atomic state properties*). For a given ontology Ont, the propositional language signature consisting of all ground atoms based on Ont is denoted by APROP(Ont). One step further, the *state properties* based on a certain ontology Ont are formalised by the

propositions that can be made (using conjunction, negation, disjunction, implication) from the ground atoms. Thus, an example of a formalised state property is has_delinquency(agent1,0.35) & has_delin-quency(agent2,0.45). Moreover, a *state* S is an indication of which atomic state properties are true and which are false, i.e., a mapping S: APROP(Ont) → {true, false}. The set of all possible states for ontology Ont is denoted by STATES(Ont).

To describe dynamic properties of complex processes such as the development of criminal behavior, explicit reference is made to *time* and to *traces*. A fixed time frame T is assumed which is linearly ordered. Depending on the application, it may be dense (e.g., the real numbers) or discrete (e.g., the set of integers or natural numbers or a finite initial segment of the natural numbers). Dynamic properties can be formulated that relate a state at one point in time to a state at another point in time. A simple example is the following (informally stated) dynamic property about the delinquency of agents:

For all traces γ,
there is a time point t such that
all agents have a delinquency that is lower than d.

A *trace* γ over an ontology Ont and time frame T is a mapping γ : T → STATES(Ont), i.e., a sequence of states $γ_t$ (t ∈ T) in STATES(Ont). The temporal trace language TTL is built on atoms referring to, e.g., traces, time and state properties. For example, 'in trace γ at time t property p holds' is formalised by state(γ, t) |= p. Here |= is a predicate symbol in the language, usually used in infix notation, which is comparable to the Holds-predicate in situation calculus. *Dynamic properties* are expressed by temporal statements built using the usual first-order logical connectives (such as ¬, ∧, ∨, ⇒) and quantification (∀ and ∃; for example, over traces, time and state properties). For example, the informally stated dynamic property introduced above is formally expressed as follows:

∀γ:TRACE ∃t:TIME ∀a:AGENT ∃x:REAL
state(γ, t) |= has_delinquency(a, x) & x≤d

In addition, language abstractions by introducing new predicates as abbreviations for complex expressions are supported.

To be able to perform (pseudo-)experiments, only part of the expressivity of TTL is needed. To this end, the executable LEADSTO language (Bosse et al., 2007) has been defined as a sublanguage of TTL, with the specific purpose to develop simulation models in a declarative manner. In LEADSTO, direct temporal dependencies between two state properties in successive states are modelled by *executable dynamic properties*. The LEADSTO format is defined as follows. Let α and β be state properties as defined above. Then, the notation α →→ $_{e, f, g, h}$ β means:

*If state property α holds for an interval with duration g,
then after some delay between e and f
state property β will hold for an interval with duration h.*

As an example, the following executable dynamic property states that "if during 1 time unit the attachment between agent a1 and a2 is x1, and the difference in delinquency between both agents is x2, then for the next 5 time units (after a delay between 0 and 0.5 time units) the attachment between both agents will be β*x1+(1-β)*|x2|":

∀a1,a2:AGENT ∀x1,x2:REAL
has_attachment_to(a1,a2,x1) ∧
delinquency_difference(a1,a2,x2) →→$_{0, 0.5, 1, 5}$
has_attachment_to(a1,a2,β*x1+(1-β)*|x2|)

Based on TTL and LEADSTO, two dedicated pieces of software have recently been developed. First, the LEADSTO Simulation Environment (Bosse et al., 2007) takes a specification of executable dynamic properties as input, and uses this to generate simulation traces. Second, to automatically analyse the resulting simulation traces, the TTL Checker tool (Bosse et al., 2006) has been developed. This tool takes as input a formula expressed in TTL and a set of traces, and verifies automatically whether the formula holds for the traces. In case the formula does not hold, the Checker provides a counter example, i.e., a combination of variable instances for which the check fails.

