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Cognitive Social Learners: An Architecture for Modeling Normative Behavior

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Abstract

In many cases, creating long-term solutions to sustainability issues requires not only innovative technology, but also large-scale public adoption of the proposed solutions. Social simulations are a valuable but underutilized tool that can help public policy researchers understand when sustainable practices are likely to make the delicate transition from being an individual choice to becoming a social norm. In this paper, we introduce a new normative multi-agent architecture, Cognitive Social Learners (CSL), that models bottom-up norm emergence through a social learning mechanism, while using BDI (Belief/Desire/Intention) reasoning to handle adoption and compliance. CSL preserves a greater sense of cognitive realism than influence propagation or infectious transmission approaches, enabling the modeling of complex beliefs and contradictory objectives within an agent-based simulation. In this paper, we demonstrate the use of CSL for modeling norm emergence of recycling practices and public participation in a smoke-free campus initiative.

Introduction

Large-scale public adoption of proposed solutions is a major barrier for addressing sustainability challenges including mitigating the effects of anthropogenic climate change, improving home energy efficiency, and effectively utilizing recycling options. A dilemma facing public policy planners is that these sustainability issues often fall under the category of "wicked problems" that aren't easily evaluated and offer reduced opportunities to learn by trial and error (Rittel and Webber 1973). Modeling and simulation can serve as important tools for exploring the unforeseen consequences of potential solutions. For instance, e-Policy, a decision support system for sustainable policy making, uses agent-based modeling to assess the impact of policy initiatives (Eaton, Gomes, and Williams 2014).

One research question is how to accurately model the influence of norms at governing the adoption of sustainable practices. Norms play a significant role in determining the behavior of people in human societies, and have been used as a computational mechanism for creating coordinated action within normative multi-agent systems. Previous work on modeling norm lifecycles can be organized into two categories: internal and external. In the first category, norms are characterized as arising from internal mental processes that can be specified using cognitive modeling techniques, and normative behavior is viewed as the outcome of internalizing external preferences. The normative agents are able to acquire new norms, rather than relying on preexisting constructs, and can deliberate about norm compliance autonomously (Criado, Argente, and Botti 2010). In the second category, the focus is on social interactions, and game-theoretic models are used to quantify the bottom-up process of recognizing and complying with norms in the external social system (Sen and Airiau 2007). Convergence occurs when agents arrive at a mutually agreed upon utility maximization strategy. A limitation of this type of system is that the agents lack a sense of normative expectation and do not distinguish between a strategy and a social norm (Savarimuthu and Cranefield 2011).

Our proposed architecture, Cognitive Social Learners (CSL), bridges the gap between these two types of architectures and provides a computational mechanism for transitioning behaviors learned during repeated social interactions into the agent's internal cognitive model of preexisting beliefs, desires, and intentions. Rather than modeling the normative lifecycle as a sequence of stages (e.g., recognition, adoption, compliance), CSL implements norms through an iterative process in which the normative behavior is developed incrementally within each agent's cognitive model before it emerges in consistent patterns of observable behavior.

Normative multi-agent systems are a powerful mechanism for modeling complex social problems, including energy consumption, water usage, and soil conservation. For instance, social norms have been found to affect enrollment in payment for ecosystem services (PES) (Chen et al. 2012). The general purpose of PESs is to provide incentives for participants who voluntarily decrease the amount of harmful activities to the ecosystem. Group-oriented strategies for cultivating sustainable practices, such as community-based social marketing, have been shown to be effective, because they emphasize the cultivation of community norms (McKenzie-Mohr 2013).

This paper presents a study of group normative behavior in a public environment; we illustrate how norm emergence under our hybrid CSL architecture differs from the performance of a cognitive architecture (NBDI), a social learning only model (SL), and a specialized single-behavior normative system for modeling smoking cessation trends (LNA).

Related Work

We selected littering/recycling behaviors for our initial study as a good example of a sustainable practice governed by a combination of social norms, environmental factors, habit, and personality differences. Savarimuthu et al. (2009) also used a littering scenario to demonstrate the operation of their normative multi-agent system. Based on human subjects studies, Schultz et al. (2013) note that the presence of litter positively predicts future littering behavior; unsurprisingly, the availability of trash receptacles is negatively correlated with littering. The next sections present an overview of cognitive (internal) and interaction (external) normative systems.

