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Adaptation and the Social Salience Hypothesis of Oxytocin: Early Experiments in a Simulated Agent Environment

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ABSTRACT

Allostasis is a mechanism that permits adaptation of an organism as a response to changing (physical or social) environmental conditions. Allostasis is driven by a number of factors, including regulation through hormonal mechanisms. Oxytocin (OT) is a hormone that has been found to play a role in regulating social behaviours and adaptation. However, the concrete effects that OT promotes remain unclear and controversial. One of these effects is on the attention paid to social cues (social salience). Two opposing hypotheses have been proposed. One hypothesis is that adaptation is achieved by increasing attention to social cues (increasing social salience), the other that adaptation is achieved by decreasing attention to social cues (decreasing social salience). In this paper, we present agent simulation experiments that test these two contrasting hypotheses under different environmental conditions related to food availability: a comfortable environment, a challenging environment, and a very challenging environment. Our results show that, for the particular conditions modelled, increased social salience through the release of simulated oxytocin presents significant advantages in the challenging conditions.

1 INTRODUCTION

Endowing artificial (robotic or simulated) agents with the ability to “survive” in constantly-changing environmental conditions poses interesting challenges. In areas such as autonomous robotics and human-robot interaction, robots must be able to both anticipate and adapt to new conditions, in order to adapt to realistic, dynamic physical and social environments. Affect is one of the mechanisms that permits adaptation (Panksepp, 2004). Through this adaptation, expression and emergence of affect-based behaviour will become more context-relevant, able to evolve over time, adapting to changes whenever necessary (Schulkin, 2011).

In previous work undertaken in our research group (e.g., Avila-Garcia and Cañamero, 2002; Attwood et. al., 2013; Cañamero and Lewis, 2016; Lewis and Cañamero, 2016), regulation of the internal environment (milieu) has largely been through homeostatic processes. Homeostasis describes the process that an agent undergoes in order to maintain its internal milieu at a stable level, for example through error-correcting behaviours. In these models, the internal milieu is corrected through negative feedback loops once “physiological” deficits occur. Anticipation of changing environmental circumstances is difficult when regulation is approached in this way.

A more anticipatory adaptive process is *allostasis* (Schulkin, 2011). Allostasis describes the regulatory process that an agent undergoes to adjust its internal milieu when presented with, and even in anticipation of, a change in environmental conditions. Given influences from or changes in the external environment, allostasis allows for the range of values of the internal milieu to change dynamically - a fundamental difference with homeostasis, where this range doesn’t change. Whilst homeostatic regulation is effective in static and some types of dynamic environments, it is limited in its approach, particularly in conditions where the range of the internal milieu needs to be adapted to accommodate changes in the environment, for example to accommodate changes in temperature under different seasons. Allostasis can therefore be seen as an adaptation of the mechanism that permits adaptation to the environment, and proposes longer-term viability (Ashby, 1952) of agents through mechanisms of adaptation and anticipation.

Allostatic process can be triggered as a response to changes in either the physical environment (Sterling, 1988) or the social environment (Schulkin, 2011), in which case it is called social allostasis. Social allostasis describes the mechanism of allostasis taking into account the social environment by using social behaviours to regulate the internal conditions. Schulkin (2011) states that social regulation of internal conditions is a fundamental behavioural adaptation, and that the evolution of allostasis was largely driven by social adaptation. Hormones are one of the mechanisms that are involved in social allostasis. Within the social allostasis literature, different hormones have been mentioned (Bethlehem et. al., 2014). One such hormone that has consistently been found to play a role in this social regulation is oxytocin (De Dreu et. al., 2016). Oxytocin (OT) is a neuromodulatory hormone that has been gaining increasing attention in recent years due to its presumed facilitation of prosocial behaviours in mammals (Neumann, 2009, Chang et. al., 2012, Krueger et. al., 2013). Recently, Ebitz and Platt (2014) argue that prosocial behaviours may not always be the most optimal approach when considering an agent’s overall viability and adaptation to a social environment. In their paper, these authors cite several examples of population-level simulation studies where success of the population was driven by antisocial behaviours such as deception and defection. They therefore hypothesised that oxytocin should reduce social vigilance, rather than enhance it, in order to contribute to the viability of social agents.

OT has also been found to be context-dependent (Bartz et. al., 2011; Bos et. al. 2012), and has also been shown to drive more seemingly antisocial behaviours, such as defensiveness towards out-group members (De Dreu et. al., 2010, 2011) and envy (Shamay-Tsoorey et. al., 2009), despite also being heavily correlated with prosocial behaviours such as bonding (Williams et. al, 1994), reward-sharing in macaques (Chang et. al., 2012), and parental care (Gordon et. al., 2010). Due to the observed facilitation of social

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behaviours, the mechanisms of oxytocin provide a good initial framework on which to build models of social regulation and social allostasis. However, the precise effects that oxytocin has on social behaviours within biological agents is still not unanimous, with opinions divided as to whether prosocial behaviour equates to a more viable life. What this provides is an opportunity to test some of the hypothesised effects of OT, and to use these findings as a framework to build a social allostatic model upon in future research.

In robotics, very little work has been done so far modelling OT as a mechanism for social adaptation. For example, Anumandla et al. (2011) modelled OT release within a robot in order to assess the impact on trust in human-robot interactions. Although less directly related to our work, since it doesn't involve the use of OT, it is also worth mentioning work on social adaptation of robots such as Zahadat et al. (2014), who studied the social adaptation of robots through a combination of hardware configurations and evolutionary algorithms.

As an initial study into this long-tailed research of social allostasis, the experiments in this paper investigate the effects of the prosocial hypothesis of the mechanisms of oxytocin, modelled using the NetLogo simulation framework (NetLogo, 2001). We have modelled a small society of agents under conditions implementing two opposing effects on social salience: either increasing attention to social cues, i.e., increasing social salience (Gordon et. al., 2010), or decreasing attention to social cues, i.e., decreasing social salience (Ebitz and Platt, 2014). The aim of our study is to investigate if mechanisms of oxytocin that modulate social salience would contribute, or be detrimental, to the overall viability and survival of agents under different conditions in our simulated environment.

The remainder of the paper is structured as follows. Section 2 discusses the agent model of social salience and its action selection architecture. Section 3 describes the metrics used to assess the results of the experiments. Section 4 describes the experimental methodology. Section 5 presents the results of our experiments and a discussion of our findings. Finally, section 6 summarizes our conclusions and proposes future work.

2 AGENT MODEL

2.1 INTERNAL VARIABLES

In all experiments, agents have two homeostatically controlled physiological variables – *Nutrition* and *Socialness*. Both variables have identical lower limits (set to 0), upper limits (set to 1) and ideal values (set to 1) and are controlled through a homeostatic process using an architecture inspired by the work done by Avila-Garcia and Cañamero (2002). The value of both *Nutrition* and *Socialness* must thus be within a range between 0 and 1; they are satiated by the eating of resources and grooming with other agents, respectively. What is important to note is that, although both internal variables (*Nutrition* and *Socialness*) drive error-correcting behaviours, only a maximum error of the *Nutrition* variable can cause the agent to die. In other words, an agent cannot die of *loneliness*, but can die of *hunger*. The drive to correct the socialness variable deficit still drives the *loneliness* motivation and the grooming behaviour, despite the possibility of death. Drives are

Physiological Variables Update Rate	
Nutrition	-0.0003
Socialness	-0.0003
Oxytocin (when enabled)	-0.0005

Table 1. Rate of change, per time step, of each internal variable for each agent. Rates have been determined through a series of pre-experimental runs in order to create enough difference between conditions to investigate.

calculated concurrently for each agent at each time step. All agents are subject to the same rate of decay for each of their internal variables. The decay rate for each internal variable can be found in Table 1.

2.2 AGENT MOVEMENT

The default movement pattern of an agent is a random wander through the world, until that wandering behaviour is interrupted by another behaviour or perception of resource. Agents perceive the world through a cone of vision of length 20 and 80 degrees (-40/+40) and, for the sake of simplicity, are able to determine the distances, resource type and resource colour without requiring any additional cognition or computation. However, this may not be the case in future experiments.

2.3 AGENT BEHAVIOURS

Aside from the appetitive behaviour of wandering, agents have the following two consummatory behaviours:

Eat: During the execution of this behaviour, the agent will stop at a food resource and begin consuming it. For each “bite” (which is updated every time step) the agent recovers its nutrition at a rate of 0.01. At the same time, the food resource reduces in size at a rate of -0.01 – an inverse of the physiological effect on the agent. Therefore, the nutritional value that is taken from the resource is equal to the value that is consumed from it.

Groom: Grooming is achieved through tactile feedback of another agent. When *groom* is executed, agents who pass each other and are within the defined “touching” distance will satisfy that behaviour through touching. Grooming lasts as long as is necessary for the error to be corrected to a point where the motivational state changes (when *hunger* becomes the motivation). The *robot-radius* for *grooming* was set at 2 after initial tests of different radius sizes led to negligible differences, and is the value that is included in this model.

		Effect on Physiology (Per Time Step)		
Behaviour	Stimuli	Nutrition	Socialness	Oxytocin
b_i	S			
Eat	Food	+ 0.01	0.0	0.0
Groom	Agent	0.0	+ 0.05	+1

Table 2. Effects on internal variables for both of the possible consummatory behaviours the agent can execute. Again, rates have been determined through a series of pre-experimental runs to create enough variance for investigation.

Table 2 describes the effects that the successful execution of each of the consummatory behaviours has on the internal variables of the agent. As we will see in the next section, these effects are used during the calculation of behaviour intensity in the penultimate step of the action-selection architecture described below.

The choice of having asymmetrical effects of both behaviours was not random. Initially, both physiological effects (*Nutrition* and *Socialness*) were set at the same values (+0.01) in order to create symmetrical effects for both behaviours. However, modelling this into the agents resulted in no differences across all conditions. Conversely, bringing the physiological effect of *groom* up to 0.1 (ten times the effect of *eat*) did bring changes, but these were too small to analyse in detail. After experimenting with these values, the physiological effect for *grooming* behaviour was set at +0.05 to the *socialness* variable. As *eat* is satisfied by consuming static resources, and *groom* is satisfied by a consummatory behaviour on dynamic resources, the relative difficulty of satisfying that drive should be offset by an asymmetrical rate of satisfaction.

2.4 ACTION-SELECTION ARCHITECTURE

The action-selection architecture is a motivated architecture following the model in (Cañamero 1997). In addition to the above-mentioned physiological variables and behaviours, the architecture uses motivations that combine the intensity of the internal needs set by the physiological variables, and the observed external stimuli, in order to select the behaviour that the agent needs to execute. The particular way to calculate motivations and winning behaviours was inspired by the winner-takes-all motivated architecture described in (Avila-Garcia and Cañamero, 2002). Table 3 summarizes how these different elements of the architecture are connected, showing a breakdown of each internal variable, with the motivation it drives, the resulting behaviour that is executed by that motivational drive, the stimulus that is affected by that consummatory behaviour and the resulting physiological effect on the internal variables.

The action selection algorithm, running continuously in a loop, can be described as follows. For both behaviours, at each time step:

- Calculate the *drive/error of each internal variable*. Errors are calculated as the difference between the current values of the variables from their ideal value. At each time step, for each variable, v :

$$e_v = p_v - j_v \quad (1)$$

where e_v is the error value, p_v is the ideal value for that internal variable, and j_v is the current value of that internal variable.

- Calculate the *cues, i.e., the value of each external stimulus*. The value of *food cues* is calculated as:

$$C_{food} = \Sigma nutritionValue \quad (2)$$

where $\Sigma nutritionValue$ is the total nutritional amount of food resources seen in an agent's cone of vision.

Internal Variable	Motivation	Behaviour	Stimuli	Physiological Effect
Nutrition	Hungry	Eat	Food	+ nutrition
Socialness	Lonely	Groom	Agent	+ socialness

Table 3. Relationships between internal variables and motivations, through to the effects on physiology of both consummatory behaviours.

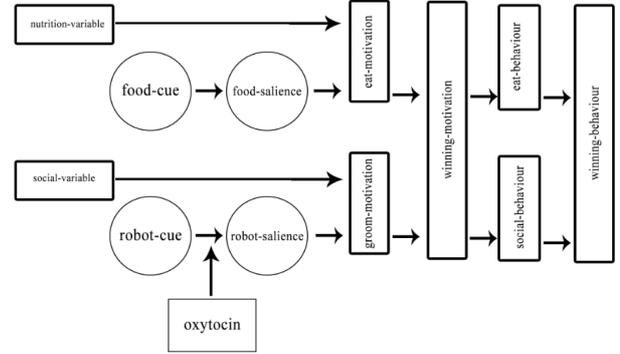


Figure 1. Overview of the action-selection architecture as described. The order of computation is from left to right, and both drives are calculated concurrently.

The value of *robot cues* is calculated as:

$$C_{robot} = \Sigma robots \quad (3)$$

Where $\Sigma robots$ is the *count* of the number of other agents seen in an agent's vision.

- Calculate the *salience of each stimulus*.

The value of *food salience* is the same as *food cues*, therefore:

$$S_{food} = C_{food} \quad (4)$$

The value of *social salience* is calculated as:

$$S_{robot} = C_{robot} \times \alpha \quad (5)$$

where α is the effect of oxytocin defined in the next section.

- Calculate the individual *intensity of both motivations, hungry and lonely*. Motivation is calculated as follows:

$$m_i = e_v + (e_v + S_i) \quad (6)$$

where e_v is the error of internal variable v and S_i is the stimuli linked to that motivation. The motivation with the highest intensity is selected as the winning motivation:

$$m_{winner} = \max[m_{hungry}, m_{lonely}] \quad (7)$$

- Calculate the *intensity of both behaviours* by multiplying the winning motivation by the physiological effect of each of the behaviours:

$$b_i = m_{winner} \times f_{i_{winner}} \quad (8)$$

where m_{winner} is the winning motivation and $f_{i_{winner}}$ is the physiological effect that m_{winner} has on behaviour b_i .

- The behaviour with the highest intensity is the winning behaviour, and the one that is executed.

$$b_{winner} = \max[b_{eat}, b_{groom}] \quad (9)$$

Figure 1 above gives a visual representation of the architecture.

2.5 EFFECTS OF OXYTOCIN

Within the context of this work, oxytocin is described as a hormone that affects, through a modulation function, the salience of social cues. *Salience* is defined here as the likelihood of a stimulus being given attention. The definitions of each effect are as follows:

- *None*: Oxytocin does not have any effect on social salience
- *Increased Social Salience*: Social salience is increased proportional to the oxytocin within the agent:

$$S_{robot} = C_{robot} \times (1 + Oxytocin) \quad (10)$$

- *Decreased Social Salience*: Social salience is increased proportional to the oxytocin within the agent:

$$S_{robot} = C_{robot} \times (1 - Oxytocin) \quad (11)$$

3 METRICS

3.1 DEFINITIONS

Taking note of what Avila-Garcia and Cañamero (2002) stated, caution must be taken in assessing performance on a single indicator of viability. For instance, a longer lifespan is not, in itself, necessarily indicative of greater viability. Additional aspects, such as comfort or life quality, may supplement the understanding of an agent's viability. The definitions of each viability indicator observed in this study are below:

- *Life Length*: The time that the robot survived (remained viable by keeping the *nutrition* variable above 0) during each run, as a percentage of the maximum simulation time. Time is defined as the number of steps in each simulation:

$$S_{life} = \frac{t_{life}}{t_{simulation}} \quad (12)$$

where t_{life} is the time the agent remained alive and $t_{simulation}$ is the maximum length of the simulation (in this case, 25,000 time steps).

