Towards a classification framework for social machines

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ABSTRACT

The state of the art in human interaction with computational systems blurs the line between computations performed by machine logic and algorithms, and those that result from input by humans, arising from their own psychological processes and life experience. Current socio-technical systems, known as 'social machines' exploit the large-scale interaction of humans with machines. Interactions that are motivated by numerous goals and purposes including financial gain, charitable aid, and simply for fun. In this paper we explore the landscape of social machines, both past and present, with the aim of defining an initial classificatory framework. Through a number of knowledge elicitation and refinement exercises we have identified the polyarchical relationship between infrastructure, social machines, and large-scale social initiatives. Our initial framework describes classification constructs in the areas of *contributions*, *participants*, and *motivation*. We present an initial characterization of some of the most popular social machines, as demonstration of the use of the identified constructs. We believe that it is important to undertake an analysis of the behaviour and phenomenology of social machines, and of their growth and evolution over time. Our future work will seek to elicit additional opinions, classifications and validation from a wider audience, to produce a comprehensive framework for the description, analysis and comparison of social machines.

1. WHAT ARE SOCIAL MACHINES

Once upon a time 'machines' were programmed by programmers and used by users. The success of the Web has changed this relationship: we now see configurations of people interacting with content and with each other, typified by social Web sites. Rather than drawing a line through such Web-based systems to separate the human and digital parts (as computer science has traditionally done), we can now draw a line around them and treat each such compound as a 'social machine' — a machine in which the two aspects are seamlessly interwoven. This was the insight behind Berners-Lee's original characterisation of the concept of a social machine [1]. This crucial transition in thinking acknowledges the reality of current socio-technical systems, and is essential to underpin any understanding of the science and engineering of their future development towards pervasive ecosystems of co-evolving social machines.

Essentially social machines can be characterised as assemblies of manually executed and machine-driven (as in 'automatised') services and the interaction of such services. A traditional database, with users looking up records independently of each other and an administrator responsible for the management of the content, has some of the right ingredients, but there is really no social element in this strict provider-consumer relationship. When we fill out a form (e.g., health information, birds spotted in a garden, new construction sites on the way to work) the systems supporting this activity are minimal forms of social machines because the users are part of the 'social computation', in this case the data creation and collection process facilitated through the site. This social component becomes richer when the database is curated by members of the broader community (e.g., Wikipedia) and when the social network adds value implicitly (e.g., Amazon) or explicitly (e.g., Facebook) to the overall system through individual or joint activities of the participants.

In general we still see a divide between conventional IT systems dedicated to data- and computation-intensive tasks, and Web 2.0 sites offering some combination of well-known participatory features, in which user-generated content and the underlying social network evolve dynamically and hand-in-hand. However, as technology becomes more and more ubiquitous, many of the challenges we face will increasingly require solutions that rely on both of these axes: a sophisticated combination of data-intensive, complex automation, and deep community involvement. This suggests the need for new types of systems to tackle these emerging challenges, and these systems will not be able to be built and used in a sustainable way without a thorough understanding of the science and engineering of (the continuum of) social machines.

As an early step towards achieving this principled understanding, we propose in this paper a first outline for a classification framework for social machines. The primary aim of the framework is to identify and define the constructs to describe, study, and compare this expanding field of interdisciplinary research. We seek to better describe the increasing number of systems combining human and computational intelligence — systems that are continuously being created in

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areas as diverse as traffic management, healthcare, media and journalism, or design and natural sciences.

The current version of our framework is the result of a knowledge elicitation process performed internally in our lab. Our goal is to present it to the broader community and then to extend and revise it based on feedback in order to achieve a shared understanding of the basic notions and of the associated terminology. We aim to develop a descriptive framework to enable a systematic study of existing and future social machines. We anticipate that the framework will be a useful tool for both researchers in social and computer sciences, and for developers and operators of such systems. Using a common conceptualisation allows the former to become familiar with the landscape, and identify topics of research that so far have remained unexplored or underexplored. They are given a means to observe the effects of specific technical properties of a system configuration on social behaviour, discover design and evolution patterns, learn about social network formation and dynamics, and devise incentive mechanisms to encourage wide participation. For developers and operators, the framework may inform the engineering of new systems in terms of critical features and community development.

This paper makes two main contributions: First, we introduce the notion of 'social machines' and how they relate to other concepts. Second we propose a set of constructs to capture the most important features of social machines and to compare existing instances thereof.

