Learning Actors in Spatial Planning: Incorporating Bayesian Networks in an Agent Based Model

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INTRODUCTION

Agent Based Models (ABMs) have been extensively applied to simulate social-spatial processes for land use change and spatial planning (Agarwal et al., 2002; Bousquet and Le Page, 2004; Parker et al., 2003; Sengupta and Sieber, 2007). In Agent Based Modelling, a social process is modelled as a collection of autonomous decision making entities called agents. Each agent individually assesses its environment and reasons over it. The reasoning about the state of the environment and other agents often follows a reactive architecture according to a set of rules defined through some sort of logic. However, social processes based on cooperation, conflicts and trust, like the ones found in interactive spatial planning, require a different reasoning that better accounts for the complexity of individual and group behaviour (Agarwal *et al.*, 2002). Decision making in spatial planning often includes a variety of issues which are relevant to multiple actors. Actors may have different beliefs about the environment, have different preferences and may follow different strategies when making decisions (Parker *et al.*, 2008). Often actors do not fully reveal their holdings and beliefs.

Many current Agent Based Modelling approaches for spatial planning maintain a decision making mechanism based on expert systems, often combined with cellular automata, distance decay functions and utility functions (Bousquet and Le Page, 2004; Parker et al., 2003). The main drivers behind these approaches are maximization of utility and minimization of risk. Utilities in this context represent an agent-specific value for an environmental aspect. Communication and negotiation among agents require common understanding of these values and a constant representation of the environment. During an interactive spatial planning however, decision making is often based on a highly subjective valuation of the environmental aspects. Moreover, in most models agents have either complete knowledge of other agents' values or no knowledge at all while in reality the development of knowledge about beliefs and preferences of others is a dynamic process. Through observing other agents' actions additional knowledge is gained and included into the decision making process.

A Bayesian Network (BN) is a graphical representation of set of variables (*nodes*) and their causal relationships (*links*) forming a directed acyclic graph (Charniak, 1991). A link from node A to node B can be interpreted as 'A affects B'. These causal relationships are encoded with probabilities that represent the extent to which one variable is likely to affect another. These probabilities are displayed in the *Conditional Probability Table* (CPT) of the node. A BN is an elegant and mathematically correct representation for causal inference from observations (Nielsen and Parsons, 2007). Its learning properties fit complex adaptive systems showing a high path dependency. Although the use of BNs for modelling land use change is not new (Bacon et al., 2002; Lynam et al., 2002; Stassopoulou et al., 1998), examples of the incorporation of BNs in spatial ABMs are scarce and confined to maximize utility (Lei *et al.*, 2005) or calibrate cellular automata transition rules (Kocabas and Dragicevic, 2007).

This research explores the use of Bayesian Networks (BN) to improve on the representation of cooperation between agents in an ABM simulating an interactive spatial planning process (Ligtenberg et al., 2009; Ligtenberg et al., 2001). The agents in the ABM search for mutually acceptable locations for new land use. Therefore, their cooperation can be regarded as a distributed search through a space of potential agreements (Saha and Sen, 2005). A BN is expected to add the ability to deal with partial knowledge of the agents about the others and to offer a learning mechanism that allows the development of knowledge based on the observations of the environment and the other agents (Watthayu and Peng, 2004). In particular, this paper describes how BNs have been incorporated into an ABM, adding capabilities to agents to 1) learn by enabling them to take into account experiences from the past, and 2) adapt their spatial preferences in accordance with their experiences following a cooperation strategy with other agents.

The first section of the paper briefly describes the ABM and the implementation of BNs. The second section presents the results of applying the proposed approach to a spatial planning scenario for the 'Land van Maas en Waal', an area in the Eastern part of the Netherlands. In the last section, the conclusions are presented and discussed.