- *Overall Comfort*: The average level of satisfaction of internal variables, measured at each time step.

$$q_t = 1 - \left(\frac{\Sigma Err}{max_{Err}} \right) \quad (13)$$

where ΣErr is the sum of errors of the robot's two internal variables at time t , and max_{Err} as the sum of the maximum

errors of all the internal variables. The average comfort level per run is given by:

$$Comfort = \frac{\Sigma q_t}{t_{life}} \quad (14)$$

- *Motivational State Balance*: The time that each robot spent in each motivational state (either *hungry* or *lonely*), measured as a percentage of their life-length. For each motivation i :

$$m\delta_i = \frac{t_i}{t_{life}} \quad (15)$$

where t_i is the time (in time steps) spent with the winning motivation i .

- *Behaviour Execution Balance*: The time that each robot spent executing each of the behaviours (either *eat* or *groom*), measured as a percentage of their total time spent executing behaviours.

$$b\delta_i = \frac{t_i}{t_{behaviours}} \quad (16)$$

where t_i is the time (in time steps) spent executing winning behaviour i and $t_{behaviours}$ is the total time spent executing behaviours.

3.2 STATISTICAL SIGNIFICANCE TESTING

In order to gain confidence in the findings, tests of statistical significance were performed on the experimental results. The test used was *One-Way ANOVA*, declaring significance at a p-value of $p \leq 0.05$. Significance testing was performed on the two key viability indicators – length of life and overall comfort – across all experimental conditions.

4 EXPERIMENTS

4.1 EXPERIMENTAL HYPOTHESIS

Extending upon the hypotheses proposed in previous literature, the null hypothesis for this experiment is as follows:

H_0 : Increased social salience will not significantly increase viability of agents.

4.2 EXPERIMENTAL METHODOLOGY

In order to study the discussed effect of oxytocin, the experiments in this paper model a society of six homogenous agents within a simulated environment, each equipped with an action-selection architecture, responsible for driving a homeostatic process for two internal variables (*Nutrition* and *Socialness*). Additionally, each agent has an internal value of *Oxytocin*, which either increases or decreases the salience of social cues. This was tested over three different environmental conditions over 180 simulation runs.

4.3 WORLD DESCRIPTION

The simulated world is modelled in NetLogo (2001) as a flat, two-dimensional environment with a fixed size of 99 * 99, encapsulated between four blue walls which the agents cannot pass through. If an agent perceives the edges of the world, it turns around in a random direction and continues as normal. Agents perceive a wall if it falls within $max\text{-}vision\text{-}length / 4$ of the agent. Food resources are represented in the simulation as yellow circles, and agents have a priori understanding of what a food resource is. The size of these resources is dynamic – and is dependent on the “nutritional value” available within each food resource (a resource with nutritional availability of 1 will be size 1, for instance). In each world, the nutritional value of each food resources regenerates at a rate equivalent to 1/10,000th of its maximum nutrition value at each time step. Inspiration for this slower rate of regeneration was taken from natural biology, in that – in the real world – the rate at which “natural” food grows is much slower than the rate at which it is consumed.

Initially, six homogenous agents of the same species exist in each world. The agents are visually represented as “bugs” within the simulation of size 3. The starting position of each of the robots is always a random space in the simulation, but is set so that agents do not initialise too close to the food resource. Each experimental condition (as defined in the next section), was run a total of twenty times to a maximum of 25,000 time steps per simulation run. This equated to 180 total experimental runs.

4.4 EXPERIMENTAL CONDITIONS

Each experimental condition is defined by a combination of two variables:

- The conditions of the world (i.e. “easy”, “challenging” or “super challenging”.)
- The presence, and directional effect, of oxytocin within the action-selection architecture.

The combination of these variables creates nine different experimental conditions to be tested. Each combination, along with its corresponding experiment number for ease of readability in later sections, can be seen in Table 4.

Oxytocin / World Condition	No Oxytocin	Increase Social Salience	Decrease Social Salience
Easy	E0	E1	E2
Challenging	C0	C1	C2
Super Challenging	SC0	SC1	SC2

Table 4. Experimental conditions, defined by the effects of oxytocin on social salience paired against each of the world conditions.



Figure 2 - Screenshots of the model with “easy” conditions (left) and “challenging” conditions (right). “Super challenging” is as “challenging”, with smaller resources. Food resources are represented by yellow circles; agents are represented as bugs.

The world conditions (see Figure 2) describe the availability and distribution of food resources in the environment. More specifically:

- “Easy” conditions are defined as a world with an abundance of food resources (18 resources), distributed in small clusters throughout the world.
- “Challenging” conditions are defined as a world with scarce (6) food resources in two clusters, placed towards the corners of the world.
- “Super Challenging” conditions are exactly the same as Challenging conditions, although the food resources have half of the nutritional amount.

In each experiment, viability indicators are logged for each individual robot, but reported using the mean results for each experimental condition across all the simulated runs as discussed in a later section. Finally, should all initial food resources be consumed, an additional cluster of four food resources is regenerated in one corner to allow agents to be able to correct their nutrition deficit, albeit with less food availability.

5 EXPERIMENTAL RESULTS

5.1 RESULTS

Regardless of the effects of oxytocin, all agents survived for the full length of all simulation runs during easy world conditions (E0, E1 and E2), resulting in a 100% survival rate across all runs. Despite the consistency in life length, average comfort levels for the easy conditions vary slightly. Little variance (0.3) is seen between E0 (no oxytocin) and E1 (increased social salience), though agents in E2 (decreased social salience) experience a considerably lower average comfort rate. In this case, the easy world had sufficient resources to allow agents to survive, regardless of oxytocin effects.

In the challenging condition, where oxytocin has no effect on the social salience (C0), the life length was, on average for all agents, 75% of the total simulation time. Physiological comfort during these runs was 0.66 (out of a possible 1.0). When oxytocin increased social salience in these challenging conditions (C1), average life length improved to 83%, whilst average comfort levels of agents also increased to 0.71, denoting both a longer and more comfortable life. Decreasing social salience (C2) had the inverse effect, reducing

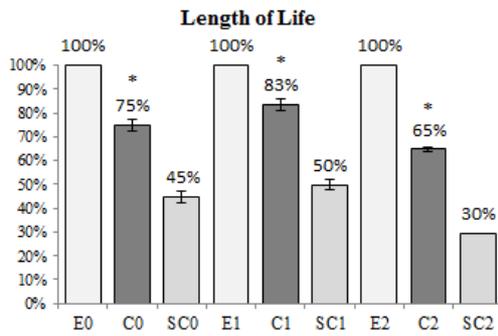


Figure 3. Average life length (survival) for all agents across all simulation runs in three environmental conditions (Easy (E), Challenging (C) and Super Challenging (SC)) and with three effects of OT (No effect (conditions labelled 0), increased social salience (conditions labelled 1) and decreased social salience (conditions labelled 2)). Bars represent standard error of +/-1 SD. Asterisk denotes statistical significance.

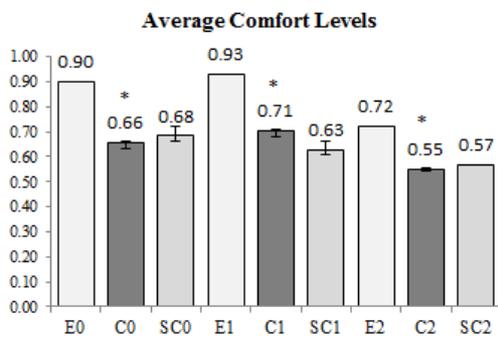


Figure 4. Average comfort levels for each experimental condition. As before, we show results for all three world conditions (E, C and SC) with three effects of OT (0, 1, and 2). Bars represent standard error of +/-1 SD. Asterisk denotes statistical significance.

average life length to 65% - down 10% vs. the control group of no oxytocin, and a 0.11 reduction in average comfort levels to 0.55. Statistical significance was observed across all results for both the length of life and comfort levels. There was a statistically significant difference between SC2 and the other OT conditions, although no significant effect was found between SC0 and SC1. The same is true for average comfort levels in super challenging conditions.

Figure 5 shows the distribution of motivational states (as defined in the Viability Indicators section) across all three oxytocin effects in both world conditions. For E0 and E1, motivational states are fairly balanced, with agents spending a similar amount of time in each of the motivational states. In conditions with decreased social salience (E2), agents appear to be motivated by groom slightly more than in E0 and E1. The more noticeable differences are noted in the challenging conditions. In C0, there is a variance of +/- 2%pts between motivational states, and C1 has a variance of +/- 5%pts; both slightly favouring the motivation to eat. Once again, in conditions where social salience is decreased (C2), the motivation to groom outweighs the motivation to eat by a factor of ~5 (83% to 17%). Again, the potential causes for this are discussed in the next section. A similar split is seen for super challenging conditions, with agents in decreased social salience (SC2) being

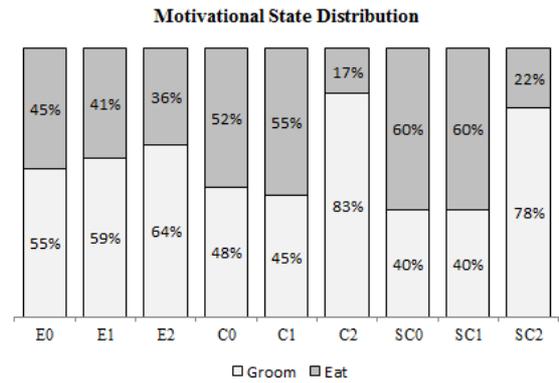


Figure 5. Distribution of time spent in each motivational state for each oxytocin effect for all world conditions. Light grey denotes the % time spent under the groom motivation, dark grey is % time spent under the eat motivation.

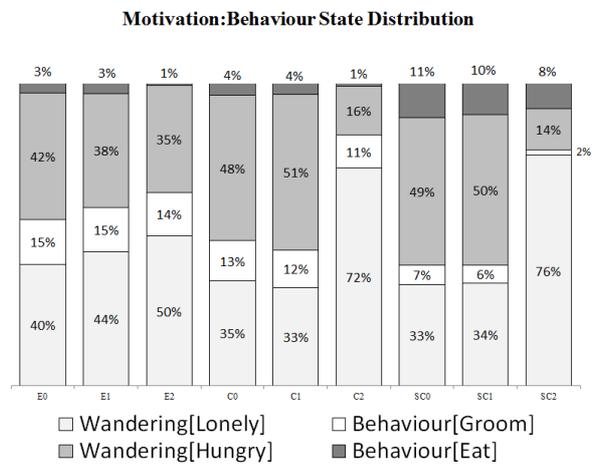


Figure 6. As figure 5, with the inclusion of time spent executing each behaviour in each motivational state.

heavily skewed towards grooming motivations (78% vs. 22%). Figure 9 shows the time spent executing the behaviours during each motivational state. Any time not spent executing the behaviour is therefore an agent searching for the relevant resource.

5.2 DISCUSSION

Despite Ebitz and Platt's proposed hypothesis that decreased social salience would result in more viable agents, agents in this environment remained more viable when oxytocin increased social salience. Although the model is currently absent of any additional context outside of the maintenance of homeostatic variables, this conclusion is in line with the prosocial hypothesis discussed previously.

The distribution of motivational states across decreased social salience conditions support this stance. Looking at figures 4 and 5, agents would primarily be motivated to eat and, as social stimuli is not salient enough to follow to food resources, would eventually find the resources without any social assistance. Once food has been eaten and the nutrition error has been corrected, agents would then look to satisfy their (non-lethal) social need. As the social error increases over time, the appearance of food resources, despite having

some salience, would eventually not be salient enough to change the motivational state of the agent (calculated by $m_i = e_v + (e_v + S_i)$).

Increased social salience does indeed aid agents in locating food resources, as following an agent that sees a food resource (and whose motivation it is to eat) ultimately draws agents to resources that they may not otherwise have immediately found. However, the more agents that successfully find a food resource cluster, the faster those resources would get consumed. Agents consume food at a fixed rate, regardless of the number of other agents that are currently also at that cluster. In other words, any propensity to share resources does not currently exist within the model. Therefore, whilst oxytocin that increases social salience correlates with viability of agents in this current model, it may not (and, indeed, should not) be the case when food availability becomes sparser. There has been ample literature (e.g., Ebitz and Platt, 2013; Kosfeld et al., 2015; Bethelam et al., 2014) to suggest that the effects of oxytocin should be context-dependent.

The lack of significance in the results from the super challenging conditions can be attributed to the severity of the challenge. With such low food availability in the environment, agents did not have an opportunity to express behaviours driven by the OT modulation. Future studies will reconsider these world conditions.

6 CONCLUSION AND FUTURE WORK

As an initial step towards creating a socially adaptive model, this study has looked into one probable effect of the neuropeptide oxytocin – that it increases social salience – and created a two-dimensional simulated system in which to test a previously-proposed hypothesis of its effects. The agents simulated within this environment were equipped with an action-selection (AS) architecture, inspired by previous AS work done in our research group, with the inclusion of a hormonal modulation function that affects the salience of social cues proportional to the amount of oxytocin in the system. By both increasing and decreasing social salience across different distributions of food resources, the hypothesis proposed by interactionists – that increased social salience would result in a more viable life for agents – was observed in the context of this study.

Whilst this model is a step towards a socially adaptive system, much work still needs to be completed. The development of a model to study social adaptation requires more than homogenous agents with fixed physiological effects of prosocial behaviour. There are further hypotheses which can be modelled, inspired by the findings and observations of this model, and the literature discussed previously.

One of the observed prosocial effects of increased oxytocin is that of reward sharing (Williams et al. 1994), and therefore an opportunity is presented here to extend beyond this study to include opportunities to share the limited resources. Should agents reach food resources at the same time, the role of oxytocin in this system should also be able to determine potential to resource-share. This rate of sharing may be dose-dependent.

Since all agents in this system are homogenous, the effects and modulation of oxytocin remain consistent for all agents and throughout the length of each simulation. This is rarely true in real-

life social groups. The likelihood is that social groups do not consist of evenly-matched individuals, and the perception of other individuals of the group is rarely uniform within the society (Mahajan et al., 2011). Both the release and effects of oxytocin has been found to have different effects in non-human primate groups, based on perceived hierarchy (Knight and Mehta, 2014) or the presence of a predatory threat (Ebitz and Platt, 2014; Muroy et al., 2016). Within a homogenous social species with no social threat, the role of oxytocin on social vigilance cannot be properly surmised, and so any findings remain limited. It is hypothesised that the introduction of a perceived stronger species, or stronger agents of the same species, would have a significant impact on agent viability, and this will be addressed in a future study. Additionally, the rate, or dose, of oxytocin released within the system could be affected by a number of factors, such as the time since an agent has last had social interaction, familiarity with a previous grooming partner, or the perceived hierarchical relationship – whether higher or lower – between the agents (Knight and Mehta, 2014). It is hypothesised that changing this rate of release from a fixed value to a more context-dependent rate will create more adaptive behaviours which will impact the viability of agents, although the direction of this impact is unknown. Much work must still be undertaken before confidence in these effects can be achieved. Taking into account additional effects of the hormone proposed in the cited literature, more rigorous experiments are planned for the future. The experiments conducted and results of this study have laid the foundations on which to build a more dynamic, socially adaptive model.

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How effective is Ant Colony Optimisation at Robot Path Planning

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Abstract. This project involves investigation of the problem robot path planning using ant colony optimisation heuristics to construct the quickest path from the starting point to the end. The project has developed a simulation that successfully simulates as well as demonstrates visually through a graphical user interface, robot path planning using ant colony optimisation. The simulation shows an ability to traverse an unknown environment from a start point to an end and successfully construct a route for others to follow both when the terrain is dynamic and static.

