ABSTRACT

The web can be seen as an engine to 'create abstract social machines - new forms of social processes that would be given to the world at large' [1]. This paper concerns social machines whose purpose is to curate, analyse, and rate legal documents. We present a case study of 'Terms-of-Service; Didn't Read', an initiative to rate website terms and privacy policies. Using open data generated by the system, we examine the relationships between its human contributors and machine counterparts, concluding with considerations for the theory, measurement and design of social machines.

Categories and Subject Descriptors

H.1.2 [**User/Machine Systems**]: Human information processing; G.2.3 [**Discrete Mathematics**]: Applications

General Terms

Human Factors, Measurement, Design, Theory

Keywords

Social Machines; User Agreements; Terms of Service; Privacy; Legal Informatics; network science

1. INTRODUCTION

Social machines are new combinations of human and machine activity that engage in complex activities and solve problems which were previously difficult or costly for humans and machines to do alone [12]. Underlying this concept is the proposition that rather than isolating machines or human users as individual units, we must consider both within the compound of a 'social machine'. Some social machines have broadly defined goals, while others have tightly-defined objectives. Included amongst the latter are social machines for studying galaxies [1], political campaigns [10], health promotion [8], and crime reporting [7].

An interesting application of social machines is to the curation, analysis and rating of legal documents and advice. Contracts, terms-of-service, privacy policies, and licenses all serve important functions in a range of online and offline interactions. However, they incur significant costs on interacting parties as they are often written in complex legalistic language (sometimes referred to as 'legalese') which is time-consuming and difficult for individuals to understand without formal training. In addition, despite advances in automatic parsing techniques made in semantic processing and legal informatics [4, 13], computational processes alone may be insufficient. Instead, social machines aimed at handling these tasks and functions are emerging. These systems aim to capture the activity of human actors who write, develop, read, modify, sign, or abide by such texts, and aggregate that activity to produce new content and services.

2. LEGALESE SOCIAL MACHINES

We used an existing classificatory framework for social machines to search for and identify systems in this area [12]. For the purposes of this paper, a broader analysis of the domain of social machines for parsing legalese has been discarded. We focus here on just one case study, the 'Terms of Service; Didn't Read' project, a platform for analysing and rating website terms and privacy policies.

3. CASE STUDY: TOS;DR

The ToS;DR platform has around 500 users, who communicate primarily through an open mailing list. Its stated aim is to 'fix the biggest lie on the internet' - namely, the statement that 'I have read and agreed to the terms'. Participants identify, discuss, and annotate clauses in terms-of-service and privacy policies, rating them as either 'good', 'bad', or 'neutral'. This activity generates the raw data which drives the service – as they explain it, 'every thread on the mailing list is a data point'. The number of good, bad and neutral points are tallied to produce an overall rating of a policy. The ratings serve data via an API to other services including a browser plugin.

In order to keep track of changing policies, an automated web crawler called ToSBACK regularly crawls an index of websites and notifies participants of any changes to the policies which may need to be reviewed. Any participant can add a website to the index, which is a list of XPath addresses. Unlike some other social machines we surveyed, this automated 'bot' is treated, according to the ontology of the service, just like any human user, i.e. a node in the mailing list which provides raw data for review.

3.1 Quantitative analysis of community structure

Our quantitative analysis uses data from the ToS;DR platform to investigate questions raised in 2.1., namely:

1. *Informal heirarchies:* What is the structure of the network of human contributors?

2. *Human-computer co-operation:* How do computational and human actors interact with each other within the system?

3. *Effect of computation:* In addition, given that we had data from before and after the introduction of a new computational actor to the platform (namely, the ToSBACK bot) we were able to measure potential effects such an actor had on the dynamics of the overall system

In order to answer these questions, we web scraped 2345 contributions from the group. Our aim was to understand the network or *community structure* of the social machine, both before and after the introduction of the ToSBACK bot. In order to examine this, we used the Girvan and Newman (GN) algorithm for identifying communities in complex networks [5].