4 SIMULATION MODEL

To study the influence of social learning on delinquent behaviour, we modelled a school class with 10 pupils. There are three groups that influence the process of social learning, namely parents, school and peers. Therefore, each pupil is represented as an *agent*; the parents of the pupils and the school are modelled as *groups*. Each pupil is related to one parent group. The agents have a number of characteristics in our model (determined based on discussions with experts). We restricted our study to the characteristics that are collected in the empirical study (Weerman and Bijleveld, 2007). The first property of an agent is its *age*. In our model the age is restricted to values between 12 and 17. The age is relevant for influence of peers on each other. The older an adolescent is (up to 17) the more

his behaviour is influenced by peers. In addition, the *age difference* between peers is relevant, since older people are often more dominant in the relationship. The influence of school and parents tends to decrease as the adolescent gets older.

In addition, agents have a *basic level of influenceability*: this represents how easily they can be influenced. Oppositely, agents and groups have a level of *dominance*: this represents how easily they can influence others. For persons this is a character trait. Schools can also have a level of dominance. A dominant school can be seen as a strict school, while a school that is less strict could be considered to be less dominant.

The social relations between pupils in a school class are modelled via *attachment* relations. All agents are attached to each other with a specific *level of attachment*, representing the intensity of the contact as defined by Sutherland and Cressey (1966). The attachment relation is also used to model the attachment of pupils to their parents and to their school. We assume that a high attachment results in a higher influence of the attached agent or group on the behaviour of the pupil.

Finally, we model a level of *delinquency* for all agents and groups, also for parents and schools. The initial value for the delinquency of an agent could be based on a measurement of the number of delinquent acts of a pupil in the past. The interpretation of the delinquency of a school is indirect: the school has a low level of delinquency if it is a good school, i.e. teachers and other staff members have a low level of delinquency. When the atmosphere in the school is less positive, then it has a higher level of delinquency.

During the simulation, the levels of delinquency of the pupils change because of the influence of others. This process is depicted in Figure 1, where the circles denote state properties and the arrows denote dynamic properties (relationships) between them. The age of each agent increases every year. Every agent starts with a basic influenceability; together with the age of the agent and the attachment to a specific group or agent, the *effective influenceability* of the agent by that agent or group is determined (denoted by has_influenceability in Figure 1).

This effective influenceability is combined with the level of dominance of the other party, the difference in delinquency between the agent and the other party, and - in case the other party is an agent - the age difference between two agents. This leads to the so-called *delta delinquency*. The delta delinquency represents all factors that influence the level of delinquency of an agent. In order to calculate the new delinquency of an agent, the delta delinquencies of all agents and groups in its environment are combined with the old delinquency (the delinquency the agent started out with).

In addition, the model is able to adapt the attachment between the agents. The idea behind this is that the strength of a relation is influenced by the overlap in values. If the difference in the level of delinquency is very high, then the attachment will decrease. However, because there are many other factors that influence the attachment as well, the difference in delinquency only causes a minor change in attachment.

In the model, the concepts of influenceability, dominance, attachment, and delinquency are modelled as a real number between 0 and 1. Furthermore, the age is modelled as an integer between 12 and 17, and the delta delinquency as a real number between -1 and 1. The relationships between the concepts have been modelled in LEADSTO. Two example relationships (to determine the delta delinquency of groups, and the new delinquency, respectively) are stated below. Here, the β's are decay factors, and the w's are weight factors. Note that these relationships correspond to (conjunctions of) arrows in Figure 1. The complete set of LEADSTO relationships is shown in the online appendix[1].

Delta Delinquency Determination (for Groups)
$\forall$a:AGENT $\forall$g:GROUP $\forall$x1,x2,x3:REAL
delinquency_difference(a,g,x1) $\wedge$ has_influencability(a,g,x2) $\wedge$ has_dominance(g,x3) $\rightarrow$
has_delta_delinquency(a,g,β2*(β1*x1+(1-β1)*x1*(w4*x2+w5*x3)))

New Delinquency Determination
$\forall$a1:AGENT $\forall$g:GROUP $\forall$d,s,p,x1,...,x10:REAL
has_old_delinquency(a1,d) $\wedge$
has_delta_delinquency(a1,school,s) $\wedge$
has_delta_delinquency(a1,g,p) $\wedge$ are_parents_of(g,a1) $\wedge$
has_delta_delinquency(a1,agent1,x1) $\wedge$ ...
has_delta_delinquency(a1,agent10,x10) $\rightarrow$
has_delinquency(a, d+ (s+p+x1+...+x10)/12))

5 SIMULATION RESULTS

A number of simulation experiments have been performed to see whether the behaviour of the model was as expected for some common scenarios. A thorough evaluation will be performed later when the results will be compared with data of an empirical study. A longer description with more scenarios and details can be found in the appendix.