1 INTRODUCTION

To be able to prove that a solution to the problem was found and that a good level of success had been achieved, the graphical user interface (GUI) displays, the pheromone trail and the obstacles that occurred which the agents rerouted around, using a grid based output shows the path the agents are taking throughout the solution. This was comparable to other examples of solving the solution with ant colony optimisation (ACO) to see if improvements have been made and whether some ACO variations are better than others depending on the environment.

Robot path planning (RPP) is used within many applications within the technological world, from helping unmanned vehicles to robotics. It is stated by (Cao, 2016) as 'to find a path from the current point (or the start point) to the target point, which is a shortest or a minimum price path without barrier'.

ACO is a heuristic based off the foraging behaviour of ants, originally created by Marco Dorigo and in 1991, and further expanded on in later years. It was originally the 'Ant System' as a basic heuristic for solving optimisation problems such as the Travelling salesman problem (TSP). However later became developed further and more optimised, becoming ACO.

Within the field of artificial intelligence (AI), ACO is becoming increasingly useful. This is especially reinforced when Google, Uber and other companies are experimenting and testing the idea of self-driving cars and thus many career paths are becoming open in the field.

2 BACKGROUND

A literature search was conducted, the scope of which includes the different techniques that have been employed historically to achieve ACO and different variants and modifications that have been made to the algorithm to optimise it in most part to solve the TSP. Furthermore, investigation was made into the area of

RPP and the implementation methods that were used to solve this issue.

As well as this, other areas of ACO were investigated such as the usage of artificial neural networks and genetic algorithm hybrid heuristics.

There are some solutions already applied to this problem, such as the artificial potential field method, neural networks, genetic algorithms (GA) and A* searching method as stated by (Yu, Wei, Wang, Ding, & Wang, 2017). However, they went on to state that each of the current solutions does have problems associated to them. There has also been attempts at hybrid models too consisting of different swarm intelligences integrated together.

There have been many different solutions created to try tackle this problem such as genetic algorithms which is the metaheuristic focussing on evolutionary algorithms that are inspired by natural selection and particle swarm optimization which iteratively searches for improvements to a candidate solution. However, the Swarm Intelligence this paper focussed on is ACO which although has proven to work effectively in solving the problem, still has improvements that could be made and investigated.

Another variation of ACO that implements GA into it is smartPath, created by (Châari, Koubâa, Bennaceur, Trigui, & Al-Shalfan, 2012). Within their work they proposed system they state that 'ACO has a stronger local search capability and faster convergence but the algorithm can easily sink into a local optimum' where as GA 'belongs to random optimize processes, so the local convergence problem does not appear; however, this makes its convergence speed slower'. This therefore clearly shows that the shortcomings of one can be improved by the other.

The way they therefore designed the algorithm was so that the initial path is created from using ACO to create a fast-converged optimal path, and the second phase which is using the GA as a way of post optimization to improve the quality of the solution. This is done by checking all the nodes and then attempting to mutate the nodes in the path if the length of a resulting new path is shorter.

When tested against other heuristics such as their improved ACO (IACO) and classic ACO (CACO) and even GA it was found to outperform each of them in a varying number of environments in terms of both finding the shortest path and the efficiency with time.

Another variation on ACO is AntFarm designed by (Collins & Jefferson, 1990). Their idea was to create a simulation of an evolving population of ant colonies, where the reproduction is based on the amount of food they can carry back to nest, thus promoting better foraging strategies. The colonies are made up of identical ants, however their behaviour is specified by an artificial neural network (ANN).

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This approach is interesting as it implements a genetic algorithm (GA) within the ACO algorithm. With this they aimed to implement natural evolution using local competition and mating. The other main interest within this research is the use of an ANN to represent each ant's behaviour. Through their use of GA, they can mutate the ANN allowing evolution of each colony of ants. The advantage of a technique such as this is that they can mutate and optimise many features of the ants such as pheromone density, how the optimal path is defined and other factors.

3 HEURISTIC DEVELOPMENTS

The way in which the heuristic functions is that the agents (ants) will go out from the start point (nest) and search for the end objective (food) when the ant reaches the food it will return to the nest and lay a track of pheromone. Until the path to the food is discovered the ants will decide on random directions, without any decision making. However, when a food source is discovered and they pick up a pheromone trail it increases the probability that future ants will then take this route. Overtime this trail will strengthen and most agents will follow this trail.

As well as being able to handle single-objective optimization problems where only one food source is available, (Dehuri, Ghosh, & Cho, 2011) states that ACO also excels at multi-objective optimization problems. These are problems where there may be conflicting objectives which solve the same solution. So, two food sources of equal value, and many ways are presented to solve this issue in their literature review.

Improvements of ACO are also becoming more common as (Yu, Wei, Wang, Ding, & Wang, 2017) states the advantages of ACO are 'its strong robustness' and more importantly that it's 'easy combination with other algorithms'. It was also investigated how much further it would optimise ACO with the addition of evolution within the algorithm brought over from GA. (Roach & Menezes, 2008) state this also, putting forward the evolutionary ant colony optimization (EACO). They further state that through using EACO, it's possible to 'give the individual ants a chance to evolve, and thus, the agents themselves can become more optimized' and they further show in their paper that it is much more powerful in dynamic environments than ACO however ACO is more efficient in static environments.

4 ROBOT PATH PLANNING ACO METHODS

Cao (2016) puts forward an improved version of ACO for RPP. Within it they stated that the initial search time takes too long. This is the result of the randomness at which the ants initially search. Therefore (Cao, 2016) uses a pheromone which decreases with distance with the idea that the ant will have a clear motion direction during the initial search.

Another criticism that (Cao, 2016) made is that the pheromone evaporation rate is unchanged throughout the running of the algorithm, which can lead to local convergence if too small, or slow convergence rate if too large. Therefore, they put forward the notion that a dynamic evaporation rate should be used. This is done with setting the evaporation rate high at the start to enhance the global search ability, then lowering it with the number of cycles so that local convergence can happen on an

optimal solution quickly. (Yu, Wei, Wang, Ding, & Wang, 2017) also criticise the original ACO for this and suggest an 'adaptive pheromone volatilization coefficient' where they again suggest that evaporation rate should change with the number of cycles.

The heuristic function in previous work was improved upon by (Cao, 2016). This is done by changing the heuristic function so that the distance between two grid points which is normally used is changed so that instead what is used is the distance between the next grid point the ant will move to and the target point if it is known. This idea is also supported by (Yu, Wei, Wang, Ding, & Wang, 2017) where they also improve the heuristic so that the point that is closer to the goal is chosen instead of blindly picking. The advantage of this is that the initial search speed will be greatly improved and give the agents some direction when searching out a path.

However, (Cao, 2016) uses the ant-cycle algorithm described by (Dorigo, Maniezzo, & Coloni, 1996) after a cycle of movements made, optimal and worst solutions are calculated and some of the best solutions are used and the pheromone quantity is updated as a result.

5 IMPLEMENTATION

The methods aimed to optimise the ACO algorithm as much as possible, so the initial work focussed on an approach to firstly work on the core system methods and then expand to optimising performance, and creating a more complex GUI to control parameters.

The system was created using the python programming language. The reasoning behind this choice was the ease to develop in a short space of time with its extensive library support, readable code and finally due to it being interpreted it is much easier to debug. Libraries used within the creation of the program include Matplotlib which aided in the creation of the graph / grid interface. Another package used is the Tkinter package which provides the GUI with the controls to modify the functionality of the simulator, and was the base GUI for the graph to be imbedded within.

The project was also designed within the Pycharm IDE created by JetBrains. The reasoning behind this decision was that the IDE provided all the tools and functionality required, especially ease of package management and syntax correction.

The ideas presented in this paper have been successfully implemented as a proof-of-concept prototype as shown in Fig. 1.

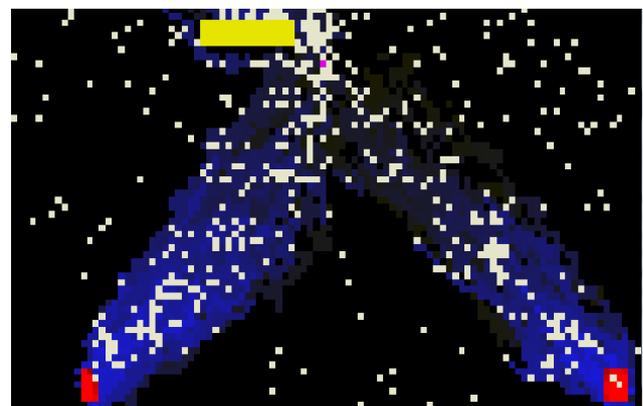


Figure 1. Ant Colony with two

The ant colony simulation was then evaluated by comparison to results in literature.

6 EVALUATION

To evaluate the developed system the best possible way was to firstly run tests using the algorithm implemented and compare the values and outputs to competitors using ACO or other algorithms to solve RPP. It was also worth comparing how the programming language or changes to the metaheuristics are used as these could possible effect performance. A good starting comparison was to compare the results achieved to work presented by (Dorigo, Maniezzo, & Colorni, Ant System: Optimization by a Colony of Cooperating Agents, 1996) in his paper or results found by (Perumal, et al., 2016) and then furthermore to other more recent variations.

7 CONCLUSIONS & FUTURE WORK

In conclusion ACO shows many potential solutions to solve the problem of RPP. Although ACO does show great ability in solving optimization problems such as TSP and RPP it has shortcomings such as falling into local optimum or not converging quick enough. Many improvements can be made not only to the heuristics itself, but also by creating a hybrid solution using a combination with other heuristics.

A further area of study within the field however would be to consider the problem of multi-objective ACO. As a problem that could occur is if two food sources or end points exist, not only would the shortest path to each must be found, but then these would have to be compared to find which is the optimal solution.

Future work could include extending this to other platforms such as embedded systems. Furthermore looking into applying the algorithm with other languages such as C++ would be ideal as this would provide much greater time efficiency due to its compiled nature and also being a low level language.

Finally another area of interest would be the implementation of evolutionary aspects of GA systems so that it further optimises route planning.

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Morphogenetic Engineering For Evolving Ant Colony Pheromone Communication

Neil Vaughan¹

Abstract. This research investigates methods for evolving swarm communication in a simulated colony of ants using pheromone when foraging for food. This research implemented neuroevolution and obtained the capability to learn pheromone communication autonomously. Building on previous literature on pheromone communication, this research applies evolution to adjust the topology and weights of an artificial neural network which controls the ant behaviour. Comparison of performance is made between a hard-coded benchmark algorithm, a fixed topology ANN and neuroevolution of the ANN topology and weights. The resulting neuroevolution produced a neural network which was successfully evolved to achieve the task objective, to collect food and return it to the nest.

1 INTRODUCTION

This research has developed a model of ant colony swarm intelligence behaviour. The novel aspect is that behaviour of pheromone navigation was not hard coded, as in most implementations, but has evolved using artificial neural networks (ANNs) and an implementation of neuroevolution. Compared to previous research which failed to evolve standard and fixed topology ANNs for ant behaviour (Collins & Jefferson, 1990a), this research produces successful evolution and applies a more comprehensive neuroevolution methodology including complexification and augmentation of ANN topology and weights, as described by NEAT (Stanley, 2004).

Inspired by biological ants, this research aims to provide insights to advance understanding of how pheromone communication evolved in biological organisms. Application of neuroevolutionary computational modelling provides a useful analogy to how brains may have evolved to produce biological organism behaviours.

There are many long standing open questions regarding the evolution of altruism, related to how any why the evolution of cooperation emerged among closely related individuals [Hamilton 1964]. Worker ants (Formicidae) are a perfect example of altruism, as they collect food for the good of the swarm but they get no individual rewards. This computer simulation method can provide new insights into altruism because each colony is only assessed by its fitness as a whole, not that of individual ants.

Pheromone trails can be seen as social memory or swarm memory used by all agents in the colony. The problem is called central place food foraging which is an optimisation problem.

The aim of foraging is to collect as much food as possible and return it to the nest. An ant's food collection consists of two phases: the search for food and retrieval of food back to the nest.

In this respect the problem relates to the new field of morphogenetic engineering (ME). In this task, the core challenge posed by ME is a reverse engineering one: How can the ants' micro-rules be inferred from the system's macro-objectives? (Doursat et al., 2013). In this case the macro objective is to optimise fitness of the swarm by using swarm communication, but the micro rules for each ant to achieve that were not provided in this system and needed to evolve autonomously with no prefabricated design.

2 RELATED WORK

Literature on pheromone communication is described by various key words: ant evolution simulation pheromone, central-place foraging algorithm (CPFA), pheromone recruitment (Letendre and Moses, 2013).

The core interest of this work is how ant pheromone communication can be evolved in a computational model. There have been some interesting works attempting to evolve ant pheromone communication, and others evolving swarm communication in general which is related closely enough.

A milestone early attempt to use a computer simulation to evolve ant foraging strategies using pheromones which resemble behaviours of biological ants was AntFarm (Collins & Jefferson, 1990a). AntFarm implemented an early form of neuroevolution, which was used to evolve the ANNs which learn behaviour for effective ant pheromone communication (Collins & Jefferson, 1990b). Neuroevolution methods in AntFarm evolved both the ANN connectivity pattern (topology) and weights of the ANN which were under genetic control in a genotype. Limitations were that: (1) AntFarm did not successfully evolve any cooperative foraging which was the main objective. (2) A basic, conventional ANN was used, when compared to the wider range of operators, sigmoids and activation functions with complexification as used in more recent neuroevolution models such as NEAT (Stanley, 2004). (3) The number of neurons and connections were not under genetic control.

The first research to evolve Ant pheromone foraging was by Panait and Luke (2004).

More recently, Beem (2017) attempted to use NEAT to evolve the controller for individual agents in a swarm. However the methods failed to produce any ability for agents to find food, or communicate, or exhibit any swarm intelligence whatsoever. The most advanced behaviour that his agents ended by evolving was to walk in circles. Perhaps that was due to the coordinate system used, or a lack of random or sin wave inputs. The inputs to the NEAT ant controller included the ant's own position; the

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intensity of pheromones at its location; whether or not the ant is carrying food at a given moment and the distance to the nearest food from two different points on the ant (for triangulation). The NEAT outputs are the agent's forward movement speed, its steering direction and the intensity of the pheromones it leaves behind. All agents within a swarm have the same neural network as controller.

Yong and Miikkulainen (2009) found that for cooperative tasks such as chase and evade, evolving several autonomous, cooperating neural networks to control a team of agents is more efficient and robust than evolving a single centralized controller. This potentially may apply in ants where two distinct roles are required – searching for food and returning to the nest.

Other attempts to evolve Swarm Intelligence using NEAT have failed, for example Chang & Worlanyo (2015) didn't see any communication being evolved. In other work, to some extent evolving swarm communication has succeeded (Floreano et al., 2007, Marocco and Nolfi., 2003, Yong and Miikkulainen., 2009). Rawal et al. (2012) successfully evolved cooperative communication between a group of predators who can only catch prey by communicating information codes to each other. A related work has evolved ants nest site localisation (Marshall, 2003).

Ant algorithms are generally most widely known through the wide literature on optimisation problems with ant colony (ACO) by Dorigo et al., (2006). Differing from this research, ACO algorithms conventionally must be hard coded by a designer and not evolved automatically.

Letendre and Moses (2013) used genetic algorithms to show that ant foraging is improved in random food distributions and using both pheromone and site fidelity foraging strategies. However their GAs were used only to adjust a set of parameters affecting behaviour, not to learn the behaviours themselves, which were hard-coded and pre-existing.