3.1.1 Girvan and Newman Algorithm

Let G be a simple weighted graph with edge and vertex sets $E(G)$ and $V(G)$ respectively. The importance of an individual edge $e_{ij} \in E(G)$ is commonly calculated in terms of *edge betweenness centrality* which is defined as follows:

$$\beta(e_{ij}) = \sum_{u \neq v \in V(G)} \frac{\sigma_{uv}(e_{ij})}{\sigma_{uv}}$$

where σ_{uv} is the number of shortest paths from vertex u to v and $\sigma_{uv}(e_{ij})$ is the number of those shortest paths that pass through edge e_{ij}.

[1]GalaxyZoo <http://www.galaxyzoo.org>

An edge with high betweeness centrality sits between two highly connected areas. For example, the much ballyhooed *weak ties* in a social network have high edge betweeness centrality.

In order to determine community structure we will apply the Girvan and Newman (GN) algorithm [5] which associates a binary, rooted tree, T, with a simple weighted graph G as follows:

(i) The root of T is assigned to be the whole graph G.

(ii) Determine the edge, e_{ij}, with the highest betweeness centrality in G.

(iii) Remove edge e_{ij} from G.

(iv) If step (iii) disconnects G then connect two vertices to the root of T (these vertices correspond to the connected components of G).

(v) Iterate until there are no remaining edges in (G).

It has been shown [5] that the degree of cohesion in a network can be detected via the GN algorithm and it has been used to identify communities in structures as diverse as scientific collaboration networks, food webs and e-mail networks [5, 6].

3.1.2 Method

We built two graphs G_1 and G_2 corresponding to the mailing list archive before and after the ToSBack bot began contributing. The vertex set of both graphs are made up of contributors to the mailing list. An edge was placed between two vertices if the relevant contributors responded, or were responded to by another contributor. These edges were then weighted by the number of interactions between the relevant contributors. Finally we applied the GN algorithm to both graphs.

3.1.3 Results

The tree, T_1, shown in Figure 1 was built via the GN algorithm from the mailing list *prior* to the introduction of the ToSBack bot corresponds to a nested hierarchy of communities within the ToS;DR mailing list at that time. In particular the vertex labeled 1 in Figure 1 represents the entire mailing list and every interaction between contributors to that list, whereas the vertices labelled 2 and 17 represent two sub-communities that we will call C2 and C17 respectively. Since 2 is adjacent to 3 and 4 in addition to vertex 1 there also exist sub-communities of C2 that we denote C3 and C4. One can easily deduce from the GN algorithm that leaf vertices (vertices incident to exactly one edge) of T_1 corresponds to a single contributor to the mailing list thus C3 is a community of precisely 1 person. On the other hand C4 indicates a much larger community – (C2 without one contributor called V1).

In general a subtree of the tree associated to a network using the GN algorithm that is “close ” to a line indicates a “hub and spoke” community since most subcommunities will consist of one actor and a community of everybody else other than that actor. We have highlighted four line-like subtrees in T_1; these subtrees can be recognised as the areas of discussion initiated by or frequently involving particular members.

We can formalise the notion of “line-like” subtrees by analysing the *symmetry* of a tree. One can measure how symmetric a graphical tree is by calculating the number of permutations of the vertices (of that graph) that preserve adjacent vertices [2]. We call the set of such permutations $\mathrm{Aut}(T)$ - the automorphism group of T. The number of permissible permutations is written as $|\mathrm{Aut}(T)|$. In general low $|\mathrm{Aut}(T)|$ coincides with the presence of one or several long line-like subtrees. We calculated that $|\mathrm{Aut}(T_1)| = 16$ and $|\mathrm{Aut}(T_2)| = 24$. This shows a marked increase in the cardinality of the automorphism group and therefore increased symmetry which is further entrenched by normalisation.

