Social machines for education driven by feedback agents

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Abstract. The aim of this paper is to explain some of the ways in which multi agent system (MAS) theory can be used to describe, design and enhance *social machines* (also referred to as *Socio-Cognitive Systems*). We believe there is a really opportunity for the MAS community to engage with emerging theory and practice of designing such systems. *Social machines* - also referred to as *Socio-Cognitive Systems* from the MAS community - are terms used to refer to the recent breed of technological systems which allow human and computational agents to socially interact, typically on a large scale and sometimes towards achieving shared goals. Examples include social networking platforms and crowd sourced encyclopaedias. The discussion of social machines and MAS is taken from three perspectives. Firstly, the theoretical notion of an abstract social machine as a socio-cognitive system containing humans and agents is introduced. Secondly, a specific instance of a social machine which has been designed to enable social music learning supported by agents is described. Thirdly, an agent architecture which is designed for operation within educational social machines is discussed, with particular focus on what we believe is the core currency of these machines: feedback.

Keywords: Social Machines, Socio-Cognitive Systems, Feedback Agents, Social Music Learning

1 Introduction

The aim of this paper is to explain how multi agent system (MAS) theory can be used to describe, design and enhance social machines. From here on in we will use the terms *social machines* and *socio-cognitive systems* interchangeably. The first term coming predominantly from the web-community in the UK whilst the latter term arises from a continental definition from within predominantly normative multi-agent systems community.

Using the specific example of an educational social machine being developed by the authors as part of an ongoing major European research project, it is shown how an MAS approach can be used to inform the design of such systems in order to better enable the human users to achieve their educational goals. The key questions addressed here are: how can social machines be described from an MAS perspective? what is a specification for a real, educational social machine? how can an agent based modelling approach be used to encourage and motivate humans operating within an educational social machine?

An MAS description of social machines. Social machines are systems which have large numbers of rational agents, each with the ability to model the other agents in the system, and that interact in order to achieve shared or individual goals. Taking the example of wikipedia, there are human agents who add and edit articles; there are software agents which perform basic formatting checks on newly edited articles and inform the authors where errors are found; there are a range of goals such as providing a free encyclopaedia, forcing one's opinion into the encyclopaedia and ensuring that articles conform to formatting guidelines. This description will be developed further later down where we provide a tentative list of characteristics of these systems.

1.1 Motivation for the MAS perspective on social machines

There has been substantial work on systems that involve humans and computational devices of different sorts. Three lines are quite representative of mainstream trends: (i) Tightly-coupled human artificial realities. Like the case of Augmented Reality, Internet of Things, and Pervasive and Ubiquitous Computing. (ii) Human-robot interactions, whose objective is mostly to enhance quality of life or to study affective relationships, usually as a pairwise relationship robot-human not always supported by a digital environment. (iii) Immersive environments and gaming where the focus is mostly in the engaging qualities of the environments. Although these three lines share features with the type of work we present here, we prefer to place this work in the space described by Castelfranchi [6] and others as (artificial) "socio-cognitive multiagent systems". A denomination that wishes to underline the distinctively social behaviour of the rational individuals involved in collective interaction. The main point being that in order to design and deploy theses systems, or to study them, one needs to "*understand and reproduce features of the human social mind like commitments, noms, mind reading, power, trust, institutional effects and social macro-phenomena*" [4]. Without going into details here –Section 2.1 has some— we should mention the key features of these socio-cognitive systems:

1. They involve two distinct type of entities: on one hand the social space and on the other the agents that participate in that space.
2. Agents may be humans or artificial entities.
3. Interactions are somehow constrained by the social environment.
4. Agents actions may affect and may be affected by the environment and by the actions of other agents.

This characterisation reflects the influence of the normative multiagent systems tradition and points to the abundant literature on that tradition that includes general outlooks like [2] as well as specialised contributions that range from cognitive dispositions [21, 1], formalisms [11], methodlogical discussions [12] and simulation, metamodelling and software engineering [5, 10]. When the focus of a work is put in the agents, rather than their social environment, (like in [26, 3]) the preferred term has been "social machines" as is the case in this paper.