3 STATE OF OUTSTANDING PROBLEMS

There are some state of art current outstanding problems specifically within the evolving pheromone communication, some of which are addressed in this work.

Collins & Jefferson (1990a) suggested future work should involve: (1) a systematic study of the effect of food distribution on the evolution of foraging strategies, testing the model of Johnson et al. (1987). (2) evolution of foraging strategies that are strongly affected by competition to see if competitor colonies sharing a single environment will interfere with each others strategies, disrupting communication by overwriting pheromone or misleading trails – which is related to Anti-pheromone which was later separately used by Panait and Luke (2004). (3) Investigate previous suggestions that pheromone evolution requires incremental changes to vary the environment, slowly making foraging more difficult over time.

Future work can also focus on the limitations of Panait and Luke (2004) which was suggested as future work. (1) When using multiple food sources which decay when eaten, this results in a dynamic changing environment and this makes pheromone evaporation more important. (2) How does pheromone navigation change with introduction of predators. (3) Future work can investigate ants which can produce more than 2 pheromones, so the ants can also learn complex tours with multiple way-points and self-intersecting paths.

4 SYSTEM COMPONENTS

There are five components in the system which occur when an ant makes a move.

1. Pre-computed Inputs (ant sensors).

Ants have 13 input sensors: (1, 2) the location within the 9 adjacent cells (Moore neighbourhood) of the highest pheromone, (3, 4) the location within Moore neighbourhood which is closest to the nest, given by a 'compass sensor'. (5, 6) location within Moore neighbourhood of food. (7, 8) the direction of the ant's previous move, (9, 10) a direction picked at random, (11) a Boolean indicating whether the ant is currently carrying food, (12) a random number, (13) a fixed value of 1 (Bias). These are referred to as the pre-computed inputs and they remain the same even when the controller is changed (BMI, ANNs, NEAT).

Having a compass avoids the requirement to use two different pheromones. Compass is calculated by Pythagoras theorem using the x and y differences between ant and nest. In a grid system following the compass does not produce a direct path, it results in diagonal motion followed by perpendicular motion.

All of the 5 direction pre-computed inputs are represented in a consistent manner using two variables for x and y. These represent the change required in the ant's current x and y coordinates. These variables can be positive, negative or neutral. If both are neutral the ant would stand still (which would never be beneficial when foraging). If both were negative, the ant would move diagonally towards the origin (NW). With this method, the two variables can encode any direction within the 9 squares of the ant's Moore neighbourhood. If the ant chooses to follow the compass, it would then ignore the pheromone and vice versa.

2. Controller.

The controller is a 'black box' brain which decides the animal behaviour at timestep t, based on the pre-computed inputs from the ant's sensors. The experiments were repeated using different controllers: a hard-coded benchmark (BM1), a fixed topology neural network and neuroevolution by adjusting the topology and weights of an ANN.

3. Outputs.

The resulting output of the controller determines the direction in which the ant moves.

4. Post move local updates.

After each ant has moved, a number of post-move local updates are automatically applied. (1) If the ant is now standing on food and isn't carrying any, it automatically picks food up. (2) If the ant is carrying food, pheromone is deposited with strength inversely proportional to the time since collection. (3) If an ant is already carrying food and is now standing on a nest, it automatically drops the food. This representation realistically assumes that biological ants already could pick up and drop food before they evolved pheromone communication. These tasks are regarded as automatic responses which we assume have been learnt previously.

5. Global updates

After a full iteration, when all ants have finished making a move, a global update is triggered in which all pheromone is evaporated (decremented). A number of different evaporation

rates including decrementing and various percentage reductions were tested to identify how evaporation rate affects the ability to evolve navigation controllers.

5 THE MACHINE LEARNING TASK

The given inputs and expected outputs were kept strictly equal for all tested controllers. Therefore here we can formally define the machine learning task based on the relationship between inputs and outputs of the controller. This is critical step because small changes to the representations of input and output can make big changes to the difficulty of the task for the controller to learn.

Inputs:

In total the task has 13 inputs: 10 (5 pairs of) input direction variables, 1 boolean input, 1 random number input and 1 fixed value (Bias). There are 2 outputs: x and y.

Of the 13 inputs 10 inputs are positional change inputs. These are in 5 pairs of x and y, relative to ants current position, to reach the optimal square within Moore neighbourhood for the 5 pre-computed inputs: food, pheromone, compass, same-move or random-move. These all have three possible values -1,0,1.

```
Closestnestx
Closestnesty
Foodherex
Foodherey
Highestpheromex
Highestpheromoney
rand_x
rand_y
same_x
same_y
```

For food and pheromone, 0,0 only occurs when none is found, which means that there is no need for having separate Booleans indicating food and pheromone presence. For compass, 0,0 only occurs when standing on the nest (in which case compass would not be useful as the ant would not be carrying food because it would have been dropped automatically).

There is one random number input called r. This is independent of random direction inputs. This is required so that ants can randomly determine when to move randomly.

r

A Boolean is included to represent whether food is currently being carried. This is an important flag because it defines one of two current states: (1) searching for food, or (2) bringing food back to nest. This information is not available in other inputs.

carryingfood

There are only two outputs. They represent the relative step the ant will take on this timestep. They can be a value from the set {-1,0,1}. Therefore the output of the controller purely

determines the position of the ant's next move, which has 3² options, one for each square in the ant's Moore neighbourhood.

```
output_x
output_y
```

6 BENCHMARK ALGORITHM BM1

The developed system included designing a custom developed hard-coded benchmark algorithm (BM1) for pheromone based food foraging behaviour, shown as pseudocode in Fig. 1. The BM1 algorithm was used in this research as a comparison or gold standard to assess the performance of the fixed topology and evolving ANN algorithms.

The benchmark BM1 does produce efficient foraging behaviour and also demonstrates that the pre-computed inputs provide all required information to complete the foraging task. The benchmark performance was measured and used to evaluate the performance of ANN driven behaviour controllers which later evolved. The pseudocode gives a description of what happens for each ant to decide which direction to move in at each timestep. This implements two modes: searching for food, and retrieving food based on the carryingfood Boolean flag.

```
if (carryingfood){
    //follow compass to nest
}else if (food in neighbourhood){
    //step onto the food
}else if (pheromone in neighbourhood){
    //step onto strongest pheromone
}else if (rand%100<90){
    //continue previous direction
}else{
    //use a completely random direction.
}
}
```

Fig. 1. Pseudocode for the Benchmark Algorithm (BM1).

In the BM1 benchmark, when a random direction has been chosen, on consecutive timesteps, the direction has 90% chance of remaining constant. This means that ants travel largely in straight lines, broken by abrupt changes on 10% of steps. This causes the ants to more effectively spread out and cover the whole grid more quickly. The main benefit is that ants then have a much higher chance of running into an existing pheromone trail. This outperforms total random movement, whereby ants often retrace their steps in consecutive turns which results in a lack of general directed movements. Also the random direction is chosen from an 8-square Moore neighbourhood – so that standing still is never chosen as it would have no benefit.

It can be seen that efficient pheromone communication (BM1) can be captured in this simple pseudocode which consists of only 5 IF statements, plus the defined actions to perform within each condition. The machine learning task is to replicate the behaviour of these 5 IF statements and associate the correct actions with each case, by using only the 12 given inputs. This summarises the difficulty of the learning task. If the machine learning fails, it must be because the IF statement structure was too complex to learn, or the actions were not associated with the

correct conditions. The BM1 already demonstrates that the given 12 inputs are satisfactorily informative to complete the foraging task.

In the event of machine learning failure, that could be investigated in terms of machine learning complexity, rather than anything specifically about the foraging task, because it could be assumed that other machine learning tasks with the same level of complexity would equally fail to be learnt.

7 RESULTS OF BM1 IN FIXED LEVELS

For a comparison between controllers (BM1, ANN, Neuroevolution), one fixed level was used. The obstacles and food were located in the same places. That ensured that each controller was subject to the exact same challenge. The fixed level is shown in Fig. 2.

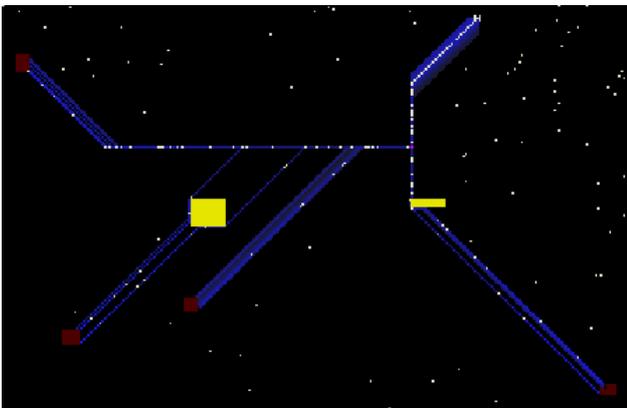


Fig. 2. This shows the layout of the fixed level used for evaluating and comparing a variety of controllers.

When the ant colony was controlled by the BM1 algorithm and foraged within this fixed layout level (Fig. 2.), the ant colony makes very consistent progress every time it is run (Fig. 3.). The small variations are due to the random movement of ants, taking slightly different times to first discover food sources before they are subsequently attended by large recruited swarms.

In total the fixed level happens to have 6630 foods. On a typical run in this fixed level, as those shown on the graph Fig. 3, BM1 collected the first food after 106 timesteps. At 2500 timesteps, 3143 foods were collected. By the time the run was halted at the 5000th timestep, food was still being actively collected, in total 4852 foods had been collected, so 1778 foods remained uncollected.

The behaviour of the BM1 can be further analysed by looking at Fig 4. which shows how often each direction was chosen. Standing still is the rarest move and diagonal bottom-right to top-right the most frequent. Also Fig. 5. shows how often each of the 5 IF statements from the pseudocode (Fig. 1) were triggered. Continuing in the same direction is the most frequent action and stepping onto food is the rarest action.

8 FIXED NEURAL NETWORK TRAINING

Using a typical run of BM1 in a fixed level, as in Fig. 1. a training set for an ANN was produced.

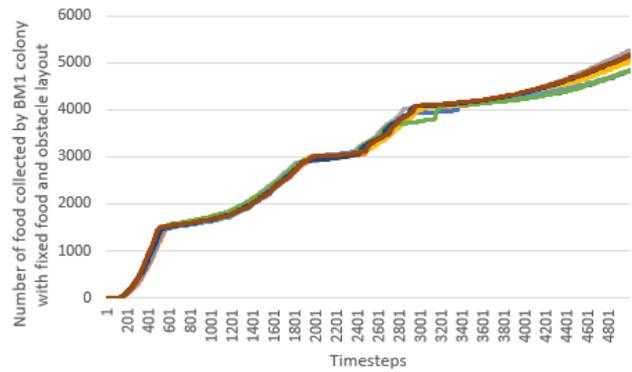


Fig. 3. Consistent results of BM1 run 8 times on a fixed level.

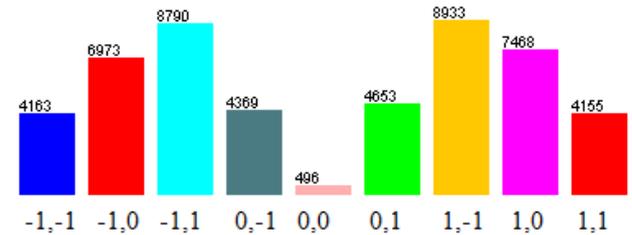


Fig. 4 How often each Moore neighbourhood direction was chosen.

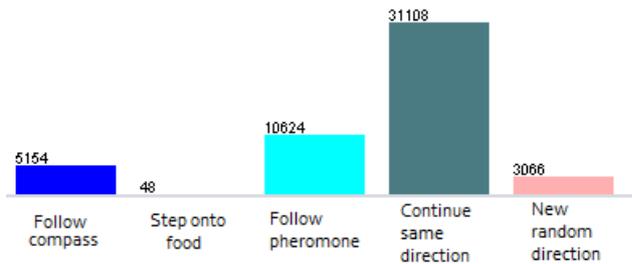


Fig. 5. How many times BM1 triggered each IF statement from the pseudocode.

This was achieved by writing to file all of the inputs and the resulting outputs for 10 ants over a 5000 timestep run. This data set contained 50,000 instances each containing the full set of 13 inputs and 2 outputs.

The training set was then used as the training set for a neural network. The aim was to identify whether an ANN could use backpropagation to learn the relationships between the inputs and the output produced by BM1. A 90% split was used to split into a 45,000 instance training set and an unseen 5,000 instance test data.

In order to use a single ANN to produce two outputs: x and y together, output_x and output_y were combined into a single output class with 9 values A-I (Fig 6). In total the ANN had 12 inputs and 9 output nodes, one for each class. With no hidden layers, the network classified 87.5% correctly. With one hidden layer of 10 nodes the MLP correctly classified 90.4% of test data. With two hidden layers of 10 nodes each (Fig. 6), accuracy improved to 92.3%. Training time increased with hidden layers.

It is not known if this trained ANN would in fact perform well as a controller for the ant simulation, or not. The misclassified instances could include important classes. It is hard to identify which situations the network failed in and if those would be critical or not to foraging behaviour.

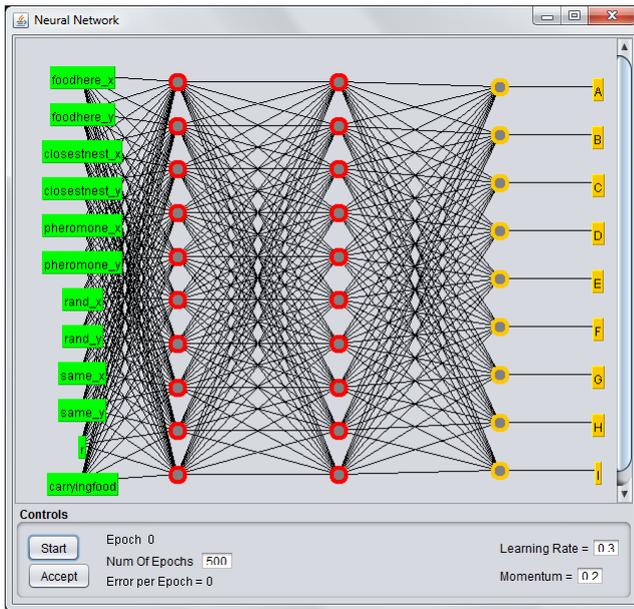


Fig. 6. The fixed topology ANN classified the optimal ant direction 92.3% of the time.

In order to clarify further, a training set was created with all the same inputs, but with 5 possible output class values, representing the 5 IF statements used in the pseudocode (Fig. 1). There are 5 pairs of directional inputs and the purpose of the 5 IF statements is to choose which of those 5 directions to follow (see pseudocode in Fig. 1). This test can clearly identify whether the 5 IF statements were correctly learnt, without having to also learn the correct actions to take within each IF statement. With one hidden layer, a fixed ANN was created and trained (Fig. 7). The ANN reliably identified the correct one of five IF statements 99.98% correctly classified. Only 1 of the 5000 was incorrectly classified.