Cognition-based Approaches

These methods provide high-fidelity models of the cognitive aspects of normative behavior, while focusing on the internal part of the norm lifecycle (Elsenbroich and Gilbert 2014). In comparison with the interaction-based models described in next section, this category relies less on the use of reward and punishment to motivate norm adoption, moving beyond the carrot and stick approach (Andrighetto and Villatoro 2011). For instance, the EMIL architecture includes a dynamic cognitive model of norm emergence and innovation (Conte, Andrighetto, and Campennl 2013). The main disadvantage of EMIL is that the agents obey all recognized norms blindly without considering their own motivations (Criado et al. 2010). However, these architectures can model norm internalization in which agents manifest behaviors, not because of existing rewards or punishments in the environment, but as a personal objective (Andrighetto, Villatoro, and Conte 2010).

Norm internalization is sometimes implemented via emotions (Criado et al. 2013) and is very closely related to deliberation. Dignum et al. (2000) presented an architecture that allows agents to use deliberation to decide when to follow or violate norms. The agent generates behavior by creating and selecting goals on the basis of beliefs and norms, before choosing actions and plans according to the selected goals. The deliberation can also be implemented with a modified BDI interpreter loop that takes norms and obligations into account (Dignum et al. 2000). A weakness with these models is that they devote less attention to norm emergence at the population level.

Like our proposed CSL architecture, several existing normative architectures also use BDI reasoning as a core component. For instance, the BOID architecture (Broersen et al. 2001) adds the notion of obligation as a fourth element to the original belief, desire and intention model. Normative BDI (Criado, Argente, and Botti 2010) extends the multi-context BDI architecture (Sripada and Stich 2005) which includes two new functional contexts (planner and communication) to support normative reasoning with additional contexts (recognition and normative). In this paper, we evaluate our proposed CSL architecture vs. NBDI.

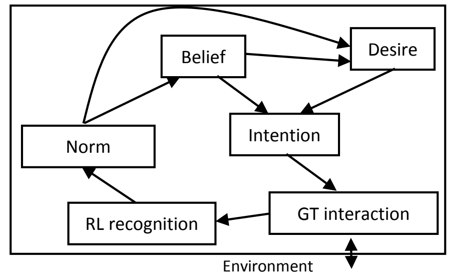


Figure 1: Cognitive Social Learners (CSL) Architecture

Interaction-based Approaches

Interaction-based approaches create agent models that can detect norms from what they observe in the environment and their interactions with other agents. Often the agents are equipped with the ability to learn from experience, and interactions among agents are modeled as repeated games with payoff matrices. The simplest interaction approach is to imitate other agents in the environment —"while in Rome, do as the Romans do." For instance, Andrighetto et al. (2008) present a normative model in which the agents mimic the majority behaviors; this type of agent is commonly referred to as a social conformer. Generally these imitation agents lack high-level reasoning and decision making abilities.

Social learning (Sen and Airiau 2007) offers a richer model of norm emergence. In social learning, agent interactions are modeled as a staged game (the social dilemma game). A norm emerges when the entire population's actions converge to the same action, based on updates to the payoff matrix specifying the reward for the possible actions. Several variants of multi-agent reinforcement learning have been demonstrated for this interaction model. However, a general concern that exists about this family of repeated game interaction models is that 1) they do not capture many of the rich interactions that take place in real world scenarios and 2) can fail to converge when the agents have a large action-space (Andrighetto et al. 2013).

Method

This paper introduces a new architecture, Cognitive Social Learners (CSL), that includes components from the two categories of normative architectures, and presents a cohesive model for modeling the emergence of norms related to sustainable practices. Figure 1 shows a schematic view of CSL. In this architecture, the belief, desire and intention components implement the cognitive aspects of norm formation, while the game theoretic (GT) interaction and reinforcement learning (RL) recognition parts implement the social aspects.