1.2 Related work in the field of agent organisation, pedagogical agents and social learning

In this subsection, some literature relating to the three main themes of this paper is reviewed. The themes are systems which aim to organise agents and humans, systems for social learning and pedagogical agents.

There is extensive work around e-earning systems, but social e-learning systems which emphasise the social interactions between members of a large learning community are a less studied area. The Massive, Open Online Course (MOOC), considered to have emerged into the popular imagination in 2012, has injected energy and funding into this area [19]. Areas of interest include the far reaching such as the appropriate pedagogical underpinnings of MOOCs [13] and the more practical, e.g. how to deal with the high dropout rates [7]. Liyanagunawardena et al. present a review of MOOC publications through to 2012, showing the rise of this field [14].

The creation and evaluation of pedagogical agents has been a popular research topic. Let us review some of this work taking as a starting point this question: What is the purpose of the agent and is it pro-active, reactive, conversational or argumentative? Skiar et al. present a review of work where agents are used to supporting learning [22]. The researchers define three main trends in the field: pedagogical agents, peer learning agents and demonstrating agents. According to Soliman and Guetl, Intelligent Pedagogical Agents (IPAs) can help learners by 'providing narrations ... creating adaptive dialogues with the learner to improve learning situations, provide guidance, resolve difficulties, and improve motivation' [23]. Quirino et al. implemented a case based reasoning driven IPA for training medical students. They define the following important characteristics: domain-specific knowledge, autonomy, communicability, learning, reactivity and pro-activity, social skills, customization, and learning abilities [20]. Magus et al. describe a math tutoring game which includes a conversational agent [17]. They have explored aspects of the visual embodiment of the agent as well as its conversational capabilities. The conversation can occur in a a focused, on topic mode mediated through multiple choice questions and a free, off topic mode. Agents capable of argumentation are beginning to appear in the education technology literature. In 2009, Tao et al. presented a pilot study where agents and learners engaged in learning through argumentation around the topic of food chains (e.g. tiger eats sheep eats grass) [25]. The user interacts with the agent through keyboard, mouse and text to speech conversion (agent talks to learner) and the agent is capable of engaging in various types of dialogue. The researchers found preliminary evidence that the learners enjoyed interacting with the arguing agent.

Leading towards our interest in agents which can support social learning, in [24], an agent based approach is used to simulate interactions between learners within a group. A parameterised learner model is presented which includes features such as ability, emotion, motivation (inc. competitiveness), learning rate, understanding, 'likeliness to help' and progress. Instances of the model are run in simulation and characteristic observed in real groups of learners are observed, such as the importance of group composition, team size and team rewards.

1.3 Structure of this paper

The paper consists of 3 main parts: in section 2 the theoretical notion of an abstract social machine as a Socio-cognitive system containing humans and agents is introduced. In section 3 a specific instance of a social machine which has been designed to enable social music learning supported by agents is described. In section 4, an agent architecture which is designed for operation within educational social machines is discussed.

2 Perspective 1: A Theoretical description of Social Machines

The aim of this section is to provide a description of the characteristics of Social Machines (Socio-Cognitive Systems) using MAS terminology and is taken from [18, 27].

2.1 General characteristics of social machines

1. The system contains agents. Agents are either computational or human and can exhibit purposeful behaviour.
2. The population with a system may be a mix of human and software agents.
3. The agents have a model of the world in which they operate.
4. The agents within the system are rational in that they are capable of choosing different courses of action based on their own models (however simple or complex these may be).
5. The agents are social in that they interact with other agents.
6. The agents are have social models (either complex or simple) of some of the other agents in the system,
7. At least some of the agents are socio-cognitive in the sense that they based their decisions on some decision-making process which takes into account the models of the social world in which they are situated. This includes the capability to plan for future desired states in the environment whilst taking into account the motivations and models of other agents. Such agents can reason about who to collaborate with other agents to achieve individual and joint goals.
8. The agents have social capabilities including potentially awareness and models of others, an ability to understand the norms of a system and adopt attitudes relating to norm-compliance and the ability to have altruistic goals