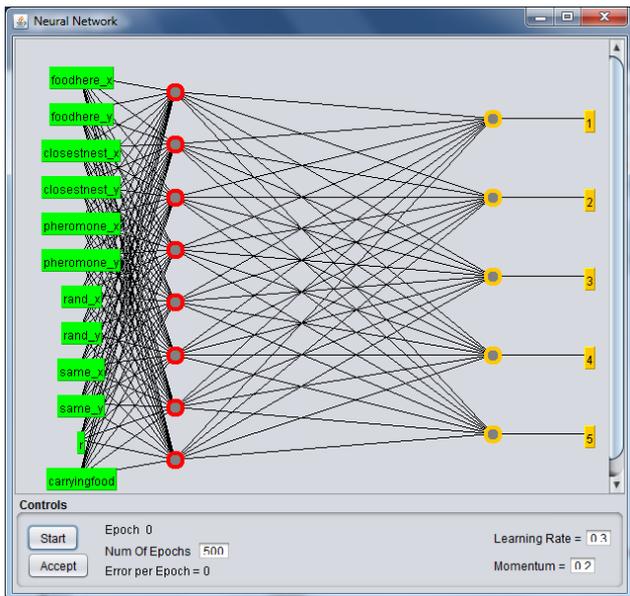


Fig. 7. Learning the 5 IF statement classes accuracy 99.98%.

To summarise this fixed ANN training section, in this approach BM1 output data was used to train an ANN by back propagation. This step was useful to demonstrate that an ANN is capable of performing this task when properly trained, so therefore the task should not be overly complex for an evolving neural network.

This result suggests that a trained fixed topology ANN can perfectly learn to recognise which of the 5 IF statements should be triggered given the inputs. A harder learning task is to also determine which actions to take when each of the 5 IF statements are triggered, the ANN achieved this with 92.3% accuracy.

It is recognised that this approach differs from biological ants with natural selection, which have no pre-existing data to train the ants. In evolution, skills must be evolved without training or guidance, not towards a particular aim or objective. Therefore, the next section focusses on unsupervised evolution.

9 EVOLVING ANN CONTROLLERS

Neuroevolution was applied to evolve neural networks which were then applied as the controller for ants. All ants in a colony had the same controller at each generation. But between generations, the controller was subject to genetic change, by modifying the ANN both in terms of the weights and the topological structure, including the number and location of connections.

Initially, the ANNs were set blank, with no hidden layer nodes. The additional nodes are added by evolution over time.

The fitness function was set to 1 point for each food picked up, 50 points for each food returned to the nest.

A comprehensive set of tests was done with 25 ants per colony, left to run for 900 timesteps. The ANN controllers were subject to neuroevolution in populations of size 15 organisms over 100 generations and this was repeated 10 times. Afterwards a further 5 repetitions of 100 generations was completed, this time with populations of 150 organisms which is a more conventional population size for neuroevolutionary algorithms.

In all runs food collection was learnt almost perfectly. By the 10th generation organisms often had peaked at a fitness of 25, meaning that every single ant successfully collected a food. In most experiments, the ANNs started to learn to return the food to the nest, which begun producing fitness of 62 in generation 13. At generation 42 the fitness was 2049, so the majority of ants were returning multiple foods to the nest. This cannot be explained by random movement alone which does not result in any food being returned. In the third run, the highest fitness reached 5059, meaning that 109 foods were collected, of which 99 foods were returned to the nest in only 900 timesteps, a highly efficient result, that means every ant on average collected food and returned it to the nest 4 times, outperforming BM1.

Visualisation of the evolved ANN structure (Fig. 8) shows that it had an additional 7 nodes had evolved, and 18 new connections, plus all of the weights throughout had evolved to optimal values.

It is hard to visualise why this ANN works so well because ANNs are a black box solution, yet some evolved nodes seem to make sense. The node in the bottom right was added by neuroevolution. It has connections to the Boolean flag pherom_here (input 14) and the pheromone x flag (input 5).

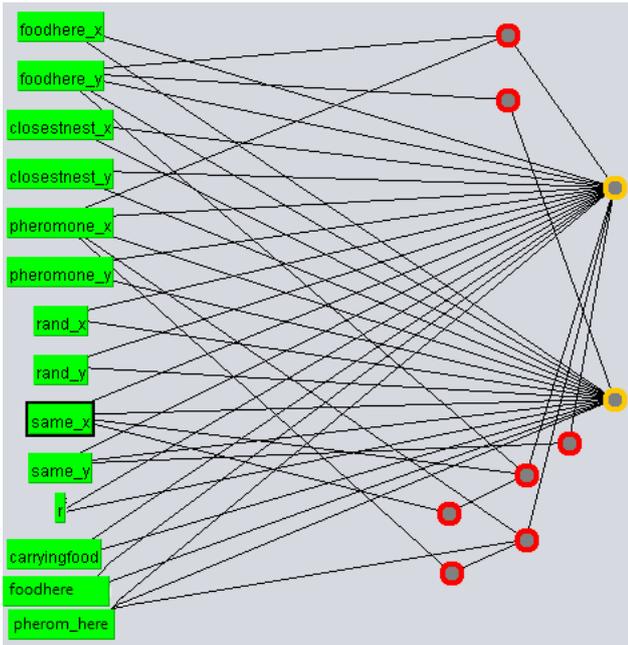


Fig. 8. The evolved ANN which has fitness 5059 and outperformed the benchmark algorithm. Red nodes were added by the neuroevolutionary algorithm, the two yellow nodes are outputs, one for the x movement, one for y movement. The green squares are the 14 ANN inputs.

That could make sense that the Boolean flag pherom_here could trigger the hidden neuron to send pheromone x information to the x output 1 only when present. Another observation is that most evolved nodes that connect to the x output do have connections coming from x inputs and the same is true for evolved nodes connected to the y output.

Subsequently the same experiment was repeated four times with a larger population size of 150. The runs produced fitnesses of 8533, 6178, 6083 and 2152. When controlled by the ANN with highest fitness 8533 the ants had collected 183 foods and returned 168 of those to the nest. Given the size of food clusters on the fixed map are over 1000 each, the score could be achieved by discovering a single food cluster.

For comparison, the BM1 was run 100 times for 900 time steps with 25 ants and the colonies had returned to the nest a range of food from 2 to 107, with an average of 60 foods. A possible reason why neuroevolution outperformed BM1 could be that it was overfitted to the test level layout.

Comparisons using purely random movement with 25 ants over 900 timesteps showed that a maximum of only 1 food was collected by ants, and no food was ever returned to the nest.

10 ALTERNATIVE SCENARIOS

A scenario was tested in which there was no compass and 1 pheromone. The compass input was experimentally removed, to identify whether a benchmark could be programmed without a ‘nest compass’ a sensor to nest direction, using only one pheromone. The algorithm would not correctly operate, because after finding the food there was no way for the ants to find a way back to the nest, so ants would move randomly, leaving

pheromone all over the place attracting other ants in the wrong directions (fig. 9).

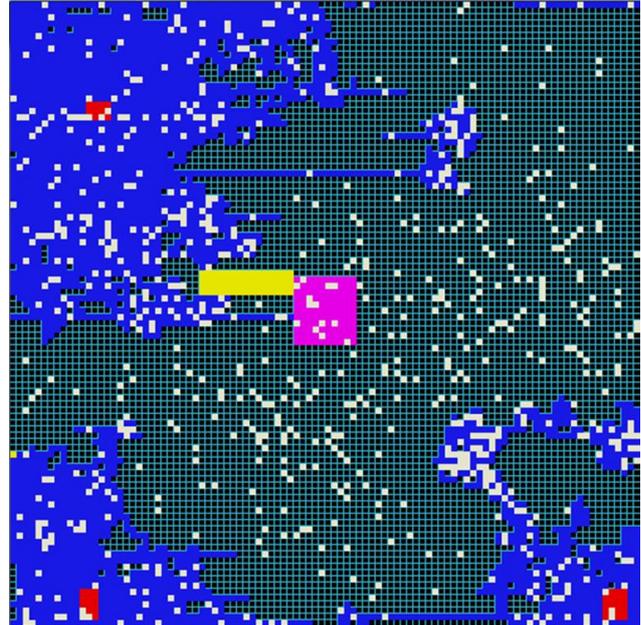


Fig. 9. The BM1 algorithm running without a compass sensor – ants have no way of finding the nest once food is discovered and pheromone is scattered randomly.

Food distance from nest has various effects. With closer food, the pheromone trail will be stronger and it takes less time to get back to the nest. But longer trails have greater chance of other ants walking into them by accident, so further food may attract more ants that way. This is shown in Fig. 10. Two foods were discovered: a small food in the upper right is favoured compared to a larger food in the bottom left, because it is closer, their pheromone is stronger and all ants abandon the larger food until the pheromone evaporates and knowledge of it’s location is lost to the swarm. In Fig. 11b, the same affect is shown. Ants recruited to the bottom two foods only collected food once and when they reached the nest, they chose to follow the top food because that pheromone was stronger and the top food quickly depleted.

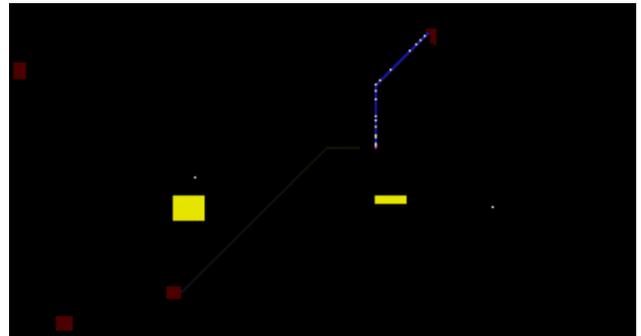


Fig. 10. A large food supply (lower left) is abandoned and forgotten in favour of a small food (upper right), because it is closer to the nest, causing a stronger pheromone trail.

Each decision that an ant makes can be subject to random probability so that ants are always capable of doing something unpredictable at any time. The effect of introducing a probability of random decisions is shown between Figs 11a and 11b.

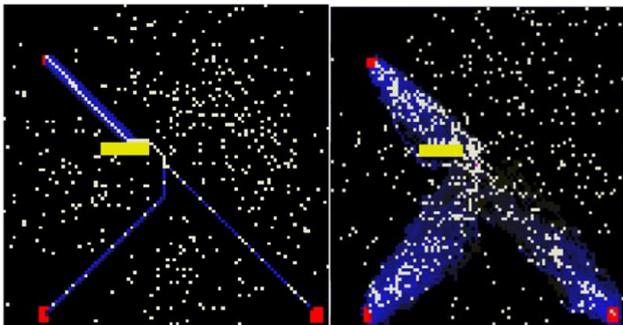


Fig. 11. (a) With 0% chance of random behaviour at each timestep. White: ants. Red: food source. Blue-black: pheromone strength. Yellow: obstacle. Central point: nest. (b) With 70% chance of random behaviour at each timestep.

11 COMMON PROBLEMS ENCOUNTERED

One problem with using a compass to return to the nest is that if obstacles block the route in a ‘v’ shape, the ant never get past. In Fig. 12 this has occurred and long after the bottom two food sources are completed, the blocked food source hasn’t been exploited yet. If two pheromones were used this may be avoided.



Fig. 12. Using one pheromone with compass, ants often get stuck behind a ‘v’ shaped yellow obstacle.

12 PHEROMONE STRENGTH DECREMENT

Hill climbing strategy has two main requirements. When an ant discovers a pheromone trail, there are usually two directions it could be followed. The ant should choose which direction using a hill climbing strategy to more easily find the food. That assumes that the strongest end of the trail will lead to the food. However, the whole trail evaporates over time, so the strongest end of each pheromone trail will naturally tend to be the end nearest the nest because the trail near the food has had a longer time to evaporate. Therefore, if hill climbing is to work, (1) the pheromone strength deposited by ants must decrease on consecutive squares as they get further from the food. Also (2) the evaporation rate must be slower than the reduction in strength left by ants on consecutive squares. This can be

instructed either automatically, or it could be part of the ant’s behaviour controller which is required to evolve. That would increase the search space for the ANN and would require two additional inputs (1) the number of steps taken since food and (2) the strength of pheromone already on this square from other ants and an output for the pheromone strength to deposit.

Problems can occur when ants are laying a pheromone trail and they walk across a separate pre-existing pheromone trail of a different strength (Fig. 13). In this case, ants should not be able to add to existing pheromone, up to a maximum limit on each square. They should also not be able to cause existing pheromone to reduce by overwriting pheromone left by other ants with a lower value. This causes problems when two paths from two food sources combine into one, and the ants from either food source will have taken a different number of steps and laying different strengths of pheromone. (Fig. 13.) The correct behaviour is that they should reset the square to their own calculated limit, unless a higher value is already present in which case they leave it as is.

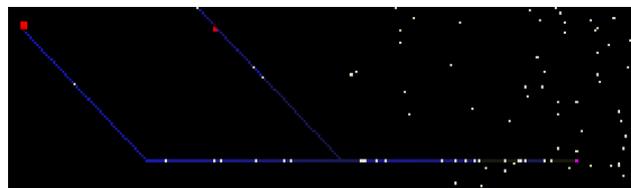


Fig. 13. When two paths combine, pheromone should not be overwritten by ants who have travelled on a longer path.

13 CONCLUSIONS & FUTURE WORK

This paper has investigated the benefits of neuroevolution (NEAT) compared to fixed topology ANN by testing how pheromone behaviour can evolve in both, in relation to a hard coded designed benchmark (BM1).

Future work could investigate simulating other colony or swarm intelligences with communication. Examples include smells in the air or environment such as territory marking, or sounds used for predator detection, warnings or communication.

This paper has demonstrated neuroevolution applied to evolve pheromone communication in simulated ant colonies. The core intelligence required to perform pheromone communication was summarised in form of the hard coded benchmark BM1, comprised of an IF block with 5 conditions. The 5 conditions were learnt by a fixed ANN and the actions to take within each IF statement were learnt with 92% accuracy.

This paper was organised into several stages: (1) Developed a benchmark algorithm which produces swarm food foraging behaviour. (2) Used the benchmark to produce a training dataset linking the ant sensor inputs to the desired output movement direction. (3) The training set was used to train a fixed topology neural network which produced the desired output in 92% of cases. (4) Implemented neuroevolution to evolve an ANN with augmented topology and weights to produce foraging behaviour. This was successful and the evolved ANN controller resulted in high number of foods being collected by the swarm and returned to the nest. The evolved controller outperformed the benchmark algorithm which presumably was due to overfitting to a fixed level layout.

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Kinetic Models of Relevant Phenomena Related to Opinion Dynamics

Stefania Monica and Federico Bergenti¹

Abstract. This paper outlines recent analytic results regarding the dynamics of the opinion in large multi-agent systems. Discussed results are based on a unifying framework which takes inspiration from mathematical kinetic theories to describe analytically the long-time asymptotic properties of the opinion in large multi-agent systems. Different models to describe the effects of interactions among agents are considered to take into account different sociological phenomena that are known to govern the dynamics of the opinion. For each of such models, the proposed framework allows the analytic derivation of the dynamics of collective properties, such as the average opinion and its variance. Discussed results are in accordance with known empirical evidence, and their analytic form contributes to a solid theory of opinion dynamics.

1 Introduction

Even if there is no agreement on a formal definition of what a multi-agent system is, in this work multi-agent systems are considered as *large* groups of agents which interact in *intelligent* ways. Note that multi-agent systems are assumed to be made of a large number of agents, so that the behaviours of single agents is less interesting than the behaviour of the multi-agent system as a whole. In addition, note that intelligence is associated with interactions rather than with agents, so that the focus is put on the *collective intelligence* [31] of the multi-agent system as a whole rather than on the possible intelligence of single agents.