The remaining sections are organised as follows. In order to pin down what constitutes a social machine, and establish the boundaries of this emerging field of research, we need to first understand the relationship between social machines and related topics such as human computation, collective intelligence, and crowdsourcing; Section 2 provides a summary of this comparative analysis. In Section 3 we present the framework in terms of the methodology used to devise it, the main clusters of constructs used for classification, and an example of using them to compare a selection of popular social machines via repertory grid analysis. We conclude with our proposed future work, including details concerning the evaluation of the framework and reference our plans to engage with the broader community to set up a 'social machine' bringing together researchers from various disciplines to help formulate a widely agreed framework for the field.

2. COMPARISON WITH RELATED FIELDS

Turing machines were once conceived as logical automata. We have experienced a 'paradigm shift' in the usage of computers, moving away from this narrow characterisation to one according to which machines facilitate a wide range of human interactions. The emergence of 'Computer-supported Collaborative Work (CSCW)' [3] is representative of the early phases of this trend. This initial concept has evolved to become the broader field of 'Computer-supported collaboration' (CSC).

The Web as a global platform for information access and sharing marked a second essential milestone; in particular, through principles and technologies promoted through Web 2.0 and the Mobile Web. These developments led to amazing growth in terms of the amounts of content available online and the extent of mass participation. They are responsible for hundreds of millions of users all over the globe creating high-quality encyclopedias, publishing Terabytes of multimedia content, contributing to world-class software, and active participation in defining the agenda for many aspects of our society. This trend towards 'prosumerism' is finding more and more adopters in the public and private sector. Governments and enterprises are not only becoming active in open initiatives, but encourage the participation of their customers and employees in taking decisions related to organisational management, product development, service offerings, and policy formulation. In this context, a number of terms are used to refer to the ways people interact with each other and with applications: 'wisdom of the crowds', 'collective intelligence', 'open innovation', 'crowdsourcing', 'human computation', and 'social computing'. As we argue below, these terms are related, but not synonymous with 'social machines' (see also Figure 1).

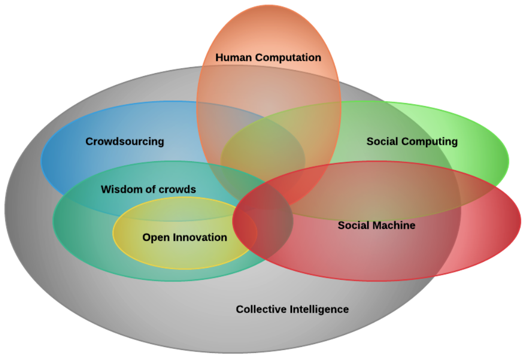

Figure 1: Social machines and related areas

Wisdom of the crowds [13] refers to a principle for decision making that takes into account the information and opinions of a group of people rather than individuals; the use of specific technologies, most notably Web 2.0, has made it possible for such processes to be carried out at scales inconceivable in the past, and to involve highly diverse and geographically distributed participants. A similar concept, though broader scoped, is collective intelligence, defined in [8] as 'groups of individuals doing things collectively that seem intelligent.' The main difference to what we refer to as 'social machines' is with regard to the extent and role of automation. In a social machine, human and computational intelligence coalesce in order to achieve a given purpose. While wisdom of the crowds and collective intelligence place their focus on identifying the situations in which groups of people perform better than individuals, social machines are concerned with the study and realisation of hybrid systems in which the two types of components co-exist. As such, theoretical and empirical insights from these two related areas are useful to understand the dynamics of the social structures underlying a social machine, but they are definitely not the only ingredient needed to build operational systems. The question of how human and automatic services can be brought together to achieve optimal results, as well as the actual engineering by which a system is developed, tested, and updated are equally important.