9. Any such system is defined by the system of interacting agents which means that the state of the system can never been known in full as there is no general access to the internal state of agents. This is often referred to as opacity.
10. Agents may enter and leave a social machine at any time. It cannot be known either by the designer of the system or by other agents which agents may join or leave. Agents may often be able to join or leave without it being known to other agents.
11. Such systems as regulated either intrinsically because of the way the system is designed, the way that some agents have been specified to operate or naturally through the agreement of agents within the system. The point about regulated systems is that not all actions are available to all agents at all times which enables more effective social coordination to be facilitated.
12. Agents are autonomous and so march to the beat of their own drum and so are not necessarily socially-considerate, benevolent, or honest and so may fail to act as expected or desired or promised.
13. All interactions are mediated by technological artefacts and may therefore be wrapped as communicative acts or messages. Systems that have this property are referred to as dialogical.

This list attempts to reflect the recent discussion on 'socio-cognitive systems' arising largely from work and discussions made possible through the Sintelnet project.

3 Perspective 2: A Social Machine designed for Music Learning

The aim of this section is to describe a specific instance of a social machine from an MAS perspective. The music circle platform is a social machine which is being developed as part of a major European research project. The main aim is to increase peoples' access to and engagement with the practicing of music. The resulting technological system has also been designed to be used as a research platform in order to explore some of the ideas discussed in this paper, amongst others. The core activity of users in the platform is to record themselves playing musical instruments, traditional or otherwise, alone or in groups, to share the recordings online with communities of interested folk then to discuss the recordings in a highly social fashion. Figure 1 contains an annotated screen shot of the current version of the platform. The key features are the media item (in this case an audio recording) at the top of the page then the social timeline showing user annotations connected to specific regions of the timeline of the media item, shown below the media item.

The intention was to develop a system which did not aim to replace existing teaching methods but to be embedded within them in a blended learning model. To this end, it was developed through a process starting with teaching observations, teaching analysis then a participatory design phase, as illustrated in figure 2.

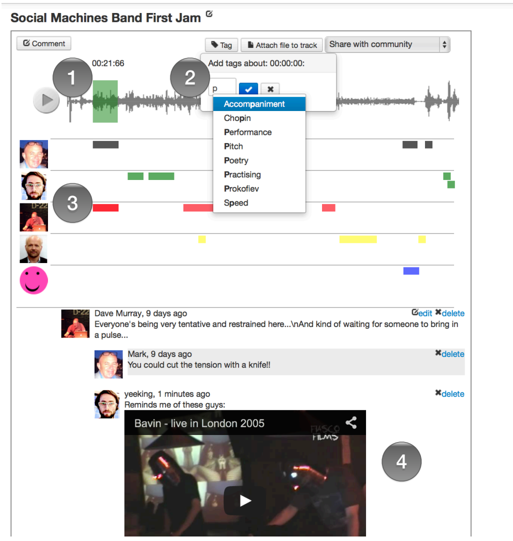

Fig. 1. The music circle media discussion interface. 1) The waveform display, showing a highlighted region, 2) The tagging dialogue, showing a drop down list of pre-used tags 3) The social timeline, showing sets of time linked comments created by several users 4) a discussion thread based on a single region in the recording, including an embedded youtube video.

One of the key outputs of this process was as set of flowcharts describing the social interactions that occurred in archetypal 'teaching patterns'. Figure 3 is an example flowchart representing a lesson where a student performs a piece of music to their peers and a teacher and then receives feedback.

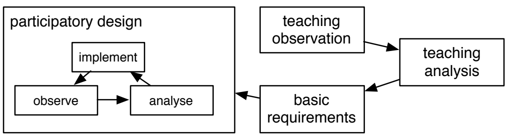

Fig. 2. The 4 phases of platform development

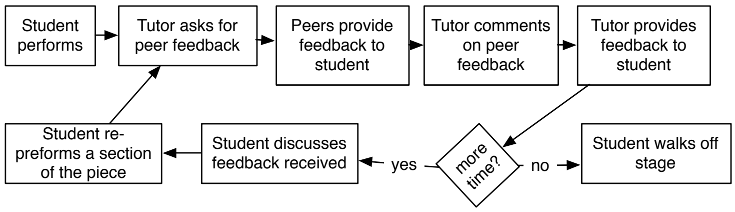

Fig. 3. A flowchart describing a peer feedback lesson where a student performs in front of their peers and tutor, then receives feedback.