We will use a littering scenario as an explanatory example, to describe the proposed architecture's elements. Later, in the experiments section, this scenario is used to evaluate the performance of the CSL architecture at modeling norm emergence. The example scenario relates to people who visit a park. They have five possible actions: littering, recycling, violating park rules regarding animal feeding, violating park rules by trespassing on the foliage, and performing no action.

The representation used for the BDI components and the norms is based on a simplified version of the framework introduced by Casali, Godo, and Sierra (2008) and Criado, Argente, and Botti (2010) in which a certainty degree is assigned to each representation. For example, $(D^{-}\text{payfine}, 0.45)$ designates a negative desire toward paying a fine with a certainty degree of 0.45.

Belief, Desire, and Intention

The CSL architecture follows a classic BDI structure. Like many normative architectures, each agent is initialized with a set of personal values that model innate preferences. In CSL, these personal values are used to create type 1 beliefs that have a certainty equal to 1; for instance $(B[happiness = 50], 1)$ indicates that the personal value of the agent regarding happiness is equal to 50. The other type of beliefs (type 2) model the agent's actions, represented as $(B[\alpha]\varphi, \delta)$. $(B[littering]botherRest, 0.30)$ indicates that the agent believes, with certainty of 0.30, that littering would bother the other agents.

Desires can be determined independently or based on the agent's beliefs. Desires are represented as $(D^{*}\varphi, \delta)$, which models the positive or negative ($* = \{-, +\}$) desire of an agent regarding state φ with certainty of δ. An agent may update its desires when its beliefs changes. This process is shown in Equation 1; the certainty value of desire D is updated based on function f, which is is a user-defined function.

$$((D^{*}\varphi, \delta_{\varphi}), (B[\alpha]\varphi, \delta_{\phi})) \Rightarrow (D^{*}\varphi, f(\delta_{\varphi}, \delta_{\phi})) \tag{1}$$

Intentions are derived from the set of positive desires, if they have a certainty value higher than sum of the certainty values of all negative desires relevant to the intention. Equation 2 shows this:

$$\begin{aligned} ((D^{+}\varphi_{i_1}, \delta_{\varphi_{i_1}}), ..., (D^{+}\varphi_{i_n}, \delta_{\varphi_{i_n}}), (plan_j, \delta_j)) \\ \Rightarrow (I_k, f(\delta_{i_1}...\delta_{i_n}, \delta_j)) \end{aligned} \tag{2}$$

while $\Sigma(\delta_{i_1}...\delta_{i_n}) \geq \Sigma(\delta_{l_1}...\delta_{l_n})$ and $_{l_1}$ to $_{l_n}$ are indices of negative desires toward effects of I_k. According to this formula, the set of positive desires (from i_1 to i_n) and plan j will determine the intention k based on a user defined function f. In the littering case, an agent might have positive desires toward higher happiness and spending less effort, but negative desires toward paying a fine and being observed by others. In this case, if the sum of certainty values for happiness and spending effort is more than the sum of certainty values for paying the fine and being observed (assuming that littering is part of the agent's current plan), it will litter.

Game-theoretic Interaction

Instead of deciding its actions based on intentions alone, which is often the case in BDI-based methods, the agent's final action is determined after playing a social dilemma game with one of its neighbor agents. The maximum certainty value of available intentions is used to create a two-by-two matrix. The two possible actions are performing or not performing that action. After calculating the payoff value for an action based on the related intentions, fixed values of α and β are used to increase the value of the elements in the matrices representing coordinated action (the agent and its neighbor selecting the same actions) (Easley and Kleinberg 2010). Example of this matrix for the littering scenario are shown in Table 1.

	L	NL
L	$\iota+\alpha$	ι
NL	ι'	$\iota'+\beta$

Table 1: Example payoff matrices for the littering (L=litter, NL=not litter). ι shows the computed payoff value for littering. ι' is the payoff for not littering.

Based on the outcome of played games, an agent decides what action to perform. What an agent observes after performing an action may cause an agent to update its personal values (type 1 beliefs) and learned norms, which in turn modifies its behavior in subsequent steps. For instance, in the case of our example scenario, after littering, an agent's happiness value will increase; or if there is a punisher in its vicinity, its paid-fine value will increase.