One of the direct consequences of the popularity of the wisdom of the crowds idea was a stronger investment worldwide in open innovation, which can be seen as an application of the concept to business environments, or, in the words of the authors, as a 'a paradigm that assumes that firms can and should use external ideas as well as internal ideas, and internal and external paths to market, as the firms look to advance their technology' [2]. At a more general level, this kind of creativity could be leveraged in almost any domain which benefits from diversity, whilst at the same time ensuring in-time access to a potentially infinite pool of skills and resources not available before the advent of social computing technologies. The term crowdsourcing is typically associated with this larger collection of situations, in which 'a job traditionally performed by a designated agent [...] [is outsourced] to an undefined, generally large group of people in the form of an open call' [4]. Human computation applies human processing power to tackle technical tasks that computers (still) find challenging [14], typically in areas such as visual, audio, and natural language understanding. These kinds of task are an important part of today's crowdsourcing landscape, in particular on so-called 'microtask' platforms such as Amazon's Mechanical Turk[1] or CrowdFlower[2], which offer small financial rewards to an anonymous crowd engaged with atomic units of work that take in the range of seconds to minutes to complete. The key difference between social machines and open innovation and crowdsourcing is at the level of the interaction between the social and the machine-driven processing components. The novelty these two other approaches bring in lies in their use of a much larger pool of human resources than traditional work environments [11]. There are clear socio-economic implications that their adopters need to deal with in order to optimally make use of this wealth of resources; technology may be needed to assist specific aspects of crowdsourcing projects, from evaluating and rewarding the results produced by the crowd to consolidating and aggregating them into a complete solution. These aspects are equally important for social machines, which, however, also look into the principled combination of human and computational capabilities and the technical means to support them. In comparison to human computation, social machines cover a wider range of scenarios. Human computation is AI-centric and uses people to perform tasks that computers are not (yet) able to tackle (in terms of accuracy) [11]; by comparison, we see many successful examples of social machines in which the role of machines is rather to facilitate interactions within groups of people or communities of interest.

An analogous line of reasoning illustrates the overlap between social machines and social computing [10]. The latter is an area of computer science that refers to systems that support 'the gathering, representation, processing, use, and dissemination of information that is distributed across social collectivities such as teams, communities, organisations, and markets' [10]. As such, compared to the general concept of 'Computer-supported collaboration', social computing puts a greater emphasis on the information management capabilities of groups and communities, and less on the way these capabilities emerge as a joint effort. This distinction is even stronger in the case of social machines, which regard the social and the technical components as equal and necessary partners, and study the ways they could be best combined to master the challenges of future socio-technical systems.

We now turn to a description of the main classification dimensions and features relevant to describe, study, and compare social machines.

3. CLASSIFICATION FRAMEWORK

3.1 Methodology

The classification framework presented in this paper was created through knowledge elicitation [12]. In particular we used the *repertory grid* elicitation technique [5] in order to derive an initial set of *elements*, which represent instances of social machines, and *constructs*, which capture their most important characteristics. The technique originated in psychology where it was used to elicit the implicit knowledge used by human subjects to conceptualise the world around them.

In repertory grid elicitation a software tool is used to ask users to describe constructs that differentiate a set of elements – for example, prompting the user to create a construct that differentiates between *GalaxyZoo*[3] and *Facebook*, as two prominent example of social machines our classification framework should apply to. The user describes the opposing poles of the construct — in this case, the user may decide on 'For Science' and 'For socialising' in order to capture the core distinction between the two system. The user then rates every element with value from 1 to 5 on this construct, where 1 represents an element that is purely 'For Science', and 5 one that mainly serves 'socialising' purposes. In triadic presentation the repertory grid software lists three elements and asks the user to generate a construct where one of the elements is different to the other two. We asked computer science researchers familiar with the field to create their own repertory grids, generating elements from their own knowledge, and creating constructs using this technique. This exercise led to 10 grids, the union of which comprised a total of 56 unique elements (social machines) and 117 different constructs (classifying factors). As the aim of this initial phase was to understand how people perceive the notion of a social machine and their most distinctive properties, we allowed the participants to choose the systems they are familiar with and describe them in their own terms.

While determining the intersection of elements was straightforward, the consolidation of the constructs required a more thorough process. We manually grouped the constructs into rough clusters, based around the areas they cover. We examined each construct to determine which were equivalent, and whether we could re-word or subsume existing constructs to reduce redundancies and overlap. Our aim was to cut the classification space down to a manageable size, while ensuring that all constructs that were initially elicited were represented in the final set. This process involved four of the authors discussing the choices, and resulted in a consolidated set of 31 constructs organised in four different clusters: popularity, tasks and purpose, participants and roles, and motivation and incentives. In our analysis we did not further consider the first cluster, which primarily covered descriptive information about a given system, such as its perceived level of maturity and current number of users. It was apparent that the constructs were not evenly distributed across

[1] https://www.mturk.com/
[2] http://crowdflower.com/

[3] In GalaxyZoo people classify galaxies with collective performance as good as professional astronomers, see http://www.galaxyzoo.org.

clusters; whereas some aspects such as roles of participants occurred frequently (in various flavours) in the grids provided by the ten experts, others such as the different types of workflows synthesising human and automatised capabilities of a social machine were less common. As discussed in Section 2 we believe that the interaction between these two types of services is an essential part of the theory and practice of social machines, being one of the elements that distinguishes them from related areas which are biased towards one or the other. Extending the framework with constructs capturing these aspects (see, for instance, [11] for examples in the context of human computation) is part of our future work.