4 Perspective 3: agent architectures for social machines - the social learning agent

The aim of this section is to describe general properties an agent operating within a social machine would need. Then to describe an agent which can operate within the educational social machine described in the previous section in order to make connections between learners, to provide feedback to learners and to make predictions about the outcomes of different learning patterns. The music circle platform has several of the characteristics listed in section 2 but one component of the system of particular interest in this paper is the personal learning agent. This is a computational agent which operates in the social machine on behalf of a human user in order to aid them in the achieving of their musical learning goals. Here follows a description of the agent.

4.1 Properties of agents that operate in social machines

We will assume that agents may need to reason not only about themselves but also about that social space, because the social space influences and determines in some sense their actions, and also because agents do influence the social space. Thus agents would have to exhibit capabilities or cognitive dispositions to be aware of other agents, to interpret what is the state of the world, and to hold expectations of what possibilities of action are available (for itself or for other agents) and what the consequences of those actions may be. Likewise, the modelling of the social space determines what inputs and outputs will be accessible to the agents, and therefore one has to device the means to model what the social space 'affords' (in the spirit of Norman [8]) agents to act upon and to be aware of, and the means by which the space may influence the activity of agents. In other words, what objects exist in that space, how agents communicate, how can activities may be coordinated, what types of organisations can an agent belong to, and so on. Consequently, in abstract terms, we shall speak of meta-models of socio-cognitive agents and metamodels of social spaces. For each of these metamodels we would then attempt to produce precise, even formal, descriptions that would allow the specification (and formal analysis) of actual models of agents and of social spaces. Metamodels that in turn need to be accompanied by technological artefacts that enable the actual implementation of socio-cognitive systems where artificial or natural agents pullulate in an artificial social space.

4.2 A description of how the agent model can make connections between users

We are developing the idea of a personal learning agent that sits with the learner and is able to make connections between users in a community of learning. We have presented a formal specification of the initial design of such an agent in other work [27] but here we simply list the characteristics of such an agent that will inhabit the mixed economy of human and computational agents.

The agent needs to record information about the user which represents a profile of the user. The learner model includes the following:

– the goals of the learner - both in natural language and machine readable form
– the intentions of the user in terms of which plans it has adopted or committed to in order to achieve some of its goals
– the current communities the user belongs to
– the history of audio uploads the user has made to the system
– the history of feedback the user has given to which members of which community (including whether the feedback was audio, text, video or a link to another resource) and how this feedback was valued within a community
– the history of how much the user *valued* various feedback it was given
– an model of the kinds of feedback that the user has provided and which feedback has been useful to the learner
– information gained from automatic tools about performances and the relationship between performances that have been uploaded over time

There are many social functions that the agent can then perform for a learner as follows by looking for connections with people that have elements of their learning profile which are similar.

– Find new communities that have similar goals and intentions
– Find new communities that have the same profile of feedback (in terms of the kind and frequency and value of the feedback)
– Propose specific learning buddy kinds of social relationships to people with similar goals/ skills/ knowledge (potential peers, potential as they must actively agree to connect to make a social relationship)
– Propose connections to people who have related but superior skills and knowledge (potential tutors), and have a history of providing valued feedback.

In specifying and designing our deliberative agent architecture we have used specification techniques developed by Luck and d'Inverno over the last 20 years or so (e.g.[8, 9, 15, 16]) and details of this work can be found elsewhere [27]. The summary here is to provide some illustration of how the agents can provide part of the social infrastructure of the social machine that we are building.

At this stage, it might be argued that the agent has the feel of a recommender which does not actively create opportunities for collaboration or engagement. However, in the next phase of agent development, we will explore the possibility of the pro-active creation of learning plans for the user through an analysis of the actions and plans of other users, who might be learning the same instrument, for example. Also, in the next subsection we will describe another capability of the agent which allows it to actively provide feedback to a user about their playing using high level idiomatic audio descriptors.