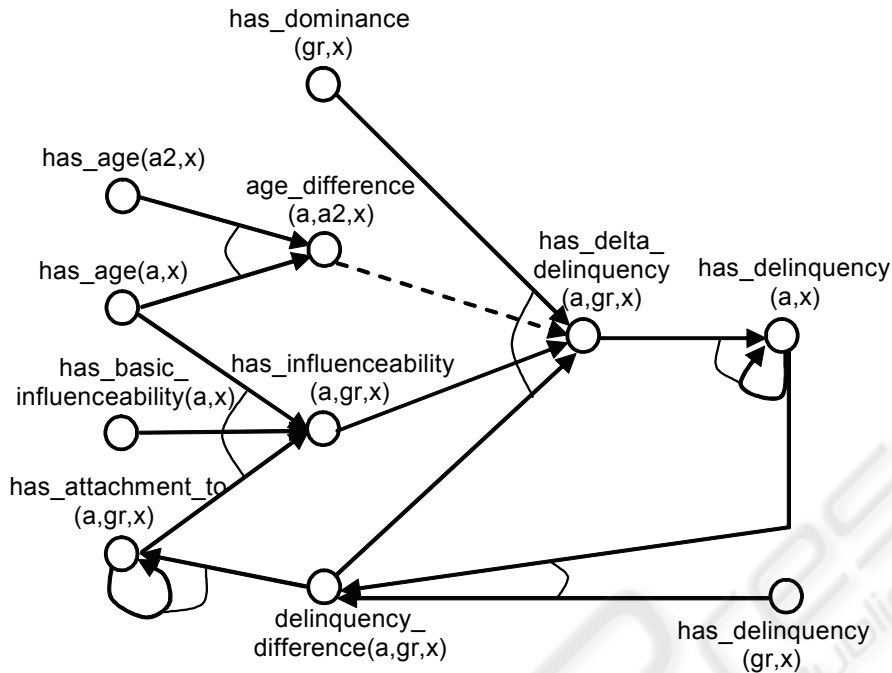[1] http://human-ambience.few.vu.nl/docs/ICAART09.pdf

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Figure 1: Concepts and relations in the simulation model.

In the **first scenario** there is one bad guy with criminal parents in an otherwise reasonable school class. We are interested in the question whether the criminal boy makes the other boys bad or whether the group is able to straighten out the delinquent. In this scenario agent 1 has a delinquency of 0.8 while the other agents have a delinquency of 0.3. All agents are male[2] and are 12 years old at the start of the simulation. They have a basic influenceability with a value of 0.4, a level of dominance of 0.6 and a mutual attachment of 0.3. The attachments are stable in this simulation. Every agent has parents with a dominance of 0.7 and a delinquency of 0.2, except for agent 1, whose parents have a delinquency of 0.8.

The resulting trace is shown in Figure 2 (this and the following figures can be found at the last page of the paper). Here, time is on the horizontal axis and the level of delinquency is on the vertical axis. The three graphs show the combined delinquencies of all pupils, the delinquency of agent 1 and the delinquency of the other agents (that all show the same behaviour; agent 10 is just taken as an example), respectively. The two lines in the first graph correspond to the lines in the second and third graph, respectively, where a more detailed scale is

used. The results show that the interaction between the agents leads to a decreased delinquency of agent 1. The delinquency of the other agents increases slightly to 0.31 and from this point on it decreases to 0.255 at time point 100. From time point 70 on, there is a more or less stable difference in delinquency between the agent with criminal parents and the others.