Norm Recognition using RL

The goal of this component is to construct a practical way of recognizing/learning norms, while connecting different components of the architecture. Our RL based recognition component plays the role of a hub among norms and personal values (beliefs) on one hand and the game theoretic interaction on the other hand.

The combination of GT interaction and RL based recognition components is used to implement the social learning process which propagates norms across the agent population. The aim of the social learning framework is different from similar processes in the domain of multi-agent reinforcement learning, in which agents play iterative games to learn a policy resulting in a competitive or cooperative equilibrium. Sen and Airiau (2007) note several differences between social learning and multi-agent RL, including the lack of equilibrium guarantees. At every timestep, each agent interacts with a single changing agent, selected at random, from the population. The payoff received by the CSL agent depends only on this interaction. We use a basic Q-learning algorithm for recognizing norms in which states are the discretized current values of an agent's payoff matrices. Learning results in modifications to the certainty degree of available norms. Rewards are calculated based on the changes in the personal values.

Norms

The process of recognizing a social norm is modeled by an agent increasing the norm's certainty value to a positive value. The agent updates the certainty values of norms based on its observations after performing an action. Our norms are represented using the format introduced in Criado et al. (2013), $\langle \Delta, C, A, E, S, R \rangle$, in which

Δ designates the type of norm, C is the triggering condition, A and E show the activation and expiration period of the norm, and S and R indicate a reward or sanction. For example, this is an example of a possible norm: $(\langle \text{prohibition}, \text{littering}, -, -, \text{payfine}, - \rangle, \delta)$, which is always valid since there is no duration on activation, A, and expiration, E.

All of possible norms are initialized at the beginning of the simulation with the certainty value of zero. Agents update their norms by increasing or decreasing the certainty value of each norm after making an observation. For instance, if the agent receives a fine after littering, it will update its current value of (δ) in the above norm example with $(\delta + \epsilon)$, where ϵ is a user defined value.

An agent's current norms are used to update its beliefs and desires. The updating procedure is shown in Equations 3 to 5. Here, norms are abbreviated as N instead of $\langle \Delta, C, A, E, S, R \rangle$ in order to shorten the formulas. Here, if there are any relevant rewards R (or sanctions S), the positive desire D^+ (or a negative desire D^-) will be updated. f functions are user defined functions.

$$((N_i, \delta_N), (B[\alpha]\varphi, \delta_\phi)) \Rightarrow (B[\alpha]\varphi, f(\delta_N, \delta_\phi)) \quad (3)$$

$$((N_i, \delta_N), (D^+\varphi, \delta_\varphi), R \neq \varnothing) \Rightarrow (D^+\varphi, f(\delta_N, \delta_\varphi)) \quad (4)$$

$$((N_i, \delta_N), (D^-\varphi, \delta_\varphi), S \neq \varnothing) \Rightarrow (D^-\varphi, f(\delta_N, \delta_\varphi)) \quad (5)$$

As an example, if there exists the norm $(\langle \text{prohibition}, \text{littering}, -, -, \text{payfine}, - \rangle, 0.75)$ and a negative desire toward paying fine $(D^- payfine, 0.55)$, assuming the agent has just paid a fine for littering $(S \neq \varnothing)$ with $f = \min(\max(0.75, 0.55), 1)$, the resulting updated desire would be $(D^- payfine, 0.75)$.

Experiments

To demonstrate the utility of our normative architecture at modeling the adoption of sustainable practices, two case studies are presented. In first case study, we evaluate the performance of CSL at simulating norm emergence in a park scenario, as compared to the normative BDI (NBDI) and social learning (SL) architectures. The second case study is designed to evaluate the ability of CSL to model the propagation of norms in real-world environments. We compare the performance of our proposed architecture with an existing architecture for simulating the propagation of smoking norms.