4.3 A description of how the agent can provide feedback to users

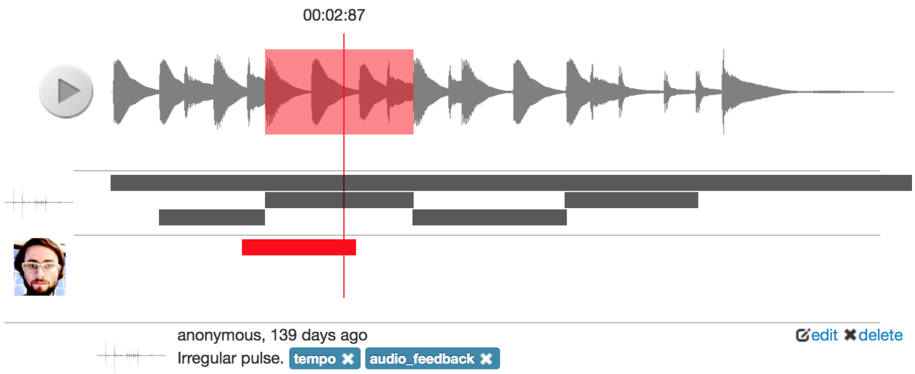

Fig. 4. The social timeline, showing sets of annotations from two users. Each block in the timelines represents an annotation connected to a specific region in the recording. Here, the top timeline was created automatically by the personal learning agent.

Figure 4 shows an example of an agent providing feedback to a user about their performance of a particular piece of music. The agent requires several pieces of information in order to generate this feedback: a machine readable score for the piece (e.g. MusicXML), a recording of an ideal performance of the piece and a recording of the student performance which requires annotation. The agent then aligns the two recordings using dynamic time warping and looks for variations in particular characteristics between the two performances, for example it might compare the tempo curves or the amplitude curves. It can then detect when and how the performance requiring feedback varies from the ideal performance and it can annotate the recording accordingly. In the example shown, the regularity of the pulse is the target for annotations. One might say that the agent is selecting elements from an ontology of desirable musical performance characterises, then comparing the appearance of these traits in an ideal (teacher) and a non-ideal (student) performance.

4.4 A description of how agent based learner analytics can be used to predict the results of learning patterns

A sophisticated model of the plans, goals and so on of the human operating within the social learning machine combined with a growing data set describing interactions between people and the platform (and its other inhabitants and content) is a powerful tool. It can be used to propose connections between people, as discussed in a previous section or to recommend courses of action (plans). It can also be used to predict the likely outcomes of different behavioural patterns. Such modelling and prediction is typically referred to as 'learning analytics'. We strongly believe that the MAS perspective can provide an accelerated insight into this problem. Within our research we are actively investigating the power of such models within the educational context, with the simple motive of furthering our goal of increasing participation in musical activity.

5 Conclusion

This paper aimed to explain how multi agent system (MAS) theory can be used to describe, design and enhance social machines. Using the specific example of an educational social machine being developed by the authors as part of a major European research project, it was shown how an MAS approach can be used to inform the design of such systems in order to better enable the human users to achieve their educational goals. Let us consider the key questions listed in the introduction: how can social machines be described from an MAS perspective? what is a specification for a real, educational social machine? how can an agent based modelling approach be used to encourage and motivate humans operating within an educational social machine? Respectively, we have described characteristics of social machines using MAS terminology, we have descried a real social machine and we have explained our approach using agent modelling to better engage people with musical activity. Our work is now entering an analytical phase where we are developing our agent models further around our real data set, with an aim to modelling the data as described above.

Our wide-ranging goals are to understand in what ways the MAS community take part in the design of social machines and what could be offered to the design of such systems in general. Could we imagine collaborative research projects with designers where research could be developed through the process of design about the nature of designing such systems and understanding how MAS techniques could be applied? Moreover, how might we highlight to the MAS community the potential of social machines that enable us to investigate mixed natural and artificial social systems from an MAS perspective? In our view the time is ripe to identify the potential influence of the MAS community on the design new kinds collective activity that can occur in social machines.

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