In a **second scenario** (Figure 3), the influence of the school is examined by increasing its delinquency to 0.8. The level of delinquency of the agents and their parents were identical to the settings in the previous scenario. The results show that the increased delinquency of the school causes an increased level of delinquency of all the agents. This influence appeared to be larger than the influence of individual agents, because it propagates through to pupils, who again influence each other.

In the **third scenario**, half of the pupils (and their parents) have a high delinquency. The other pupils (and their parents) have the same level of delinquency as in scenario 1. In this case all agents influence each other and their delinquencies grow towards each other, while a difference remains because of the influence of the parents (see Fig. 4).

Finally, the **fourth scenario** represents a school class with two groups (3 delinquent pupils with a high mutual attachment, 3 extremely non-delinquent pupils with a high mutual attachment) and 4 individuals with a high basic influenceability. One of these 'group-less pupils' has a high attachment to

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[2] Note that the model does not incorporate a direct influence of gender. Difference between male and female pupils can be modeled indirectly by giving the males higher initial delinquencies.

a person in the criminal group, one to a person in the non-criminal group, and the others had no specific relations. The attachments can change over time. The goal of this scenario is to see whether a pupil will be incorporated in a group if he has a strong relationship with one of them. Figure 5 shows the resulting delinquencies.

Interestingly, we see that all group-less pupils reach a level of delinquencies that is close to that of the pupils in the 'good group', even for the pupils that have a strong relation to a pupil in one of the groups. This observation can be explained by the fact that the delinquency of the parents of the group-less pupils is close to the delinquency of the parents in the good group. However, if we look closely at the delinquencies of the group-less people (lower graph in Figure 5), we see that they develop slightly differently (notice the different scale). Apparently, the delinquency of the pupil with a friend in the bad (good) group initially grows faster (slower), but eventually it reaches the same level as the other group-less pupils.

6 FORMAL ANALYSIS

The detailed settings and results of ten simulation experiments (including the ones described in Section 5) are shown in the appendix. Among the different experiments, various parameter settings were varied, in particular the initial delinquencies of agents, parents, and school, the initial attachment between agents, and several weight factors.

To analyse the resulting simulation traces in more detail, the TTL Checker tool (Bosse et al., 2006) has been used. As mentioned earlier, this tool takes as input a TTL formula and a set of traces, and verifies automatically whether the formula holds for the traces. For the current domain, a number of hypotheses have been expressed as dynamic properties in TTL, which were inspired by relevant questions in Criminology (see Sections 1 and 2). To give a simple example, consider the following dynamic property (P1), which expresses that the delinquency of an agent keeps on decreasing over time:

P1 Strict Monotonic Decrease of Delinquency
For all time points t1 and t2, if t2 is later than t1, then the agent's delinquency at t2 is lower than at t1.

$P1(\gamma:TRACE, a:AGENT) \equiv$
$\forall t1,t2:TIME \ \forall d1,d2:REAL$
$[state(\gamma, t1) \models has\_delinquency(a, d1) \ \&$
  $state(\gamma, t2) \models has\_delinquency(a, d2) \ \& \ t1<t2] \Rightarrow d1>d2$

Note that this formula comprises two free variables (the trace γ and the agent a), for which different values can be instantiated. For example, in order to check whether agent 1 satisfies the criterion of strict monotonic decrease of delinquency in simulation trace 5, the formula P1(trace1, agent1) should be checked. Similarly, it is possible to check whether the property holds for all agents and all traces, or for a certain percentage of them.

Besides checking whether the delinquency of agents keeps on decreasing, also other properties can be verified. A relevant question in Criminology is what the relative influences of (respectively) parents, peers, and school on the development of a person's delinquency are. For example, might it be the case that the biggest contribution is provided by parents and school only, and that the influence of classmates can almost be neglected? To analyse these kinds of hypotheses, properties like the following have been established:

P2 Agent Converges to Parents and School
At the end of the trace, the delinquency of agent a lies within a margin δ of the average of the delinquencies of its parents and the school at the start of the trace.