THE MODELLING APPROACH

To explore the application of BNs to improve on the representation of the cooperation an agent based spatial planning model of Ligtenberg (2006) was extended. This model simulates an interactive multi-actor spatial planning process at a regional scale, inspired by the 'regional dialogue approach' (Mansfeld, 2003), which distinguishes four phases: socialisation, externalisation, internalisation, and combination (Nonaka and Takeuchi, 1995; te Brömmelstroet and Bertolini, 2008). Socialisation serves to create trust among the participating actors as well as to get some insight in the desires and preferences of each participating actor. Externalisation refers to the process of making implicit (or tacit) knowledge explicit, while internalisation refers to the process of accepting explicit knowledge as part of the joint stock of knowledge of participating actors. Combination means using internalised information to build new concepts together. The model was previously focused on externalisation, internalisation and combination phases. The BN aims to add to the socialization component. The agents represent actors, being organisations or interest groups rather than individuals as these tend to show a more consistent behaviour regarding their desires and objectives. Every agent is coupled with a BN that enables it to learn from its own actions and the actions of the other agents. While the planning process advances through time, the BN evolves and, as a result, each agent becomes better at anticipating reciprocity. The next section will give an example of this process. Figure 1 shows the general overview of the spatial planning process.

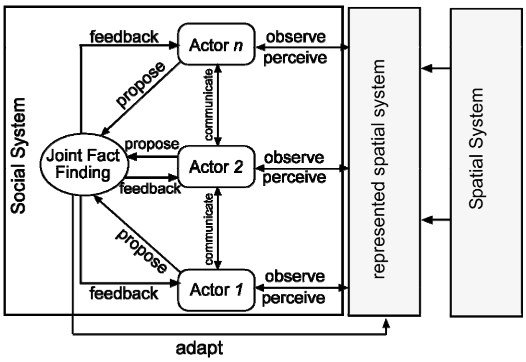

Figure 1: Interactive spatial planning process as implemented in the model

The main inputs for the BN-ABM are a cell-based representation of the current environment and the desires of the actors regarding the future state of this environment. Desires are basic elements that drive the knowledge sharing process. Based on Figure 1, the model is implemented according to the following procedure:

1. Agents generate beliefs about the current state of the environment based on their perception of it. They observe the environment and acquire information about its aspects related to a specific desire (observe/perceive arrows in Figure 1). This results in a set of beliefs accounting for the current state of the environment according to an individual agent. For example, a desire to realise new urbanisation near existing urbanisation requires information about the distance of each location (cell) to existing urbanisation. Consecutively, this information requires information on the areas that are regarded as urbanised by the agent.
2. The set of beliefs is evaluated by the agents using a utility function. This utility function combines the values of each cell (the preference for a certain distance) with the attached weight of the attributes (e.g. existing urbanisation).
3. The agents take turns in proposing a cell they want to be changed into a new urbanisation cell. They accomplish this by selecting the cell with the highest utility, given that is was not accepted before or already proposed in the former round. This proposal is communicated to the other agents (communicate arrows in Figure 1).
4. All other agents decide whether they accept this proposal by examining their own utility for that cell and comparing it with their threshold, the lowest acceptable utility. These decisions are brought forward (vision arrows in Figure 1) and the proposal is accepted when all agents agree upon it (decision market box in Figure 1).
5. The decisions and characteristics of the agreed cell serve as new evidence for the BN of the agents. As a consequence the CPTs of the nodes in the BN are updated, so that the relation between the cell characteristics and the decisions is strengthened.
6. The decision nodes are set to the desired state, the situation in which everyone cooperates, and the utility functions are updated using the new values (feedback arrow in Figure 1). Utilities of the agents will now be higher in areas where cooperation is anticipated. Additionally, utilities for the neighbouring cells are increased by 10% to favour a clustered over a scattered pattern.
7. The simulation stops when the objective is reached, i.e. the required area of new urbanisation is allocated, or when a deadlock is reached, i.e. in a predefined number of subsequent rounds no proposal is unanimously accepted.

The BNs are implemented in Netica (Norsys, 2009), a software product that offers Bayesian Network construction, evidence processing and inference. Figure 2 shows the initial configuration of one of the Bayesian Networks designed to represent three types of actors. The network belongs to an agent representing farmers involved in a spatial planning procedure with two other agents (citizens and nature-culture conservationists).