The paper presents the current version of the framework. We envision iterating the main clusters and constructs based on discussions with and feedback from various scientific audiences. We provide initial evidence of the usability of the framework as a tool to examine commonalities and differences between social machines in Section 3.4, in which we applied the repertory grid elicitation technique to a set of 20 social machines instances ranked by popularity according to the Alexa service.[4] A more thorough evaluation will determine the extent to which the classification constructs identified can be meaningfully used by researchers and system designers and operators. We will test the completeness, correctness, and comprehensibility of the constructs in experiments in which a new set of social machines will be classified by framework users; we will ask the participants to assess the quality of the framework along these general dimensions, and measure inter-annotator agreement to learn about the usefulness of the classifications produced.

3.2 The polyarchical relationship of social machines

When defining the boundaries of what we call social machines, one important observation was related to the distinction between platforms and technologies such as wikis and GWAP ('games-with-a-purpose'), which enable social machines to be created, and their instantiations into social machines that were brought to life for a specific purpose, such as Wikipedia and EteRNA[5], a game in which participants design RNA that is evaluated automatically using simulators. A second observation is concerned with the relationship between broader and narrower-scoped instances of social machines; general-purpose examples such as Facebook, Twitter or Amazon, or even the Web, enable the formation of more specific social machines and communities within them, that are working to solve solve different problems. An example illustrating this relationship is the Obama'12 US Presidential campaign [9], which relied on Twitter and Facebook as basic social machines; most forms of customer relationship management and community engagement carried out in the digital space use similar tools. Finally, social machines are interconnected into a greater ecosystem, both at the social and at the computation levels. For example, insights on the classification of space objects gained through GalaxyZoo may influence the content of the corresponding articles, and the associated editorial processes, within Wikipedia. At the same time,a large number of communities within Wikipedia focus specific topics and activities, such as those contributing to science and technology.[6]

Looking at the set of social machines in a polyarchy leads to a broad/specific relationship emerging that lets us talk about behaviour at various levels of granularity. We propose looking at nested machines with 'The Web' as one of several potential roots, with the next level down consisting of sub-platforms (such as Facebook, Twitter, MediaWiki, Ushahidi) that spawn more specific social machines. A resulting polyarchy is shown in Figure 2, which classifies levels as infrastructure, frameworks, services, and projects and initiatives.

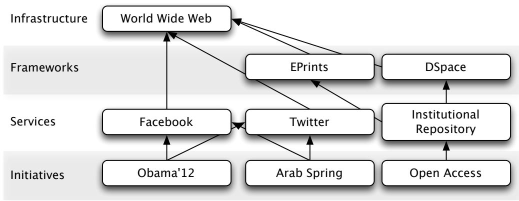

Figure 2: A polyarchy of social machines, illustrating the infrastructure and frameworks used by social machines, and machine-machine usage

This approach enables us to start with a more detailed analysis of certain levels over others; and to see what similarities flow up and down the polyarchy. For example, what do specific instances of Ushahidi/Zooniverse/MediaWiki have in common with other instances, and how do they differ dynamically? How do certain design decisions taken at the level of the infrastructure, frameworks and service propagate into narrower-focused systems that are built on top of them? Similarly, how will such decisions affect a broader ecosystem of social machines, each with their own, though overlapping, purposes and communities?

The polyarchy is complementary to the classification constructs we elicited. The constructs apply to all levels of the polyarchy, though some of them might be more easier to understand and describe in the context of some levels. For example, instances of social machines residing at the bottom of the polyarchy are likely to be built with a very concrete audience in mind, and as such the mechanisms to incentivise participation are likely to be clearer and more straightforward to study and adjust than in cases in which such boundaries cannot be defined, such as Facebook, or even Wikipedia. At the same time, these systems will have to decide among an array of diverse basic services and frameworks for their implementations; the impact of such engineering decisions is difficult to predict in great detail as a thorough understanding of what makes certain social machines more successful than others, in terms of technology choices and beyond, is largely missing for most application domains.