$P2(\gamma:TRACE, a:AGENT) \equiv$
$\forall d1,d2,d3:REAL \ \forall p:AGENT$
$[state(\gamma, start\_time) \models has\_delinquency(p, d1) \ \&$
  $state(\gamma, start\_time) \models has\_delinquency(school, d2) \ \&$
  $state(\gamma, end\_time) \models has\_delinquency(a, d3) \ \&$
  $are\_parents\_of(p,a) \ \& \ ]$
  $\Rightarrow d3-\delta < (d1+d2)/2 < d3+\delta$

If this property were true (for a small δ), this would indicate that the development of a pupil could be predicted by taking into account the delinquency of the parents and the school only. Some initial checks have pointed out that the lowest δ for which the property satisfies all generated traces is 0.22. In other words, for all of the traces the influence of parents and school was relatively high. In addition to P2, a property was created to compare the change in delinquency between two agents a1 and a2.

P3 Bigger Change in Delinquency
During the whole trace, agent a1 made a bigger change in delinquency than agent a2.

$P3(\gamma:TRACE, a1,a2:AGENT) \equiv$
$\forall d1,d2,d3,d4:REAL$
$[state(\gamma, start\_time) \models has\_delinquency(a1, d1) \ \&$
  $state(\gamma, start\_time) \models has\_delinquency(a2, d2) \ \&$
  $state(\gamma, end\_time) \models has\_delinquency(a1, d3) \ \&$
  $state(\gamma, end\_time) \models has\_delinquency(a2, d4)]$
  $\Rightarrow |d1-d3| > |d2-d4|$

This property can be used, for example, to find out whether in a school class with many "good" pupils and one "bad" guy (see scenario 1), the bad pupil tends to move towards the good ones, or vice versa. In our simulation traces, such a bad pupil

indeed turned out to converge towards his classmates.

To summarise, a number of TTL properties have been checked against the generated simulation traces, as a first pilot study of the applicability of the approach. Although no real conclusions can be drawn as yet, these checks pointed out that the traces satisfy basic properties that were inspired by criminological theories, such as property P2 and P3.

Finally, it is important to note that, in addition to simulated traces, the TTL Checker can also take empirical traces as input. In future work, several properties as those introduced here will be verified against empirical traces that are constructed on the basis of experiments in real classrooms

7 RELATED WORK

With respect to related work, the research presented in this paper on the one hand has commonalities with literature from the social and behavioural sciences (in particular, the area of Criminology), and on the other hand with literature in AI and Computer Science (among others, agent-based simulation).

Concerning the criminological and psychological area, first of all the current paper is related to early articles from the 60's and 70's such as Bandura (1977), Burgess and Akers (1966) and Sutherland and Cressey (1966), which were the first to formulate (different variants of) the social learning theory. Here, the theory put forward by Bandura (1977) is more generic, whereas the other two focus specifically on social learning in Criminology. For an overview of these theories, see Lanier and Henry (1998), Chapter 7. In fact, these theories formed the basis of the research questions addressed in this paper. Based on these theories, Opp (1989) identified a number of (informal) properties that are expected to hold for social learning in Criminology, such as "the more frequently persons show deviant behaviour, the more frequently they will have contact with patterns of deviant behaviour". Although a detailed verification (using larger-scale experiments and statistical techniques) is left for future work, an initial analysis provides evidence that our model indeed satisfies these properties. Next, a number of papers in Criminology propose more refined models for social learning, often focusing on specific aspects of the learning. For example, Thornberry et al. (1994) compared three theoretical models of the interrelations among associations between delinquent peers, delinquent beliefs, and delinquent behaviour. A main difference with our work is that these models are not computational. Nevertheless, their conclusions are in agreement with the initial results found in this paper. Finally, several authors have performed empirical studies on social learning of delinquent behaviour in schools (Bruinsma, 1984) and Weerman and Bijleveld, 2007). Our model was designed explicitly with the purpose of reproducing such data.