The lower three nodes show the values of the Farmers agent attached to certain distance ranges from a spatial object. The distributions over the states in the node 'DistanceVillages' for example indicates that the farmers prefer new urbanisation to be located far away from believed villages. The upper three nodes relate the distance distributions to the satisfaction of the network owner (Farmers agent), and the level of cooperation by the other agents (Citizens and NatureCulture). The possibilities for these nodes are a-priori evenly distributed, since the simulation has not started, so the agent has not learned anything yet. The network is updated using Bayesian inference when a proposal is made by an agent. This means that the characteristics of the proposed cell (the distances to the considered spatial objects) are related to the decisions and satisfaction regarding that proposal. Consequently, the CPTs change. After the updating, the upper three nodes are set to the desired situation, i.e. the agent itself is satisfied and the others cooperate, and the distance distributions belonging to that situation are exported and used to calculate the new utility maps.

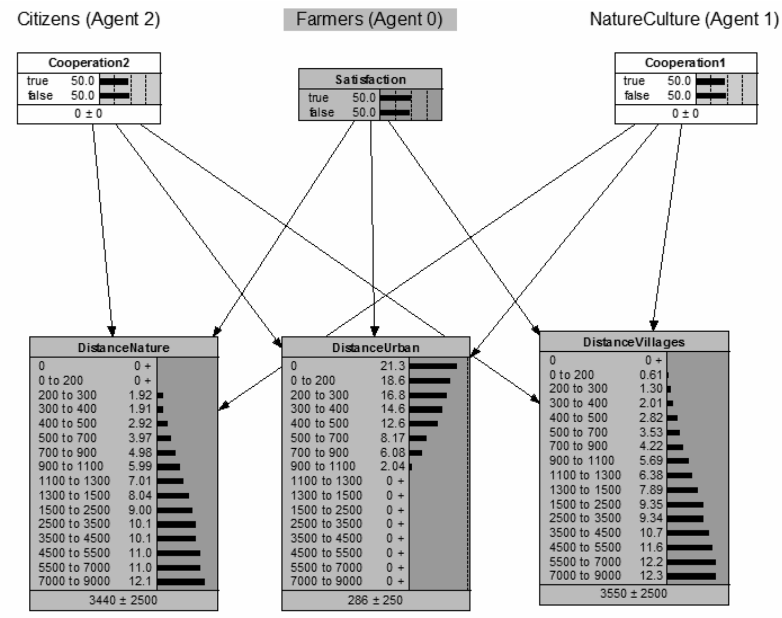

Figure 2: Initial Bayesian Network for the Farmers agent

RESULTS

The above described ABM was implemented in Repast (Repast, 2009) coupled with the Netica API (Norsys, 2009) for a hypothetical planning process for a study area in the 'Land van Maas en Waal', which is located in the Eastern part of the Netherlands (Figure 3). The area roughly consists of 66% pasture and 26% agriculture and, in addition, orchards are a prominent feature. The 'Land van Maas and Waal' has a number of small towns. Part of the study area belongs to the nodal point 'Arnhem-Nijmegen'. This generates pressure to supply new urban areas. Therefore, the question where to locate new urbanisation is highly relevant.

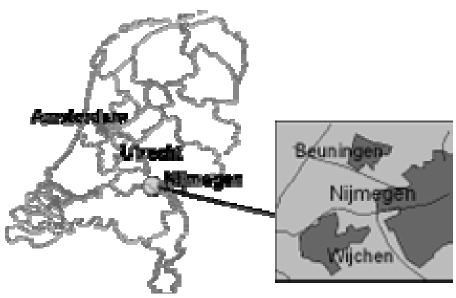

Figure 3: Study area

In this case study, three agents have been implemented, representing farmers', citizens' and nature-culture conservation organisations. Table 1 shows the desires that have been assigned to each agent. Based on these desires the agent observes the environment and specifies its preferences for new urbanisation using its utility function. In the Bayesian Network the desires are represented in three generalised classes about which can be learned (Table 1). A simulation is carried out in which these three agents have the objective to allocate 100 cells (representing 100 hectares) of new urbanisation. A deadlock is assumed to occur when the agents are unable to accept a proposal in 30 subsequent rounds.

Table 1: Desires of the agents

Role	**Desires**	**Category**
citizens	new urbanisation around present urbanised areas near forest and nature	urban nature
farmers	new urbanisation around existing urbanised areas not near present agriculture not near small villages	urban nature villages
nature-culture conservationists	new urbanisation not near nature areas not around 'historical' villages	nature villages

Given the current set of desires, the simulation results in a deadlock after 147 rounds and agreement on 47 cells. Figure 4 shows the locations for newly assigned urban areas. The allocated cells are mainly clustered around existing urbanisation in the south.