Since in this work multi-agent systems are assumed to be composed of a large number of agents, the detailed description of the properties of single agents is unfeasible. For this reason, the results described in the rest of this paper are focused on the study of collective properties of a multi-agent system, which can be broadly defined as properties that characterise the multi-agent system as a whole. Traditionally, the study of such collective properties is performed using simulation, and many results concerning the dynamics of multi-agent systems are obtained by directly simulating interactions among agents (see, e.g., [8]). The major drawback that is traditionally associated with such simulation approaches is that the validity of results obtained by simulations depends on the choices of the specific parameters used to perform simulations and, hence, it is limited to simulated scenarios. Even if simulated scenarios can be considered representative of other scenarios, there is often no clear identification of the generality of results obtained by simulations. For this reason, it is of interest to study analytic models to describe the dynamics of multi-agent systems. The results of analytic models are often more

general than the results of simulations. In addition, their generality is clearly identified by the assumptions taken in the development of the model. Note that analytic models are typically simpler than those considered in simulations, but they guarantee more robust results. Finally, note that analytic results can be verified by simulation in interesting cases.

The analytic study of the collective properties of multi-agent systems can be performed using a framework inspired from *mathematical kinetic theories* (see, e.g., [4]). Such a framework can be used to study the asymptotic characteristics of collective properties of multi-agent systems under the assumption that studied systems are completely decentralized and with no form of supervised coordination. According to the proposed framework, observable collective properties of a multi-agent system can be derived analytically from the description of the effects of single interactions among agents. In this work, interactions are limited to message exchange which involve only two agents. Time is modelled as a sequence of discrete steps, which may not have the same duration, and each step corresponds to a single interaction among two agents. No restriction is imposed on the topological properties of the multi-agent system, and each agent is free to interact with any other agent. Note that mathematical kinetic theories are commonly described as generalisations of classic kinetic theory of gases. Such an approach is certainly possible, but it is worth noting that the class of systems, either physical or not, that can be described using the generic framework of mathematical kinetic theories is much wider than gases. Mathematical kinetic theories can be used to study all systems in which the major cause of evolution is given by interactions, and the system is so large that a statistical approach is justified.

In the rest of this work, it is assumed that each agent is associated with a scalar value intended to quantify the opinion of the agent regarding a fact. The adopted framework inspired from mathematical kinetic theories is used to study the long-time asymptotic dynamics of collective properties of the opinion in multi-agent systems. Therefore, discussed results can be broadly considered as part of *socio-physics* [9], which is an emerging discipline that uses models and tools from physics to study sociological phenomena. In addition, it is worth remarking that the ideas behind the adopted framework are not limited to the study of opinion dynamics and the proposed approach can be applied to describe other collective properties (see, e.g., [10,30] for examples relative to economy).

This paper is organised as follows. Section 2 briefly recalls relevant sociological phenomena. Section 3 outlines the major elements of the adopted framework based on mathematical kinetic theories, and it summarises major results obtained from the application of the framework. Finally, Section 4 concludes the paper and outlines future research directions.

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2 Relevant Sociological Phenomena

The study of the dynamics of the opinion is a traditional topic of the research on multi-agent systems. It has been faced using a number of different approaches and it originated a large body of literature. In addition, in recent years, its importance increased rapidly because of the explosive and pervasive diffusion of online social networks.

Models designed to describe the effects of social interactions among agents are not only studied in the context of multi-agent systems, but they are also central to various fields of sociology (see, e.g., [13]). In particular, starting from empirical investigations, sociologists intend to derive scientific theories and models to explain collective behaviors and socio-cultural differentiation [15]. The central idea of most of proposed model is the sociological phenomenon called *compromise* [1], which is the tendency of individuals to change their opinions towards those of others they interact with, trying to reach consensus. According to the idea of compromise, consensus among all individuals in a society should be reached after a sufficiently large number of interactions.

It is well known that empirical observations [3] do not confirm the long time asymptotic property of compromise, so to find models to explain pluralism, sociologists have described a variety of phenomena related to opinion formation. One of such phenomena is *homophily* [29], according to which individuals tend to communicate with those with similar opinions. In order to properly integrate homophily in models, *bounded confidence* models are considered. Such models assume that two individuals interact only if their opinions do not differ more than a given threshold. Bounded confidence models allow explaining opinion clustering, which is used to justify the existence of groups of individuals with similar opinions inside the same group, and also to account for the existence of different opinions among different groups [12]. Another important sociological phenomena, intended to avoid monoculture is *negative influence*, according to which individuals evaluate other agents on the basis of some parameters, and they only interact with those with positive scores. Negative influence can explain bipolarism [14]. According to sociologists, however, the idea of negative influence is not supported by empirical evidence [15] and, for this reason, other phenomena have been considered, such as *opinion noise*. Opinion noise is modeled as a random additive quantity which leads to arbitrary opinion changes with small probability [11]. Moreover, in [16], the idea of *striving for uniqueness* is introduced to avoid the convergence of opinions to a single value. This is related to the idea that single individuals may want to get distinguished from others and, therefore, they may change their opinions if too many individuals share the same opinion. This idea is opposed to the idea of fashion trends [2]. Finally, the sociological phenomena according to which the opinion of each agent can be influenced by the social context is known as *diffusion* [8].

We have already proposed analytic models to study, under proper assumptions, all mentioned phenomena [7, 17–21, 24, 26, 28] and to derive properties concerning the temporal evolution of the opinion in the considered system, in terms of the average opinion and its variance. Among the wide variety of studied models, this paper focuses on compromise, which is a key ingredient of all sociological models intended to describe the dynamics of the opinion in a society. Note that the adoption of the general framework of mathematical kinetic theories ensures that studied models can be combined into complex models which consider various phenomena. Actually, all mentioned phenomena can be modelled as additive terms of the interaction rules adopted to describe how single interactions modify the opinions of interacting agents.

3 Kinetic Models of Opinion Dynamics

In order to apply the general framework of mathematical kinetic theories to study the dynamics of the opinion, a number of assumptions on studied multi-agent systems and on the sociological phenomena considered in the formation of the opinion are needed. A few assumptions have been already mentioned in the introduction of this paper, and they are rephrased here to make this section self-contained.

The general framework of mathematical kinetic theories can be used to study the asymptotic characteristics of collective properties of multi-agent systems under the assumption that studied multi-agent systems are composed of a fixed number of $n \in \mathbb{N}$ interacting agents. In addition, studied systems are assumed to be completely decentralized and with no form of supervised coordination. Observable collective properties of a multi-agent system can be derived analytically from the description of the effects of single interactions among agents. Interactions are limited to message exchange among two agents. Time is modelled as a sequence of discrete steps, which may not have the same duration, and each step corresponds to a single interaction among two agents. No restriction is imposed on the topological properties of the multi-agent system, and each agent is free to interact with any other agent.

Opinion has been modeled in the literature both as a discrete [32] and as a continuous [12] variable. While discrete models are typically used to address situations where a finite number of options are available, e.g., in political elections, continuous models are typically used to study opinions related to a single topics, varying from strongly disagree to completely agree. In the adopted framework, the opinion is modelled as a continuous variable $v \in \mathbb{R}$. With no loss of generality, throughout the paper it is assumed that $v \in I = [-1, 1]$, so that ± 1 represent extremal opinions and values close to 0 correspond to moderate opinions.

Finally, opinion models differ because of the sociological phenomena adopted to describe how the opinions of agents change after single interactions. Opinion may change because of a variety of phenomena, which are briefly recalled in previous section to set the accepted nomenclature of sociology. Single models typically include a specific subset of such phenomena depending on the specific characteristics of the studied multi-agent systems, on targeted application scenarios, and on the background of authors. The proposed framework can accommodate all mentioned phenomena, but in this work the focus is on compromise.

The results discussed in the rest of this section are organised according to the common approach of identifying two types of models. In the first type, called *homogeneous models*, all agents are considered equal and agents can be treated as indistinguishable. Such models are commonly used to study multi-agent systems that are so large that the individuality of single agents does not contribute to the collective properties of the system. Mathematically, such models are easier to study and they form the basis for the second type of models, known as *heterogeneous models*. In heterogeneous models, agents are grouped into disjoint classes on the basis of some characteristics. The characteristics used to group agents into classes are arbitrary, but it is common to group agents on the basis of the ways they interact with other agents. The classification of agents allows accommodating different types of agents into the models, and it allows accounting for agents with diverse propensity towards other agents. Note that the general framework of mathematical kinetic theories allows classes to collapse to singleton sets, which allows single agents to be modelled as an individuality. In such an extreme case, each agent can be associated with a specific behaviour, but the framework is still capable

of providing results on collective properties of the multi-agent system as a whole. Note that the specific description of each and every single agent is practically feasible only if the multi-agent system is composed by a limited number of agents. Therefore, heterogeneous models with singleton classes are used when the size of the studied multi-agent system is sufficiently small to model each agent in isolation, and sufficiently large to justify the statistical approach of mathematical kinetic theories.

3.1 Homogeneous Models

In the case of homogeneous models, mathematical kinetic theories postulate the existence of a distribution function $f(v, t)$ whose temporal evolution is described according to the *Boltzmann equation* (see, e.g., [23, 24]). The distribution function $f(v, t)$ represents the number of agents with opinion in $(v, v + dv)$ at time t , and it is defined for each $t \geq 0$ and for each $v \in I$. According to the definition of $f(v, t)$, by integrating $f(v, t)$ over I , one obtains the number of agents n , which is assumed to be known and fixed

$$n = \int_I f(v, t) dv. \quad (1)$$

Similarly, the average opinion of the multi-agent system can be computed as

$$u(t) = \frac{1}{n} \int_I v f(v, t) dv. \quad (2)$$

In addition, it is also possible to compute the variance of the opinion of the multi-agent system as

$$\sigma^2(t) = \frac{1}{n} \int_I (v - u(t))^2 f(v, t) dv. \quad (3)$$

In agreement with mathematical kinetic theories, we assume that the distribution function $f(v, t)$ evolves according to an integro-differential equation which is a generalization of the Boltzmann equation. More precisely, homogeneous models assume that the temporal evolution of $f(v, t)$ can be described using the following equation

$$\frac{\partial f}{\partial t}(v, t) = \mathcal{Q}[f](v, t) \quad (4)$$

where the left-hand side represents the temporal evolution of the distribution function and the right-hand side is called *collisional operator* to adopt the nomenclature of mathematical kinetic theories. The explicit expression of the collisional operator depends on the specific rules which govern interactions among agents and it ultimately embeds studied sociological phenomena in the model.

Following a common approach of mathematical kinetic theories, rather than studying the Boltzmann equation (4), its *weak form* is considered. The weak form of a differential equation is obtained by multiplying both sides of the considered equation by a smooth function with compact support, denoted as *test function*, and then integrating the obtained equation. Hence, the weak form of the Boltzmann equation (4) is

$$\frac{d}{dt} \int_I f(v, t) \phi(v, t) dv = \int_I \mathcal{Q}[f](v, t) \phi(v, t) dv \quad (5)$$

where the right-hand side is called *weak form of the collisional operator* \mathcal{Q} with respect to test function $\phi(v, t)$. Functions that satisfy (5) are called *weak solutions* of the Boltzmann equation. Proper choices of test functions can be used to describe the temporal evolution of collective properties of multi-agent systems. In detail, the use of (5) allows studying

1. The average opinion of the multi-agent system, using test function $\phi(v) = v$; and
2. The variance of the opinion of the multi-agent system, using test function $\phi(v, t) = (v - u(t))^2$.

In order to exemplify the analytic results that can be obtained using the described framework (see also previous works [5, 6, 22, 23, 25, 27]), we briefly summarize the major results obtained in the study of a very simple model of opinion dynamics which, among the variety of sociological phenomena cited in previous section, considers only compromise. Note that compromise is the key ingredient of all models of opinion dynamics and it is based on the idea that the opinions of two agents becomes closer after each interaction. Mathematically, denoting as v and w the pre-interaction opinions of two agents and as v' and w' the post-interaction opinions of the same agents, compromise corresponds to the following inequality

$$|v' - w'| \leq |v - w|. \quad (6)$$

In order to ensure that compromise is properly studied, the following interaction rules can be used

$$\begin{cases} v' = v - \gamma(v - w) \\ w' = w - \gamma(w - v) \end{cases} \quad (7)$$

where γ is a parameter of the model that quantifies the effects of compromise. The value of γ measures the propensity of an agent to change its opinion in favor of the opinion of another agent. Note that in order to properly model compromise, namely to satisfy (6), the values of γ must be chosen in the interval $I_\gamma = (0, 1)$. As a matter of fact, it is easy to prove that values in I_γ guarantee that (6) is satisfied. Using the interaction rules in (7), right-hand side of the weak form of the Boltzmann equation can be written explicitly as

$$\beta \int_{I^2} f(v, t) f(w, t) (\phi(v', t) - \phi(v, t)) dv dw \quad (8)$$

where β represents the probability of interaction among two agents.

Under proper assumptions detailed in [24], the study of the solutions of the weak form of the Boltzmann equation can be used to prove relevant properties of the long-time asymptotic behaviour of the average opinion. In detail, the use of $\phi(v) = v$ in the weak form of the Boltzmann equation can be used to show that the average opinion of the multi-agent system is conserved. In addition, the use of $\phi(v, t) = (v - u(t))$ allows proving that all agents tend to the same long-time asymptotic opinion (see [24] for further details).

As an illustrative example, Figure 1 shows the values of the variance of the opinion in a homogeneous system where interactions among agents are governed by the rules defined in (7). Such results are obtained by considering a system composed of 10^3 agents and by assuming that $\gamma = 0.1$. Figure 1 shows that the variance of the opinion exponentially tends to 0 as the number of interactions increases, thus leading to consensus.

3.2 Heterogeneous Models

When agents cannot be considered equal with respect to their attitude towards interactions, previous homogeneous models cannot be applied. The rest of this section is devoted to extend previous results to cases where agents can be classified into disjoint groups with respect to their specific behaviours at interactions. Resulting heterogeneous models can be used in more realistic situations, and they can be also adopted in the extreme case of singleton classes. In such a case, each

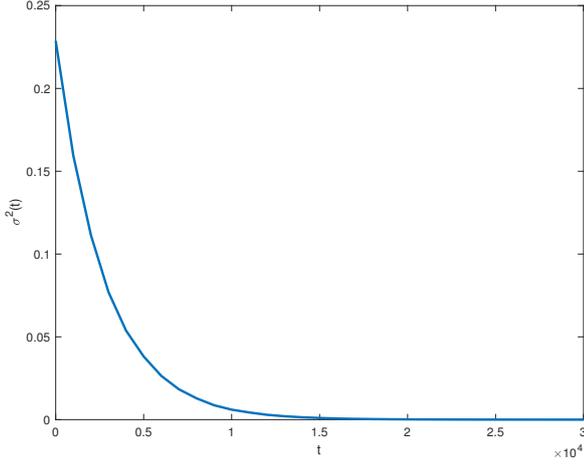


Figure 1. Values of the average opinions $\{u_s(t)\}_{s=1}^6$ as a function of the number of interactions for the parameters discussed in Section 3.2.

agent has specific characteristics that describe its behaviour during interactions with other agents. Note that even if such a case could be ideally used to model all multi-agent systems, it is feasible only when the number of agents is sufficiently small to ensure that every agent can be described independently.