3.3 Constructs

The clustering process described in Section 3.1 yielded both a reduction in the overall number of constructs (in particular an elimination of over-represented areas) and the identification of three themes: first the nature of tasks, problems and activities performed through and using the ma-

[4]www.alexa.com/

[5]http://eterna.cmu.edu

[6]Visualisation of Wikipedia Science Communities: http://www.olihb.com/WikiCommunities/

chine, second the users and roles within each machine, and third, motivation for participation.

Each of these clusters contain between five and eight constructs as illustrated in Table 1; we describe each of these themes in the following subsections.

Tasks, purpose and context of participation
Activities involve creative production of content
Activities involve subjective appraisal of content
Activities involve solving (a definable) computation task or set of problems
Tasks are domain-specific
The machine owner derives benefit from participation
Activities and tasks are pre-defined or participant-defined
Variation in types of contributions and tasks
Participants' participate to fulfil needs of a role
work-related/professional role
home/family related
social role
leisure/entertainment role
Participation is done via:
mobile devices
Web browsers
apps
sensors/sensing (location sensing and wearable devices)
Participation is done in a mobile context
Physical location is relevant to the service
Participants and roles
Generality of audience
Participant autonomy
Participant anonymity
Extent of hierarchical organisation of roles
Clear separation of roles among participants
Motivation and incentives
Participants are intrinsically motivated:
to gain/share knowledge
to "get something done"
to "be for fun/entertainment"
to "be social"
for the benefit of a specific group of people who need help
for the benefit of society as a whole
Participation is motivated by extrinsic reward (payment, status)

Table 1: Consolidated constructs of social machines

3.3.1 Tasks, purpose, and context of participation

The first set of constructs pertain to *what* the participants do, both individually within the system, and collectively as a whole. Individual activities might include creation of content, subjective appraisal of existing content, posing of problems, solving of problems, and so on. The resulting 'computation', looked at from a macroscopic whole, might be the identification of high-quality artistic content, insight, or creative works, collective problem solving, and so on. Such tasks might be pre-defined by the system designers, or brought to the system by participants. Further, these tasks might be of a specific type or class, or of many varied types or encompass a general class of activities. To capture this diversity, we include a construct that differentiates machines with pre-defined problem spaces or those that are open to participant-provided tasks and activities. Finally, we ask whether the benefit derived by participants is distinct from that gained by machine/platform owners and service providers.

The second set of constructs pertains to the context(s) of each participant's greater (life-) activities in which the interaction with the system occurs. This context could be in a work context, home/family context, for leisure, and at a desk or away from a computer (in a mobile context). Participation could be conducted via apps, Web browsers, sensors and other technologies. Due to the predominance of geolocation services, one of the constructs collected through knowledge elicitation identifies the degree to which the user's location is used by the machine.

3.3.2 Participants and roles

This set of constructs pertain to the human participants of social machines and the way(s) participants are organised within them. One construct identifies whether participants constitute members of the general public, or are of a specific demographic, external group or organisation, occupation, or possess a particular expertise. Two constructs, *autonomy* and *anonymity* pertain to the degree to which interaction is constrained among participants, and the degree to which participants' identities are used and disclosed within the machine. An additional two constructs pertain to the roles: first, as to whether multiple roles are pre-differentiated by the machine or whether all participants essentially initially assume the same role, second whether roles (pre-defined or emergent) are hierarchical.

3.3.3 Motivation and incentives

These constructs relate to the social structure and motivation that sustains continued participation in these systems. We identify six different kinds of common sources of intrinsic motivation; first, that participation is fun, second that it accomplishes an activity that the participant enjoys or wants to get done, third, that it satisfies the desire to gain or share knowledge, or, fourth, the desire to be social. The last two pertain to philanthropy, whether participation is seen to benefit a particular group of disadvantaged people or individuals who need assistance, or, finally, if participation is beneficial to society as a whole. Finally, we ask whether extrinsic motivational factors also contributed to sustained participation – such factors could include money reward, status, recognition and so on [6, 7, 15].