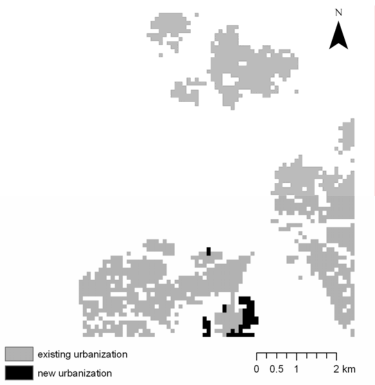

***Figure 4*: Newly assigned urban areas**

The resulting Bayesian Networks (Figure 5) show the cooperation and satisfaction of the agents averaged over the total simulation time. From these it can be derived that the farmers and nature-culture conservationists often cooperate (71% and 85% of the time), while the citizens are less cooperative towards them (54%), which denotes that the citizens were not willing to accept their proposals. This is also indicated by the fact that the citizens are about 23% less satisfied with the proposals than the other actors. The inferred distance distributions are comparable for the three agents, meaning that they have learned to generate proposals with similar spatial characteristics. Cells that exhibit the combination of the distances with the highest possibilities are most probable to be agreed on.

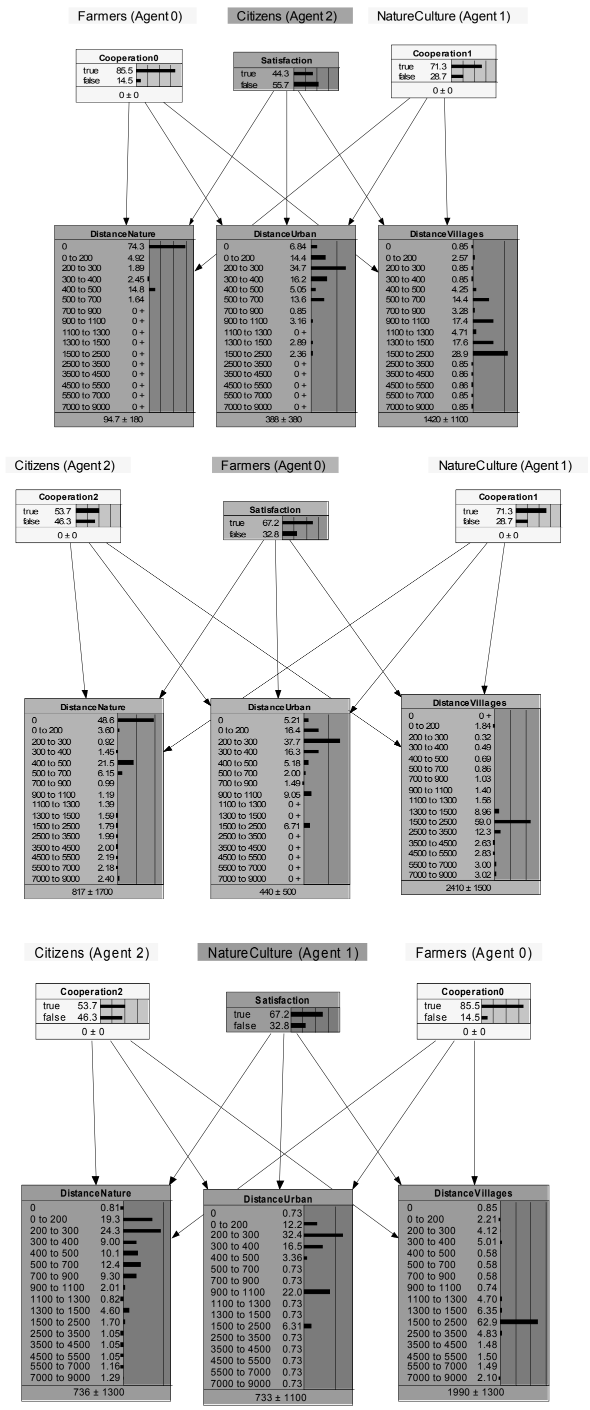

Figure 5: Resulting Bayesian Networks for the citizens (a), farmers (b) and nature-culture conservationists (c).