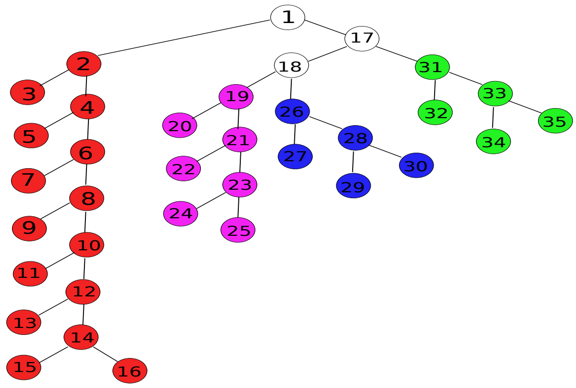

Figure 1: The tree, T_1, built via the GN algorithm that corresponds to the mailing list prior to the ToSBack bot contributions.

We conducted similar analysis for the mailing list after the ToSBack bot contributions began and found that the network structure had changed significantly. Tree T_2 (shown in Figure 2) has less line-like subtrees and greater symmetry, indicating that there is no participant accounting for a highly disproportionate number of interactions.

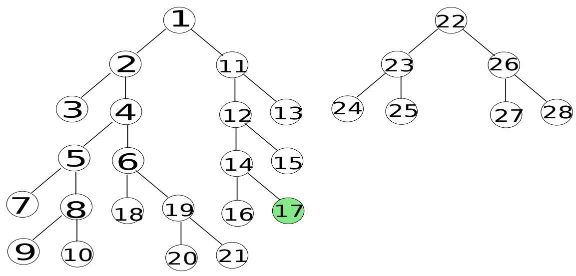

Figure 2: The tree, T_2, built via the GN algorithm that corresponds to the mailing list after the ToSBack bot contributions began. Vertex 17 [green] indicates the bot.

3.2 Discussion

We see two distinct community structures before and after the introduction of the ToSBack bot. In particular notice the asymmetry of the very long branch in (red in T_1), which represents one particular user’s tendency to interact with a disproportionate number of contributors during this period. In contrast, after the introduction of the bot, there is no longer one main information hub and the network is more balanced. The first graph consists of one connected tree while the other is two largely separate trees, indicating two separated communities.

One possible explanation for this is suggested by research into how structures naturally become optimised. Self-similarity and self-replication in natural structures like rivers ensures that these structures develop in an optimal way (for example they satisfy Murray's principle of minimum work [9]). Guimera *et. al.* show that this principle is also true for communities; they tend to self-organise to form an optimal structure [6].

One way of measuring self-similarity in a graph is to find the order of the symmetry group or group of automorphisms of that graph. The increasing symmetry discovered in this network may therefore be an indication of self-organisation for more efficient dissemination of information.

Finally, focusing in on the nodes around the ToSBack 'bot' suggests that it may have introduced a different dynamic to the network. One particular user, who had previously made a great number of contributions which were largely ignored by others, began interacting heavily with the bot. In fact, this user accounted for the overwhelming majority of all interactions with the bot (86%). During this period, the user's importance in the network grew, triggering more reponses than in the previous period (while her total contributions remained stable). A possible explanation for this is that this user found a new role after the bot arrived; she went from being a producer of content, to become a filter between the new content generated by the bot and other (human) participants.

4. IMPLICATIONS FOR THEORY, DESIGN AND MEASUREMENT

Our preliminary classification exercise identified a range of what could be termed 'legal social machines'; platforms and communities who create, curate, rate, and annotate legal documents and information in ways that make them more usable by non-experts. They generally feature a relatively constrained set of roles (such as contributions and ratings) and make use of automated systems to cut down on repetitive tasks which might be boring for human participants (such as checking for changes in website policies).