Concerning the literature in AI and Computer Science, we are not aware of approaches using multi-agent technology to simulate delinquent behaviour of individuals in a group. However, various papers have similarities to the work proposed here. First, Van Dijkum and Landsheer (2000) present a model that is rather similar to ours, but which uses differential equations to describe the development of juvenile criminal behaviour. Another difference with our model is that they aim for an integration of multiple criminological theories (namely social learning theory, career theory, and rational choice theory), whereas we focus (in more detail) on the former only. Moreover, several authors have created models that address social learning and criminal behaviour at a more global level. For example, Chamley (2003) presents an economic model for social learning, although not explicitly focussed on learning of delinquent behaviour. Similarly, Winoto (2002) presents an agent-based economic model for the market for offenses. This model addresses the global development of delinquency in a population. These models differ from our model in the sense that they are situated at a macroscopic level, thereby abstracting from differences between individuals. An approach that does consider individual differences, but that addresses a different domain, is presented by Tsvetovat and Carley (2005). They present a simulation model of the dynamics of terrorist networks, based on networks of non-deterministic finite automata. Furthermore, a large number of approaches address simulation of the environmental aspects of criminal behaviour, such as the displacement of crime and the emergence of "hot spots", e.g., Liu et al. (2005) and Bosse and Gerritsen (2008). Finally, relevant work is put forward by Conte and Paolucci (2001). They identify a number of (cognitive) factors that are relevant in social learning in general. However, in contrast to our work, they do not provide a computational model.

8 CONCLUSIONS

This paper presented an agent-based approach to simulate and formally analyse the process of social

learning of delinquency during adolescence. The general mechanism of change by influences of peers is possibly also useful in other domains in which social learning is relevant. In this paper, however, we focused on learning of delinquent behaviour. Inspired by criminological literature, the approach incorporates the influences of three types of groups, namely peers, parents, and school. Various relevant factors were identified, such as influenceability, dominance, and attachment, and their mutual relationships were formalised by means of the hybrid modelling language LEADSTO. Moreover, it was shown how the approach can be used to generate simulation traces, and how such traces can be automatically verified against relevant properties, expressed in the language TTL. Although preliminary, the first results are promising. Firstly, they provide evidence that the proposed model is a useful experimental tool to give insight in social learning processes as described in the criminological literature. Secondly, some interesting patterns have already been found. For example, the simulation results suggest that the influence of the school on delinquency is relatively high (scenario 3), that the impact of attachment is relatively low (scenario 4), and that every individual learning process approaches a final delinquency near the average of the delinquencies of parents, school, and peers.

In the current paper, no detailed empirical validation of the model has been presented. However, as mentioned in the introduction, various empirical studies have been performed, of which large data sets are available (Bruinsma, 1985) and Weerman and Bijleveld, 2007). The model has been explicitly designed with the objective of using such data sets for validation in the future. Currently, some initial steps in this direction are taken. During such a validation, several questions are addressed, such as "is it realistic that the average delinquency almost always decreases?", or "is it realistic to have a relatively stable delinquency for school and parents?". When these questions are solved, the model can be further fine-tuned, in particular by choosing realistic values for all parameter settings and weight factors involved.