The assumptions and the nomenclature of heterogeneous models do not differ from that of homogeneous models. The only difference is that agents are assumed to be statically classified into $m \in \mathbb{N}$ classes, with $m \leq n$. Such a difference imposes that heterogeneous models need m distribution functions $\{f_s(v, t)\}_{s=1}^m$, each of which represents the number of agents of a single class with opinion in $(v, v + dv)$ at time t . In agreement with the relative equation of the general framework of mathematical kinetic theories, the number of agents of class s at time t can be written as

$$n_s = \int_I f_s(v, t) dv, \quad (9)$$

and it does not depend on time because the adopted classification is assumed to be static. The total number of agents is obtained by summing the number of agents of each class, as follows

$$n = \sum_{s=1}^m n_s. \quad (10)$$

Moreover, following the same approach used in the general framework of mathematical kinetic theories, one can compute the average opinion of agents of class s as

$$u_s(t) = \frac{1}{n_s} \int_I v f_s(v, t) dv. \quad (11)$$

The definition of the average opinions of all classes allows computing the global average opinion of the system at time t as

$$u(t) = \frac{1}{n} \sum_{s=1}^m n_s u_s(t). \quad (12)$$

Observe that the average opinion of the system is obtained by a properly weighed sum of the average opinions of all the classes. Finally,

the variance of the opinion of agents of class s can be computed as

$$\sigma_s^2(t) = \frac{1}{n_s} \int_I (v - u_s(t))^2 f_s(v, t) dv. \quad (13)$$

The general framework of mathematical kinetic theories assumes that each distribution function $f_s(v, t)$ evolves according to a balance equation, which is the analogous of the Boltzmann equation (5)

$$\frac{\partial f_s}{\partial t}(v, t) = \sum_{r=1}^m \mathcal{Q}_{sr}[f_s, f_r](v, t). \quad (14)$$

From (14) it is evident that the collisional operator relative to class s corresponds to the sum of the contributions $\mathcal{Q}_{sr}[f_s, f_r]$ of the interactions between the agents of class s with the agents of class r .

The study of the *weak form* of the Boltzmann equation is useful to derive proper differential equations involving the temporal evolution of interesting macroscopic parameters of the system, namely the average opinion of each class and the variance of the opinion of each class. Just like for the case of homogeneous models, the weak form of (14) is obtained by multiplying it by a test function $\phi(v, t)$ and by integrating with respect to v . Hence, the weak form of the Boltzmann equation can be written as

$$\frac{d}{dt} \int_I f_s(v, t) \phi(v, t) dv = \sum_{r=1}^m \int_I \mathcal{Q}_{sr}[f_s, f_r](v, t) \phi(v, t) dv. \quad (15)$$

In order to exemplify the analytic results that can be obtained using the described framework (see also previous works [5, 17–24]), we briefly summarize the major results obtained in the study of a very simple model of opinion dynamics which, among the variety of sociological phenomena cited in Section 2, considers only compromise. Let us denote as s and r the generic classes of two interacting agents, whose pre-interaction opinions are v and w , respectively. The post-interaction opinions v' and w' of the two agents are computed as

$$\begin{cases} v' = v - \gamma_{sr}(v - w) \\ w' = w - \gamma_{rs}(w - v) \end{cases} \quad (16)$$

where $\{\gamma_{sr}\}_{s,r=1}^m$ are the deterministic parameters of the model. The value of a parameter γ_{sr} measures the propensity of an agent of class s to change its opinion in favor of the opinion of an agent of class r . Note that, just like for homogeneous models, in order to reproduce compromise, the values of $\{\gamma_{sr}\}_{s,r=1}^m$ must be chosen in the interval $I_\gamma = (0, 1)$.

As a matter of fact, using (16) it is possible to observe that (6) is equivalent to

$$|1 - (\gamma_{sr} + \gamma_{rs})| < 1$$

for all pairs of s and r , which is always satisfied if all parameters $\{\gamma_{sr}\}_{s,r=1}^m$ are restricted to I_γ . Using the interaction rules in (16), the right-hand side of the weak form of the Boltzmann equation for each class $s \in \{1, \dots, m\}$ can be written explicitly as

$$\beta \sum_{r=1}^m \int_{I^2} f_s(v, t) f_r(w, t) (\phi(v', t) - \phi(v, t)) dv dw \quad (17)$$

where β represents the probability of interaction among two agents, as in the homogeneous model.

Under proper assumptions detailed in [23], the study of the solutions of the weak form of the Boltzmann equation can be used to prove relevant properties of the long-time asymptotic behaviour of the average opinion. In detail, under the assumption that $\gamma_{sr} = \gamma_{rs}$

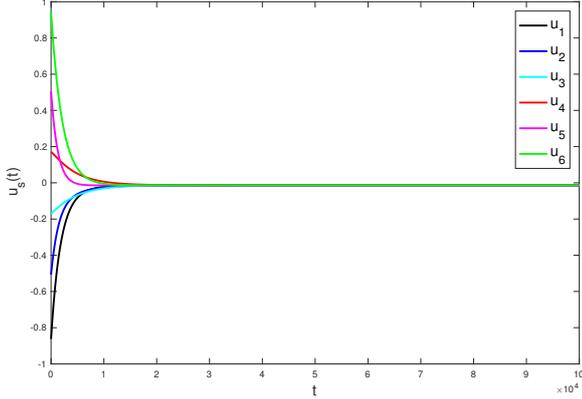


Figure 2. Values of the average opinions $\{u_s(t)\}_{s=1}^6$ as a function of the number of interactions for the parameters discussed in Section 3.2.

for all pairs of s and r , the use of $\phi(v) = v$ in the weak form of the Boltzmann equation can be used to show that the average opinion of the multi-agent system is conserved. In addition, the use of $\phi(v, t) = (v - u_s(t))$ allows proving that all agents tend to the same long-time asymptotic opinion, regardless of their specific class (see [23] for further details).

Figure 2 shows illustrative results concerning a system composed of 10^3 agents, divided into 6 classes. In detail, Figure 2 shows the values of the average opinions $\{u_s(t)\}_{s=1}^6$ of each class, as a function of time (i.e., as a function of the number of interactions). Such results are derived on the basis of the analytic framework which is shortly outlined above and which is detailed in [23]. To obtain the results shown in Figure 2, the following parameters are considered. We assume that the 10^3 agents are divided into the 6 classes with:

$$\begin{matrix} n_1 = 9 & n_2 = 150 & n_3 = 400 \\ n_4 = 300 & n_5 = 140 & n_6 = 1. \end{matrix} \quad (18)$$

Let us remark that, according to (18), some classes are large (e.g. class 3 and 4), while other classes are composed of a few units of agents (class 1) or of a single agent (class 6). Concerning the values of the parameters that characterise compromise, we assume that $\gamma_{sr} = \gamma_s$, which means that the propensity of an agent to change its opinion through an interaction only depends on its class and not on the class of the interacting agent. In detail, the following values are considered:

$$\begin{matrix} \gamma_1 = 0.1 & \gamma_2 = 0.2 & \gamma_3 = 0.3 \\ \gamma_4 = 0.35 & \gamma_5 = 0.25 & \gamma_6 = 0.15. \end{matrix} \quad (19)$$

Finally, the initial distribution functions of the opinion are supposed to be the following:

$$\begin{matrix} f_1(v, 0) = \mathcal{U}(-1, -2/3) & f_2(v, 0) = \mathcal{U}(-2/3, -1/3) \\ f_3(v, 0) = \mathcal{U}(-1/3, 0) & f_4(v, 0) = \mathcal{U}(0, 1/3) \\ f_5(v, 0) = \mathcal{U}(1/3, 2/3) & f_6(v, 0) = \mathcal{U}(2/3, 1) \end{matrix} \quad (20)$$

Figure 2 clearly shows that the values of the average opinion of different classes converge to the same value after a (relatively) small number of interactions.

4 Conclusion

This paper outlined how the general framework of mathematical kinetic theories can be applied to study the dynamics of the opinion in multi-agent systems. After a brief introduction intended to motivate the need of analytic models to study the dynamics of the opinion in multi-agent systems, the paper surveys the major sociological phenomena that has been already studied using the proposed approach. One of the most relevant of such phenomena is surely compromise, which is introduced by sociologists to model the fact that interactions sometimes make agents change their opinions to try to reach consensus. Compromise is a well understood phenomenon, both theoretically and empirically, so its description in terms of the proposed approach is valuable. The last section of the paper first outlined how the general framework of mathematical kinetic theories can be used to study the opinion dynamics, then it detailed a model of compromise and presented relevant results. Presented results are discussed for two classes of models: homogeneous models, which assume that all agents are equal, and heterogeneous models, which allow agents to have specific behaviours. Presented results are in accordance with the general understanding of compromise, and they can be used to study analytically compromise.

Planned future developments of the described research intend to expand the expressive power of proposed models by allowing parameters to be expressed in terms of random variables. Such an option is important to devise models whose results can be compared with empirical evidence in real scenarios, where the behaviours of agents can be modelled only in terms of stochastic processes. In addition, another future development of the described research regards the application of the adopted approach to the study of other collective properties of multi-agent systems. Actually, the general framework of mathematical kinetic theories can be tailored to the specific needs of multi-agent systems to study a number of interesting properties, not strictly related to opinion formation.

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HILDA - A Health Interaction Log Data Analysis Workflow to Aid Understanding of Usage Patterns and Behaviours

Maurice D Mulvenna¹, Raymond R Bond¹, Alexander Grigorash¹, Siobhan O'Neill², Assumpta Ryan³

Abstract. Health and wellbeing products and services for individuals are becoming increasingly popular as people realise the benefits provided by lifelogging or quantified-self platforms in such areas as exercise, diet management and mood. However, in addition to the data that users record using these platforms, all user interactions and events can be elusively logged to represent usage. Such user interaction or event logs provide rich and large datasets that can fuel applied artificial intelligence. As products and services based on these digital interaction technologies are taken up across public healthcare provision, should healthcare policy and practice take more cognisance of the opportunities and risks in gathering interaction data? Is 'healthcare' ignorant that there is knowledge in such data? Are there differences between event logging in healthcare and other areas such as commerce, media and industry? In order to realise benefits in analysing such data, methods that help ensure consistency, accuracy, data protection, as well as reproducibility of knowledge derived from log data need to be examined. This paper presents methods to explore usage log data and a process workflow followed by a presentation of two real world case studies. The workflow has been coined Health Interaction Log Data Analysis (HILDA) and focuses on data prospecting and machine learning stages to show the opportunities realisable in analysing interactional or event data automatically recorded by digital healthcare services.

1 INTRODUCTION

Products and services based on digital interaction technologies typically include mobile device apps as well as browser-based apps to a lesser extent, and can include telephony-based services, text-based chatbots and voice activated chatbots. Many of these digital products and services are simultaneously available across many channels in order to maximise availability for users. The focus of this paper is to examine digital interaction technology-based products and services developed for use in the health and wellbeing domain, explore how these technologies can automatically log user interactions and events for subsequent analysis and business intelligence, and propose a methodology for data mining of digital products and service event logs in a healthcare context.

Digital interaction technologies offer useful methods for real time data capture of the interactions of users with the products and services. We have become accustomed to using tools such as Google Analytics in order to generate aggregated usage reporting for our websites, but this kind of log analysis is available for all the digital interaction technologies we design. Indeed, we have the ability to design what data are recorded, how and where it may be stored, and crucially, how it can be analysed to reveal individual or collective usage patterns. This paper reports on two case studies in digital interaction technologies service analysis, where the usage data are examined using a structured data mining pipeline that is proposed and detailed in the methods.

The main focus of previous research on the analysis of usage logs for digital interaction technologies used in health and wellbeing has been to aid in usability analysis [1] or to reveal usage patterns in using technology [2]. Research has also been carried out to explore how rehabilitation devices can have data or event logging incorporated, but this has been more to support the goal of device monitoring [3]. More recent research has examined engagement data in web-based intervention platforms but has primarily focused on visualisation of the log data [4].

Our goal in incorporating usage or event logging or metadata logging is to provide relevant data sources as a basis for identification and exploration of individual and collective behavioural patterns of products and services developed using digital interaction technologies.

This work is potentially important since many national health departments including the National Health Institute (NHS) are looking to use digital technologies such as health apps for self-management of diseases and thus logging user interactions would allow for greater insight into user needs and may provide ideas for improving these digital interventions, for example through enhanced personalisation. The NHS would benefit since the data can be automatically and hence cost-effectively collected. Such data may facilitate new ways for epidemiological analyses and provide data to inform health policies. If the NHS promote health apps and log analysis is insightful, then perhaps there is a need for a standard to maximise the utility of recorded event logs for analysis in healthcare contexts.

The structure of the paper is as follows. In the following section, methods encompassing usage log data types and process workflows is described. In the subsequent results section, the two case studies in the paper are introduced, before data prospecting and machine learning stages are described and results presented. The final sections of the paper provide for discussion and conclusions. We aim to examine the value and limitations of user log analysis in the healthcare domain.

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2 METHODS

A user event log must at least be comprised of three columns or variables as part of a tabular structure, comprising a unique identifier for the user (can be anonymous); the event that was recorded; and the date and time (preferable precision to seconds) of that event. This paper proposes a methodology for data mining such user event logs in a healthcare context (see Figure below). This study then takes a case study-based approach to examine the feasibility of using this model for analysing log data. Case study 1 involves an analysis of user event logs from a healthcare app that is used by people living with dementia and their carers for reminiscing about their past to encourage conversations, social connectedness, mutuality with their spouse and reflection as well as improving quality of life. This app was used in a 12 week trial during which all user events and features used were recorded. Log data includes the event/feature used (browsing photos, watching a video etc.), the date and time as well as a unique identifier for each user. Case study 2 involves analysis of ~3.5 million call logs made to a mental health and wellbeing helpline (Samaritans Ireland). Basic log data include time, date and duration of the call as well as a unique identifier for each caller. The results in this paper are very much autoethnographic of using our user log analysis workflow detailed in this paper. However, we do provide actual results of data analytic workflows in the case studies to provide an example of the insights revealed by the data mining process.

2.1 Proposed workflow model for log data analytics

Standardising workflows are crucial in order to ensure consistency and that best practices are adopted in a domain. A number of standards for carrying out a data science, data mining or a machine learning project have been proposed. For example, the Cross-industry standard process for data mining (CRISP-DM) is a data mining process model encompassing the following stages: Business understanding, Data understanding, Data preparation, Modeling, Evaluation, Deployment [5]. CRISP-DM has been available in various guides since 1996. An updated variant developed by IBM, called Analytics Solutions Unified Method for Data Mining/Predictive Analytics (ASUM-DM) [6] expands on CRISP-DM.

However, to date, there has not been a standardised workflow that embraces data mining in log analysis. Figure 1 below depicts Health Interaction Log Data Analysis (HILDA) workflow, which has been applied to two health and wellbeing log datasets: a mental health helpline call log dataset; and a user log dataset from a healthcare app to facilitate reminiscence for people living with dementia and their carers.

The first phase of the HILDA workflow model involves data cleaning. This comprises of data quality checks and imputations for missing data (NULL and NA fields). This is followed by a normalisation of the date stamps. That is to say that each date of each event is converted to a relative date for each user. For example, the first logged event for each user will be transformed to 'day 1', allowing like-for-like temporal analyses for all user logs. Moreover, seasonality is also often determined as a separate feature. The time stamps are converted to a simple integer from 0 to 23 denoting hour of the day. Oftentimes, classification of morning, afternoon and evening are used.