Park Case Study

This case study is designed to recreate the frequently observed "tragedy of the commons" in which humans are moving through a public area like a park and have the option to improperly dispose of trash and recycling on the ground, stow their waste for future disposal, or proactively recycle objects dropped by other passersby. Additionally, there are two other actions that the agents can perform, which are violating park visitor rules by feeding the animals and trespassing on the grass. Among this set of actions, littering, feeding animals and walking on the grass are negative, but potentially contagious, behaviors. Our scenario is a useful model for describing many public policy social dilemmas, and is more complicated than the *rules of the road* scenario, often used to simulate the emergence of driving conventions.

Agents - In this scenario, the agents have the following action selections: litter, recycle waste, violate park rules by feeding animals, violate park rules by trespassing on grass, or take no action. For these experiments, we fixed the population size at 1000. There is an observable vicinity defined for each agent. Within that range an agent can observe other agents' actions. A certain percentage of agents are assumed to be punishers (20 percent), which means they will punish agents who litter, feed animals, and walk on the grass, if those agents perform these actions in their observable area. Moreover, recycling while there is someone to observe the agent, will increase the reputation of agent.

Beliefs, Desires, and Intentions - Each agent has a set of beliefs, desires and intentions. Also, as part of its beliefs, each agent has a set of personal variables: *happiness*, *park usability*, *reputation*, *spent time*, and *paid fine*. The certainty values (δ) for beliefs and desires are assigned uniformly at random at the beginning of the scenario. Intentions are derived from the set of beliefs, desires and plans. The intentions are determined according to Equation 2.

Payoff Matrices - In both CSL and SL, the agent plays a game with the closest agent within its observable area each time that it needs to make an action decision. For each action, an agent has a two by two payoff matrix that determines the agent's decision. The agent picks the intention with the highest certainty value. The values of this payoff matrix are determined by the certainty degree of the selected intention, as described in the method section. This means that in our architecture, the intentions do not directly determine agent's actions, instead they define payoff matrix values. For instance, each time that an agent generates a piece of trash, and needs to decide whether to litter or not, it uses its littering payoff matrix, and plays a social dilemma game with the closest agent. Similarly, every time that the agent observes garbage in its vicinity it uses its recycling payoff matrix to decide whether to recycle the garbage or not. Since the agents move through the park in a random walk, they have the possibility of encountering new agents during every round.

Q-learning - The learning component is implemented using the Q-learning algorithm. The current values of the payoff matrices determine the states of the Q-table. The selected action modifies the certainty value of norms. After an agent performs an action, it observes the consequences of its action to compute the overall received payoff, which is then used to update the Q-table. Each of the agent's actions increases or decreases agent's personal variable values according to a fixed formula applied to all agents in the scenario. For example, littering would increase *happiness*, but would decrease *park usability*. Littering decreases *reputation* when there is an agent in the vicinity; in the presence of a punishing agent, the offending agent pays a fine.

Norms - All possible norms are initialized as having a certainty value of zero. During initialization, we create all of possible norm combinations based on the introduced norm representation: $\langle \Delta, C, A, E, S, R \rangle$. The type of norm and its reward or sanction nature can be determined by the value for C. We assume that all norms are always valid during the experiment, so we don't need to take A and E into account. Thus 24 possible norms are defined for this scenario: |obligation, prohibition, permission|*|littering, recycling, feeding animals, walking on grass|*|reward, sanction|.

Figure 2 shows the pseudocode describing an agent's behavior for one time-step in the CSL implementation. The certainty value of beliefs and desires are initialized uniformly at random at the beginning of the scenario.

```
init(blf, des, pln, q-tbl)
repeat
    generateIntention(blf, des, pln)            ▷ Equation 2
    updatePMatrix(maxIntention)
    if (converged-Qtbl) then
        playGame(pMatrix,neighbors)
        performAction()
        update-qTable(rew, san)
    else
        performAction()
    end if
    update-norms(rew, san)
    update-beliefs(rew, san, norms)             ▷ Equation 3
    update-desires(rew, san, norms)   ▷ Equation 1, 4 & 5
until agent not selected
```

Figure 2: CSL pseudocode
(blf=Beliefs, des=Desires, pln=Plans, rew=Rewards, san=Sanctions)