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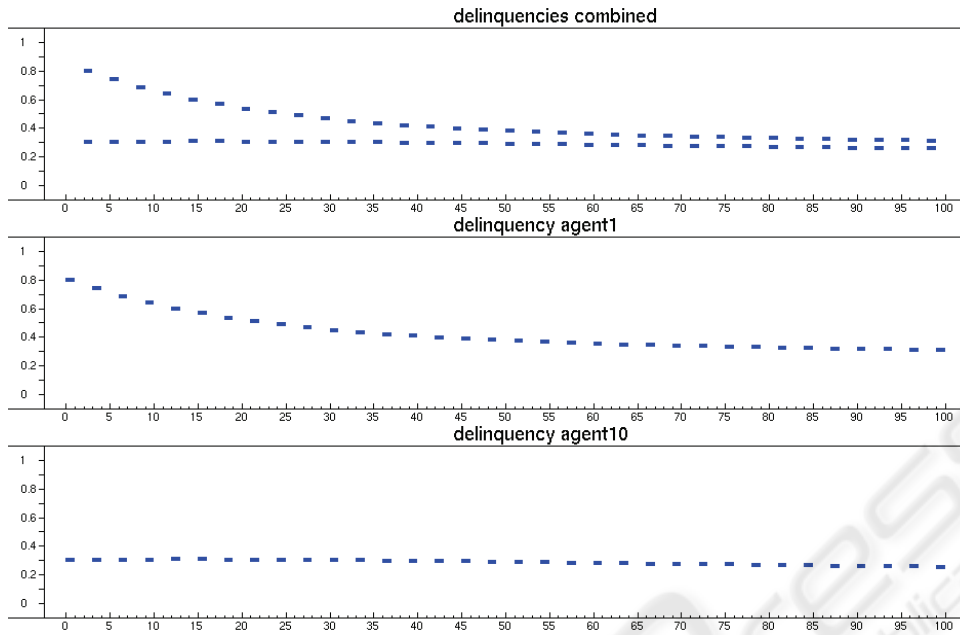
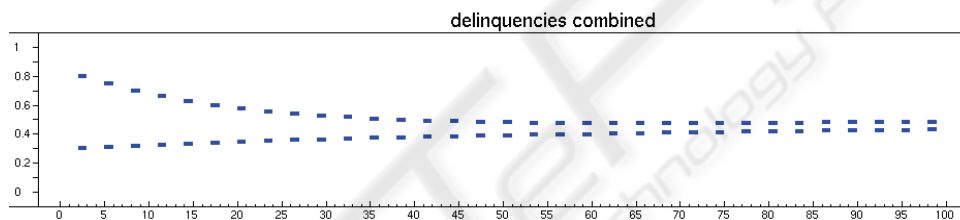Figure 2: Delinquency in a school class with one bad guy.

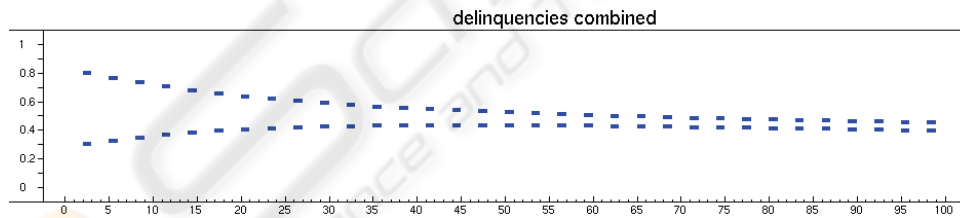Figure 3: Influence of a bad school.

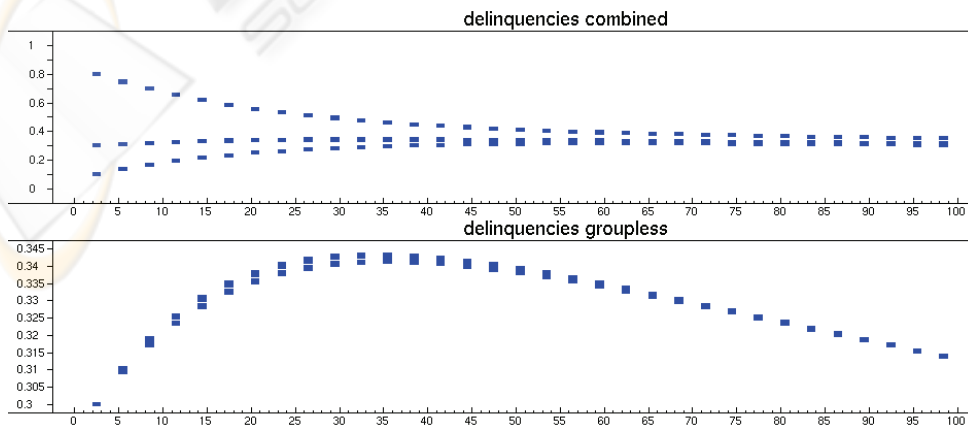Figure 4: Delinquency in a school class with half of the pupils being criminal.

Figure 5: Delinquencies in school class with two groups.