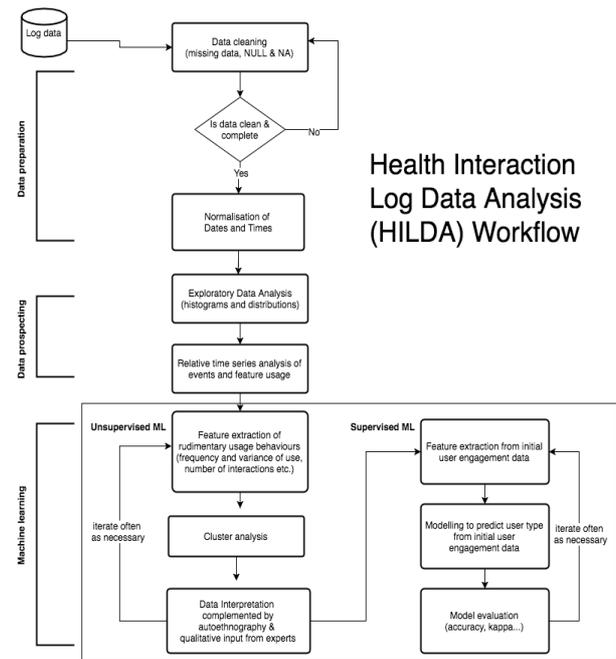


Figure 1. Workflow for Health Interaction Log Data Analysis (HILDA), involving three high level phases of data preparation, data prospecting and machine learning

Following data preparation, data prospecting is carried out. This comprises of analysing each variable for inherent characteristics by viewing histograms and probability density functions as well as identifying correlations via bivariate analysis. This is followed by time series analysis of a representative sample of users, or all if possible. This involves data visualisations of user events over their entire journey of using the service.

Following data prospecting is often a machine learning phase which can involve both unsupervised and supervised machine learning. Unsupervised machine learning comprises of extracting simple features that characterise basic usage behaviours such as frequency of use and number of interactions per week. These features are used in a clustering algorithm to determine the type of users that exist in using the service. This helps to understand the client base by behaviour. Having determined the type of service users that exist, one can proceed to predict service user type using features extracted from initial user behaviours, allowing for example the early detection of abstainers and adopters [7]. These predictive models can be developed using established supervised machine learning techniques such as decision trees and support vector machines which are very popular and arguably the most efficient methods that exist today.

The HILDA workflow model covers data preparation, data prospecting and machine learning in some detail. Deployment and usage is not explored in this version. Arguably, a focus on deployment was lacking in CRISP-DM as context for usage varies to such an extent that it is not helpful to be prescriptive about model deployment and usage.

3. RESULTS

The following sections outline the results and reflections of analysing user event log data in the health domain for each case study, describing the data prospecting and machine learning phases of the HILDA workflow in each.

3.1 Case study 1: Reminiscence health app user log data

This case study reports on the analysis of log data from a tablet application, specifically designed and developed to facilitate reminiscence for people with early to moderate stage dementia. Reminiscence is the sharing of memories relating to personal life experiences. It is the act of remembering and reflecting on real past events. The act of reminiscing can serve many functions that create bonds between people and in doing so, supports them to reflect on important life events and to attribute meaning to their lives [8]. The development of the app was a component part of a larger feasibility study to investigate the effects of individual specific reminiscence activity using a range of outcome measures, to explore users' views on the app; and to incorporate an economic analysis, examining the cost of implementing the app intervention in comparison with quality of life outcomes. The feasibility study incorporated a paired sample of 28 dyads (person living with dementia and their carer), and applied several scales at start, mid-and end-point of a 12-week use of the app in the homes of people living with dementia and their carers, with one-to-one interviews with participants carried out at the end of the 12 weeks.

Data prospecting

The app was designed to incorporate a logging facility for key events by users across 45 specific activities, covering five different types of events. The five different canonical events include: entry (Logging in), admin (Adding a photo, deleting an audio, etc.), reminiscing (Viewing a video, viewing a photo, etc.), in the moment (ITM) questions and exit (Logging out). Thus, the behaviour of users can be analysed within and across each usage session, over the 12-week trial. The ITM questions comprise items from the primary outcome measure for the study, the Mutuality Scale developed by Archbold et al. [9].

The data show that the app was primarily used for reminiscing as expected. A total of 71% of interactions from people living with dementia were within the reminiscing sections of the system whereas only 47% of interactions from carers were within the reminiscing sections ($p < 0.001$). It is reassuring that people living with dementia mainly used the system for reminiscing. Only carers could carry out 'Admin' events such as adding a photo, as mandated by their access rights set at login. It can perhaps be seen as a positive sign that carers generally added to the music, pictures and videos that were uploaded to the app prior to the intervention beginning, rather than simply browsing those already there. There were twice as many interactions with photographs in comparison to music and five times as many interactions with photographs in comparison to video by people with dementia using the app. Reminiscing, with its history in photograph-based memory books, has been more about the image than music, sound or video, and this effect may be what is being seen in this data [10]. What is also interesting in this data is the popularity of music to people living

with dementia. Again, this is known from the literature [11] and anecdotally from carers of people living with dementia but it is useful to see this behaviour replicated in this trial data. The most popular times that the dyads of people living with dementia and carers prefer to use the app peak around 11am, 3pm and 8pm. These times correspond to post-breakfast, post-lunch and post-evening meal times. We also calculated the number of unique days in which users interacted with the system, and there is a significant statistical correlation between the number of days the carer interacted with the system and the number of days the dyad's corresponding person living with dementia interacted ($r = 5.77$, $p < 0.001$).

Machine learning

In this study, we used K-means clustering algorithm given it is the most widely used and established clustering algorithm in the unsupervised machine learning literature. Using the elbow method, we discerned that 4 is a reasonably small number of clusters that would provide reasonable resolution in terms of explained variability. Clustering was based on the following features five features: number of interactions by person living with dementia, number of interactions by carer of person living with dementia, number of daily interactions by person living with dementia, the mean usage interval by a user and the standard deviation of usage interval by a user.

Four clusters were revealed by the k-means algorithm. The first cluster, 'the hooked adopter' constituted one dyad, who fully adopted the system. They had 7.2 times more interactions than their carer. Whilst the person with dementia obsessively used the app, the carer showed a normal amount of usage, hence the person with dementia was independently dedicated. The hooked adopter and dyad uses the app for over half the days in a month (55% of days) and with little variability uses the app every two days. The second cluster, labelled the 'typical user' encompassing the plurality of users, where 12 dyads or 43% fall into this cluster, hence making them the most typical user. These people living with dementia user only have 1.7 times more interactions with the app than their carer. This indicates that these users have some dependence on the carer for app usage. This dyad uses the app 15% of days in a month. This dyad are unpredictable when they will use the app but on average interacts with it every 6.61 days (approximately once per week). The third cluster, labelled 'disengaged irregular user' encompassed 7 dyads or 25% of users. These users had 25% fewer interactions with the app than the carer. Whilst the people with dementia had fewer interactions than their carers, the carers had fewer interactions than other carers in all other clusters. These dyads use the app 9% of the days in a month. However, typically they can go for 20 days without using the app making them the least consistent users of the app. The final cluster labelled the 'well supported dependent user' encompassed 8 dyads or 29% of users, the second largest group of users. These users have 36% fewer interactions with the app than their carers. The carers are very enthusiastic and have more interactions than other carers in all other clusters but they seem to struggle to get people with dementia users to the same engagement level. Similar to the typical users in cluster 2, these dyads interact with app 16% of the days in a month and on average use the app every 6.97 days. This unsupervised learning provided clusters that were clear and transparent to the health science researcher involved in the project. The next stage in this work is

to seek to identify correlations between the post-trial interviews with the dyads and the clusters enumerated above.

3.2 Case study 2: Mental health helpline call log metadata

Helplines are key elements of mental wellbeing and suicide prevention efforts, however little is known about how these services are used. This study involves analysis of digital telephony data sourced from a mental health and wellbeing charity in Ireland. The charity operates a national helpline to provide emotional support to anyone in distress or at risk of suicide. Whilst support is also offered via SMS, email and face to face, 95% of the contacts remain via telephone. Data was provided for all calls made to the charity in the Republic of Ireland for almost a 4-year period (April 2013 to December 2016). A total of 3.449 million calls was analysed, amounting to 725 calls per 1,000 population.

Data prospecting

Novel data analytics and machine learning approaches were used to identify populations of callers based on caller behaviour variations. Key findings include the identification of five clusters of callers based on caller persistence, that persist regardless of which year or group of years is considered. The volume of calls exhibits strong intra-day and intra-week repetitive patterns, while intra-month repetitions are conspicuously absent. The influx of new helpline callers is remarkably stable, at a rate of about 1,200 per month. This rate remains constant over time, showing virtually no fluctuations across months or years. The observed probability distribution of call durations cannot be adequately explained using simple modelling techniques. The complexity of this distribution indicates that a mixture of distributions generated by several sub-populations of callers is being observed. The dataset comprises a number of fields, however only the following fields were used in this study: the date-time stamp of the call arrival precise to the last second; the Boolean engaged field meaning that the call was dropped with a busy tone; the answered flag meaning that the call was passed to a volunteer from the charity; the duration of the call in seconds; and the unique caller ID. The caller IDs allowed us to enumerate the callers uniquely while providing no personally identifying or sensitive details. The IDs were associated with most, but not all, call arrivals. About 20% of the calls had the caller ID missing. At a first glance, the duration of calls appears to follow an exponential decay distribution, where the volume of calls decreases at a rate proportional to call duration. However, the distribution follows a complicated decay pattern with a rate that associates with the call duration in a non-obvious manner.

Machine learning

In this study, cluster analysis involves grouping a set of objects (e.g., callers based on their attributes) in such a way that objects in the same group (called a cluster) are more similar to each other in comparison to other groups (clusters). Clustering was initially performed for 2013-2015 timespan, and then on the 2016 data to check for stability of our findings. Only the calls from callers with a unique identifier were used (44,613 callers collected in 2013-2015, increasing to 61,287 unique callers by the end of 2016).

Callers were clustered using 3 caller attributes: number of calls; mean call duration; and standard deviation of call duration. We selected these parameters due to their explanatory power: the number of calls a person makes indicates their frequency of help seeking behaviour; the mean call duration indicates call length; and the standard deviation of call durations indicates a person's variability and consistency in conversation length. We also used K-means clustering algorithm in this case study.

Five clusters were revealed by the k-means algorithm. The first cluster named 'Elite prolific callers' had the largest average number of calls per caller in the cluster and the smallest cluster size. A handful (fewer than 50 callers over the 4-year time span) of extremely prolific callers, responsible for 20% of the total call volume. They call thousands of times, each call on average lasts about 4 minutes, with a small minority of calls lasting 10 minutes. The second cluster named 'Typical callers' had the largest cluster size. The majority of callers who call 5-6 times and almost always have a short 3- to 4-minute conversation each time. This cluster accumulates 40 to 50 percent of all callers depending on the time slice under consideration. The third cluster named 'Standard prolific callers' had the second largest average number of calls per caller, middling average call duration and the largest unexplained variability encompassed by the cluster. About 12 to 15 percent of callers are prolific, each calling hundreds of times and having call durations that are moderate in length (from a few minutes to half an hour long). The fourth cluster named 'Unpredictable erratic callers' had the largest average standard deviation of the call duration. About 3 to 5 percent of callers whose call duration varies considerably, with some calls lasting 3 minutes and some up to 1 hour. The final fifth cluster named 'One-off chatty callers' had the smallest average number of calls per caller accompanied by the largest average call duration. About 13 percent of callers that only call 1-2 times, have a long 30 minutes to 1 hour conversation, and do not return for any sustained support (the operational opposite to prolific callers).

Data mining of the association of caller IDs with the volume and duration of calls revealed several caller clusters, each describing a distinctive behaviour type. The most striking of those clusters, Elite Prolific callers, encompasses a small number of caller IDs responsible for a substantial share of the total call volume that the charity receives. Early identification of callers of this type and routing their calls to specialized advisers provides insight in the modelling of healthcare service usage, offering insights for evidence-based practice and operational decision-making.

4. DISCUSSION

The work presented in this paper introduces a new data analytics process workflow, called Health Interaction Log Data Analysis (HILDA), designed to accommodate processing of user, system event and interaction data logged on products and services that use digital interaction technologies. The HILDA workflow is specifically designed for use in log data pertaining to health and wellbeing products and services. We are seeing a rapidly growing use by individuals of these health and wellbeing products and services as people realise benefits provided by lifelogging or quantified self platforms in such areas as exercise, diet management and mood. HILDA is designed to enable the capture of best practices in user, event and interaction log preparation, data prospecting and machine learning phases across a broad

range of health and wellbeing usage scenarios. The workflow has been developed in response to the practical needs of our research to make use of more standardised approaches in data analytics research, but more broadly in recognition of the opportunities and threats involved as public health sector providers seek to make use of these kinds of technologies. Two case studies have been presented to illustrate the utility of the HILDA workflow in helping the transitioning from the data to actionable knowledge.

Workflows such as HILDA can help ensure reproducibility of findings as knowledge is derived from log data and also support consistency and accuracy. Broader topics such as data protection, compliance with ethical guidelines, etc., need to be accommodated within these kinds of workflows, especially as the EU General Data Protection Regulation (GDPR) (<https://www.eugdpr.org/>) comes into force in 2018. Other ethical concerns need to be discussed, for example the ethics of logging geolocation with each event or interaction with a smartphone health app. Moreover, can supposedly anonymous log analysis be used to identify individuals? Also, the ethics of consent or lack thereof for logging events need to be considered. Websites often log events and make use of logging tools like Google Analytics without obtaining consent from the user. However modern web browsers now seek consent for using cookies so the future for consenting on elusive data collection on the web has perhaps progressed.

The HILDA workflow describes three stages or phases, including data preparation, data prospecting and machine learning. Once the machine learning stage is complete, the results can lend themselves to being labelled and described in clear terms that are easily understood beyond the data science community. This is the case in our two case study examples. However, this is not always the case. Often the results of the machine learning stage if, for example generated using deep neural network methods offer little in terms of rationale for results, which can hamper take up, either because of the inherent complexity of the findings or the need for any deployment to be fair, accountable and transparent perhaps due to legal reasons. There are many other uses of log data not mentioned in this paper, for example, building a recommender engine to understanding the feature preferences for similar users, perhaps taking a collaborative filtering approach. Moreover perhaps a Markov model can be used for state predictions using a probability matrix for switching between states. In the second case study, we did use Fourier analysis to determine dominant frequencies of calls and to filter-out non-dominant frequencies to elicit a more noise free model of call volume over time. Hence, there are many techniques that be applied to log analysis that are not necessarily represented in this paper.

The HILDA workflow could arguably benefit from a fourth phase or stage that helps signpost how the knowledge and or model generated can be taken up by the sponsor or community. Variesly, this could be called deployment, uptake or operationalisation.

A major limitation of event log analysis is that it is very focused on quantitative analysis and requires significant interpretation. As such, there is no way of knowing why users take a certain journey or prefer a certain feature or even why they have certain patterns and frequency of use. Put differently, log analysis does not provide any qualitative feedback. However, this can be partly addressed using Ecological Momentary Assessment (EMA aka experience sampling) to add qualitative to the quantitative.

EMA involves prompts to users often as pop-up questions during the service experience to gather user opinion or state. As a result, we would recommend considering EMA to augment user log analysis. However, EMA could be a distractor to the service itself so it needs to be carefully considered.

5. CONCLUSIONS

In summary, this paper presented a relatively unsophisticated model for carrying out user log analysis and applied this process in two healthcare services that automatically logged events. We found that that both case studies provided business intelligence and insights that are useful for understanding service users and for improving the service itself. We would support the integration of event logging in digital health given such data can be easily collected and analysed.

In addition to the work presented on the two case studies in this paper, the research team are exploring the analysis processes involved in carrying out data analytics in several other projects. In one of these, the data pertains to the use of an app by people with learning disabilities as they rate their transport or consumer experience in their daily life. This data therefore has additional locational information, and requires careful ethical considerations as the data relates to vulnerable users. Future development of the method therefore needs to address ethical aspects as a core part of the process, perhaps to be considered horizontally across all technical phases of the process. In another project, users access a maternal mental health app that helps them to compile and curate an event diary relating to mood in addition to completion of health and wellbeing scales. The data in the project can, when analysed, offer insights back to the community of users and so the process need to take account of deployment issues.

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