Results - Our proposed framework (CSL) was compared against two other benchmarks. The first one, NBDI, is a version of the normative BDI architecture described in Criado, Argente, and Botti (2010), and the second one, SL, is the social learning framework introduced in Sen and Airiau (2007). In order to make a fair comparison between different architectures, the NBDI and SL frameworks are implemented by removing some of the components of CSL. The NBDI benchmark does not play the social dilemma game and does not use reinforcement learning to generate and update norms. In this case, intentions determine actions, and then the norms are updated based on the feedback received from the environment. Note that the way that the norm representation was implemented (by modifying the certainty value of norms) is not part of the original version of NBDI. The norm recognition part in the original NBDI was assumed to work as a blackbox, and there was insufficient detail about its implementation to recreate it. Hence we simply used the same norm recognition structure for both CSL and NBDI. For the SL framework, each agent has payoff matrices, and updates them using Q-learning. SL lacks the BDI representation, as well as the internal features and explicit norm representation. Results are presented for an average of 20 runs of the social simulation.

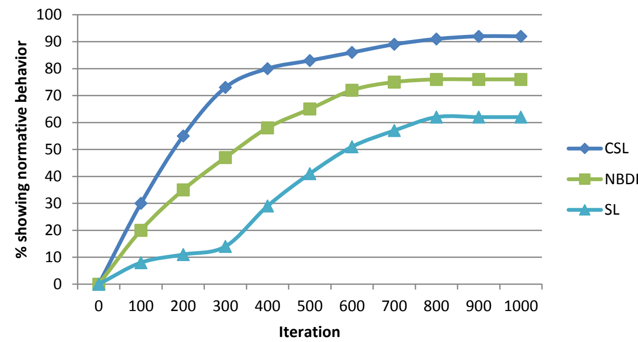


Figure 3: % of agents exhibiting normative behaviors

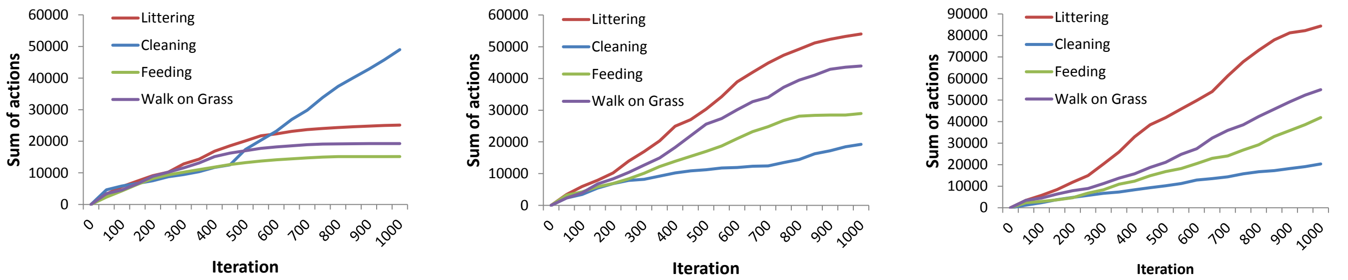
The percentage of agents demonstrating normative behavior is shown in Figure 3. The purpose of this experiment was to study the overall ability of the agent population to recognize and adopt to social norms. For each agent, normative behavior is assumed to be occurring when more than 90 actions of the agent's last 100 actions are normative actions. Normative actions refer to: recycling, not littering, not feeding animals and not trespassing on the grass. Obviously, only when the agents have the possibility of performing these actions, their action is counted. For instance, only when an agent is close to animals, it can feed or not feed them. As the chart shows, a greater percentage of the CSL agents evince normative behavior, compared to NBDI and SL.

Figures 4a, 4b and 4c illustrate differences between the cumulative normative vs. non-normative actions that were performed by a population of 1000 agents averaged over 20 runs of the models. The main goal of this experiment was to evaluate the ability of each method to propagate conformity to social norms. In all cases, the sum of all action types initially rises. In the CSL case, growth of non-normative behaviors reaches an asymptote while performance of the (normative) recycling behavior rises sharply. In NBDI and SL, the amount of recycling is low compared to the other behaviors. Moreover the speed and extent of norm emergence exhibited by CSL is more than the NBDI and SL methods.