Reflecting on ToS;DR and other legal social machines in depth raises some interesting points of connection with previous work on the theory of social machines. First, as proposed in previous work, social machines should be regarded as 'networks of networks' [11], and similarly, as 'nested' within each other at different levels of a 'polyarchy' [12]. Our examination of Tos;DR lends weight to both perspectives; our analysis reveals distinct networks of contributors within the larger network, which is itself, in part, nested within the even larger Google Groups network.

Second, ToS;DR and ToSBACK are examples of two pre-existing social machines (both of which consisted of human and machine actors), which became appropriated by each other and amalgamated into a new composite social machine (illustrating at least two distinct 'phases' of development [11]). In addition, the websites that this composite social machine interacts with (through scraping, annotating and rating), are often themselves instances of social machines (i.e. Facebook or Wikipedia). This emphasises the importance of recognising the extent to which social machines interact with each other in complex ways which might otherwise be overlooked if considered individually [3].

Finally, by applying the GN algorithm to archived interactions between both human and machine actors within a social machine, this paper suggests novel techniques for measuring and analysing several aspects of social machines. This method can reveal a) the efficiency of information flow within the social machine, b) information hubs within it, and c) identify the roles of humans and bots relative to each each other within the system.

Our findings may also suggest recommendations for anyone designing new social machines or attempting to shape existing ones. We found that the introduction of a new technological actor (TosBack) disrupted the overall structure of the network, with workflows changing and human participants re-positioning themselves around it. Designers should therefore be aware that the automation of certain roles can have wide-ranging effects on the overall operation of a social machine.

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6. REFERENCES

[1] Berners-Lee, T., and Fischetti, M. *Weaving the web: The original design and ultimate destiny of the world wide web by its inventor*. Harper Collins, San Francisco.

[2] Bollobás, B. *Modern graph theory*, vol. 184. Springer, 1998.

[3] De Roure, D., e. a. Observing social machines part 1: What to observe? In *SOCM2013: The Theory and Practice of Social Machines, Rio de Janeiro, Brazil* (2013).

[4] Francesconi, Enrico, e. a. *Semantic processing of legal texts: Where the language of law meets the law of language*. Springer, 2010.

[5] Girvan, M., and Newman, M. E. Community structure in social and biological networks. *Proceedings of the National Academy of Sciences 99*, 12 (2002), 7821–7826.

[6] Guimera, Roger, e. a. Self-similar community structure in a network of human interactions. *Physical review E 68*, 6 (2003).

[7] Maire Byrne Evans, Kieron O'Hara, T. T. C. W. Crime applications and social machines: Crowdsourcing sensitive data. In *SOCM2013: The Theory and Practice of Social Machines, Rio de Janeiro, Brazil* (2013).

[8] Max Van Kleek, Daniel A. Smith, W. H., and Shadbolt, N. R. 'the crowd keeps me in shape': Social psychology and the present and future of health social machines. In *SOCM2013: The Theory and Practice of Social Machines, Rio de Janeiro, Brazil* (2013).

[9] Murray, C. D. The physiological principle of minimum work: I. the vascular system and the cost of blood volume. In *Proceedings of the National Academy of Sciences of the United States of America* (1926).

[10] O'Hara, K. Social machine politics are here to stay. *Internet Computing, IEEE 17*, 2 (2013), 87–90.

[11] R. Tinati, L. Carr, S. H. C. P. The htp model: Understanding the development of social machines. In *SOCM2013: The Theory and Practice of Social Machines, Rio de Janeiro, Brazil* (2013).

[12] Shadbolt, Nigel R., S. D. A. S. E. V. K. M. Y. Y., and Hall, W. Towards a classification framework for social machines. In *SOCM2013: The Theory and Practice of Social Machines, Rio de Janeiro, Brazil* (2013).

[13] Spinosa, PierLuigi, e. a. Nlp-based metadata extraction for legal text consolidation. In *Proceedings of the 12th International Conference on Artificial Intelligence and Law.* (2009), ACM.