The initial (Figure 6) and final (Figure 7) utility maps illustrate the effect of the learning procedure in the Bayesian Networks. The citizens, for example, have become less determined to allocate cells directly alongside existing urbanisation. New urbanisation on agriculture (primarily located in the centre of the study area) is now more negotiable for the farmers than at first. The nature-culture conservationists have increased the utilities of areas close to existing urbanisation, because they have learned that the other two actors hold this desire.

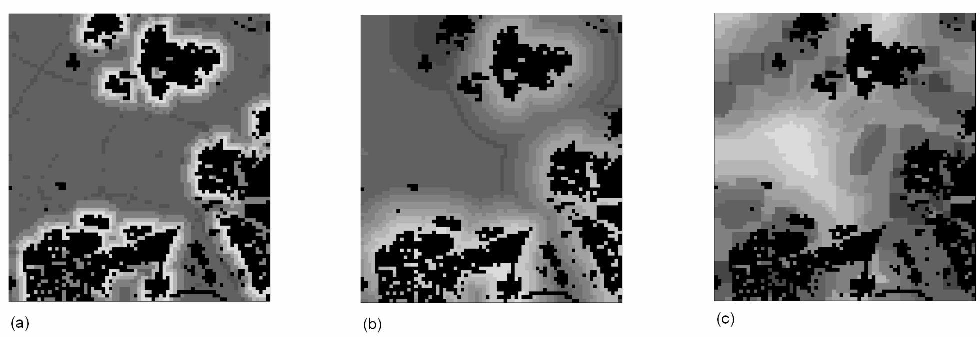

Figure 6: Initial utilities (t = 1) for the citizens (a), farmers (b) and nature-culture conservationists (c). Values range from zero (dark grey) to one (light grey). Black indicates existing urbanisation**.**

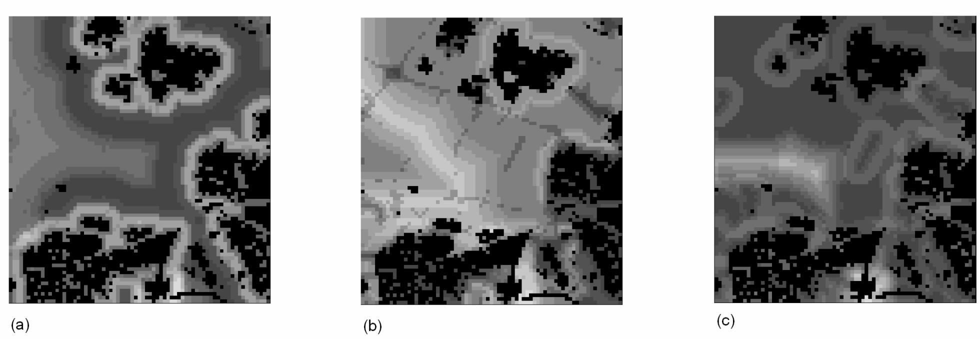

Figure 7: Final utilities (t = 147) for the citizens (a), farmers (b) and nature-culture conservationists (c). Values range from zero (dark grey) to one (light grey). Black indicates existing urbanisation.

DISCUSSION AND CONCLUSIONS

The initial and final utility maps (Figure 6 and Figure 7 respectively) illustrate that the agents have learned each others preferences and that their utilities converge. This conclusion is supported by the convergence of the mean values of the distributions in the three distance nodes throughout the simulation (Figure 8). The fact that the values of the agents diverge again at the end (especially evident in the 'Villages' graph) is a result of their incompetence to agree in the last 30 rounds. Although the actors reach an agreement for a new urban area, the joint objective of 100 hectare is not reached, given the current set of desires. When the agents concentrate on a certain area for a number of rounds, the networks converge towards the characteristics this area exhibits. The standard deviation becomes very low, which results in a narrow distribution over the distance states of nodes. This could be metaphorically explained as the agents becoming 'narrow-minded'. Consequently, all cells in the study area that do not have those particular characteristics obtain a very low utility. So, when expansion of the cluster is for some reason restricted, the allocation of new urbanisation in a different place has become almost impossible. This problem could be overcome by resetting the network when a deadlock tends to be reached, or by making the networks gradually forget some of what they have learned.