Smoking Cessation Case Study

The performance of the CSL architecture was also measured in a real-world scenario, modeling the propagation of smoking cessation norms after a smoke-free campus initiative. Here we compare CSL vs. LNA (lightweight normative architecture) that was developed specifically for modeling normative smoking behavior (Beheshti and Sukthankar 2014).

The LNA architecture follows the classic three stage norm lifecycle (recognition, adoption, and compliance) and utilizes a continuous variable (smoking value, SV) between 0 and 100 to determine the current stage of the agent. We use the same structures as the original work, and apply the CSL architecture to this model. LNA uses a set of defined personal characteristics (individualism, achievement, regret,



(a) CSL (b) NBDI (c) SL

Figure 4: The recycling (cleaning) norm only strongly emerges in CSL, not in NBDI and SL.

health and hedonism); these characteristics were expressed within CSL as fixed value elements of beliefs (Type 1).

In order to have a fair comparison between the two methods, we modified the original model as little as possible. In addition to comparing CSL with LNA, we also examine the performance of the NBDI architecture on this dataset. Since LNA includes a component very similar to the social learning method, the SL method was not implemented independently.

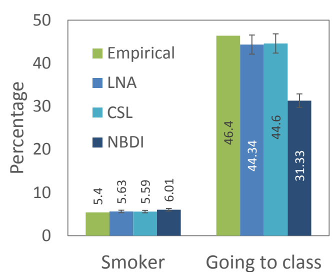


Figure 5: **Left**: % of predicted smokers vs. empirical data. **Right**: the % of predicted students willing to participate in smoking cessation classes vs. empirical data from Fall 2012.

Figure 5 shows the comparison between the number of students who were smokers and students willing to attend smoke cessation classes. The performance of CSL at predicting the actual adoption of the smoking cessation norm is comparable to the specialized smoking model (LNA) and superior to NBDI.

	Beta	p level
CSL	0.22	0.001
LNA	0.001	0.007
NBDI	-0.01	0.005

Table 2: Standard coefficient (Beta) values of the applied linear regression to perceived social acceptability of smoking (independent var.) and quit intention (dependent var.)

Table 2 shows a comparison between the different architectures at predicting the perceived social unacceptability of smoking. This phenomenon is reported in many smoking studies including Dotinga et al. (2005) and Hammond et al. (2006) as occurring when smoking bans exist in human cities. Brown et al. (2005) shows that perceived social acceptability of smoking among referent groups is independently associated with both strength of intention to quit and actual quitting behavior.

In the LNA architecture, it is assumed that an agent has the intention to quit smoking if its smoking value (SV) is within a certain range. The social unacceptability of smoking across the population of agents is determined using the value for one of the agent's personal characteristics (IND). The value of this factor was initialized based on data from a survey question asking whether the participant believes smoking is acceptable on campus. Following the works mentioned above, a linear regression model was used to examine the relationship between these two elements, and the standard coefficient (Beta) value of the applied linear regression is shown in Table 2. The CSL model produces a positive Beta value, which is consistent with the real-world data. This shows that, using CSL, agents are able to reason about the socially perceived unacceptability of smoking behavior, and modify their behaviors accordingly. Therefore, CSL is modeling norm emergence in a more realistic manner. On the other hand, the Beta values for the LNA and NBDI architectures is close to zero, which does not accurately reflect the results reported in independent smoking studies.

Conclusion

Normative multi-agent systems are a promising computational mechanism for representing group influences on human social behavior and creating large-scale social simulations for a variety of interesting public policy questions. The paper presents a normative architecture, Cognitive Social Learners, that bridges the gap between two lines of research on norms. We benchmarked our architecture against three other models (NBDI, SL, and LNA) at predicting the adoption of sustainable practices. Our results indicate that the CSL architecture is more robust than models that rely exclusively on internal or external processes at modeling norm emergence in complex real-world scenarios.

Acknowledgments

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