3.4 Using the classification framework

In order to demonstrate usage of the constructs we ordered our social machines by their Alexa ranking, and performed a full repertory grid elicitation exercise over the first 20 of the 56 collected in the first phase of the methodology (see Section 3.1). This process assessing each social machine against the constructs by choosing a rating between 1 and 5. This led to a total of 680 ratings, and the results are illustrated in a grid and accompanying dendrograms for element and construct similarity in Figure 3.

From the dendrograms we can get a sense of similarities and differences between social machines. For instance, it is clear that YouTube, Vimeo, Reddit, and Digg are similar, which is not unexpected, due to their focus on sharing content. Likewise, the exercise confirms commonalities between Quora and Stack Overflow, which can be easily understood, given their question answering purpose. There is also a dendrogram for the constructs, which can be used, as more data is collected, as an indicator for correlation between constructs. In this particular case, our dendrogram suggests that there is a correlation between the 'Single Participant Roles' and 'No Hierarchy in Participant Roles' constructs, which is because they refer to the same aspect of social machines. Another, but less obvious connection is between the 'Large variety of social features' and 'Benefit NOT for the world/society', which requires further investigation.

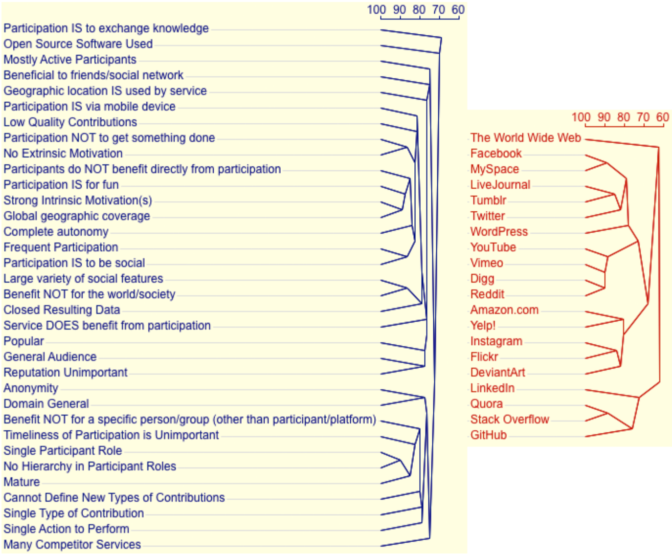

Figure 3: Dendrograms of constructs, in blue, and elements (social machines), in red, from a repertory grid exercise of the top 20 (ranked by Alexa) social machines from our element set, against our consolidated constructs.

We envisage three use cases for our framework. First and foremost the framework forms the basis for a coherent and comprehensive description and classification of social machines. The knowledge elicitation technique referred to in this paper is just one of the many tools which can assist this exercise. In addition, it enables direct comparisons between systems, and provides a platform for terminologically consistent discussions about the field as a whole and specific instantiations. Finally, we also think that with more and more classification data becoming available, for instance, with functionality that automatically monitors and computes the values of the some of the constructs introduced earlier (see work on the Web Observatory REF), researchers will wish to apply prediction techniques (such as SVMs) to social machines, their behaviour, and impact.

4. FUTURE WORK

In this paper we presented a first outline of a description space for social machines. We introduced the key features of social machines, and explained how this concept differs from related areas such as collective intelligence, crowdsourcing, and human computing. We then discussed the basic constructs of a classification framework created through the repertory grid elicitation technique. In its current version the framework consists of 31 constructs clustered according to the main components of social machines: social and machine-driven services, and the interactions between them. Our future work will seek to revise this initial list of constructs. Most notably, we would like to add a number of constructs to emphasize the importance of the interaction aspect in the theory, engineering, and operation of social machines. This includes constructs related to the human-computer workflows supported (e.g., human intelligence replacing automatic algorithms as in GWAPs vs the different bots available on Wikipedia complementing collaborative manual editing), the way inputs from the crowd are validated, aggregated and turned into a useful outcome, as well as issues related collaboration and coordination, and interface and communication design. In addition, we plan to engage with the broader researcher community by setting up a social machine to facilitate discussions and feedback collection. One specific idea that is currently under development is to build a microtask environment, including specific game elements, in which participants are asked to provide answers to atomic challenges that rate and compare a pair of social machine instances according to a construct in our framework. This classificatory work is part of a larger project in which we seek to understand the theory and practice of building social machines and where we might in future anticipate what makes social machines scale or fail.

5. ACKNOWLEDGMENTS

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