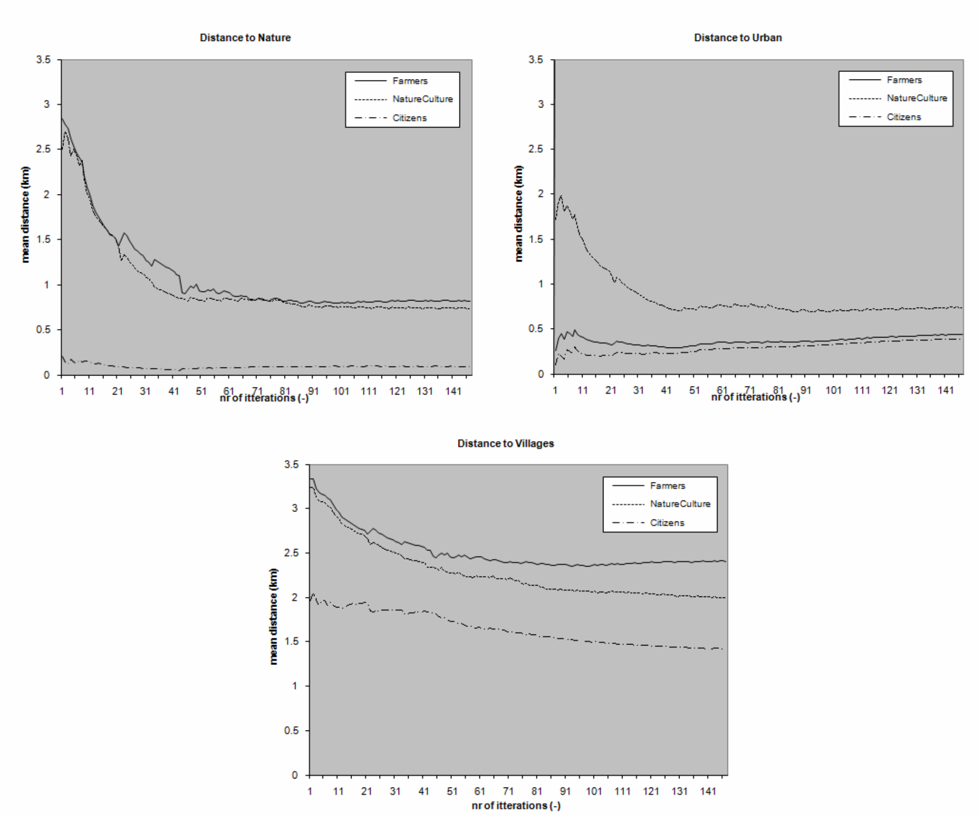

Figure 8: Mean values of the distance nodes

The innovation of the presented approach is the incorporation of Bayesian Networks in an agent based spatial planning model. This incorporation has resulted in a more natural representation of the actors. The beliefs of the agents are not static, but dynamic. They learn by taking into account experiences from the past and adapt their spatial preferences in such a way that the optimum between reciprocity and fulfilment of their own desires is anticipated. So, the agents have become adaptive, which accounts better for the complex adaptive system they are part of. In general, it can be said that now all four components of the regional dialogue approach (Mansfeld, 2003) are present, so that the entire spatial planning process is modelled.

Even though the model has implemented information gathering and learning, the social processes in the model are still far from realistic. The agents only learn 'silently' as they do not communicate about what they want and cannot give arguments for their proposals. In addition they will never be able to understand each others desires completely, because they hold different semantics (for example, from which size onwards a village becomes a city). A suitable concept and model of a multi-actor negotiation process is still lacking and will be a topic for further research.

The spatial reasoning of the agents within the Bayesian Network could be improved by facilitating the creation of new nodes, when new information becomes available. This would also partly solve the problem of the narrow-mindedness mentioned before. This is, however, a far more difficult kind of learning, since the agents would not have the methods to reason about the new feature and it will therefore need an adapted modelling approach.

Due to the explorative character of the research, the use of hypothetical actor stereotypes and an invented planning objective, validation of the proposed model is not accomplished. When the model is further developed, calibration and validation against an existing spatial planning case will become necessary. It is demonstrated however, that the use of Bayesian Networks and Bayesian inference offers an interesting and innovative approach to represent actor behaviour in a spatial planning decision making process.

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