

Human Swarming, a real-time method for Parallel Distributed Intelligence

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Abstract – Although substantial research has explored the design of artificial swarms, the majority of such work involves swarms of autonomous robots or simulated agents. Little work, however, has been done on the creation of artificial swarms that connect groups of networked humans with the objective of fostering a unified emergent intelligence. This paper describes a novel platform called **UNU** that enables distributed populations of networked users to congregate online in real-time swarms and tackle problems as an Artificial Swarm Intelligence (ASI). Modeled after biological swarms, the **UNU** platform enables online groups to work together in synchrony, forging a unified dynamic system that can quickly answer questions and make decisions by exploring a decision-space and converging on a preferred solution. Initial testing suggests that human swarming has great potential for unleashing the collective intelligence of online groups, often exceeding individual abilities.

I. INTRODUCTION

A wide variety of methods have been used by researchers to tap into the collective intelligence of human populations, from polls and surveys to prediction markets. These methods have one central feature in common – individual participants provide input in isolation, their contributions aggregated after-the-fact with the input from others. Lacking connectivity, the participants of polls, surveys, and markets can hardly be said to comprise a unified *collective intelligence*, for each user works separately, having no interaction with others members of the group. As a result, polling methods are effective at exposing an “average sentiment” that characterizes a population, but they lack the structure needed for a real-time collective intelligence to *emerge from* the population.

To make matters worse, collective intelligence methods that do allow users to influence each other, generally do so asynchronously. For example, online forums like Reddit and Digg allow popular content to rise and fall with sequential up-voting and down-voting. Similarly, prediction markets allow commoditized content to rise and fall with sequential buys and sells. While these methods are more interactive than typical polls and surveys, the asynchronous nature means that each user influences the opinions of those who follow them in time. Recent studies show that this type asynchrony greatly distorts group-wise decisions by introducing social biasing effects known as *herding* or *snowballing*. One such study [1] found that a single up-vote, when inserted first into an online forum, influenced the final decision of the group by more than 25%. Similarly, prediction markets suffer from momentum effects, price bubbles, risk-reversion biases, and over-corrections as a consequence of asynchrony [2].

Still, polls, surveys, and markets are extremely valuable for revealing the average sentiments held by groups, but that’s not the same as enabling groups to *think together* as a unified system. To foster a true collective intelligence among a large numbers of individuals, we look to biology and the process of swarming. The parallel structure of natural swarms inherently limits social biasing effects such as snowballing, which arise from sequential voting, while enabling large groups to pursue a common goal as single unified system. In the sections below, a novel platform called UNU is described that was developed to enable and study human swarming.

II. SWARMS AS DISTRIBUTED BRAINS

Before describing the technical details of human swarming, it’s useful to define the word “swarm” in the context of the current work. Many researchers use “swarm” to refer to decentralized networks of robotic or simulated agents with simple localized rules, such that a collective intelligence emerges from the local interactions among them [3]. These systems are generally inspired by flocks of birds and schools of fish, which are known to traverse complex environments using similar processes. While these types of systems have many useful applications, the swarms employed by the UNU platform are modeled less after the behavior of flocks and schools, and more after the decentralized decision-making processes used by honeybee swarms. This model was chosen because the emergent decision-making process of honeybees provides a powerful agent-based analog for how neurological brains arrive at complex decisions. This supports the primary goal of the UNU platform, which is to enable groups of networked users to make complex and nuanced decisions as a unified intelligence – *i.e., as a brain of brains*.

As studied by Seeley et al., the decision-making processes performed by honeybee swarms and neurological brains are remarkably similar in many ways [4]-[8]. Both employ large populations of simple excitable units (*i.e.*, bees and neurons) that work in parallel to integrate noisy evidence, weigh competing alternatives, and converge on a singular decision. In both, the final decision is arrived at through a real-time closed-loop competition among sub-populations of distributed excitable units, with each sub-population vying for a different alternative. When one sub-population exceeds a threshold of level support with respect to the other sub-populations, the corresponding alternative is chosen. The threshold for reaching a decision in both brains and honeybee swarms is not the unanimous excitation of units, or even a simple majority, but often just a sufficient quorum of excitation [8].

Within neurological brains, integrator neurons act to sum the activation among supportive units while inhibiting the activation of competing units. This combination of activation and inhibition helps avoid deadlocks and promote optimal decisions. Honeybee swarms have been observed to perform similar combinations of activation and inhibition to similarly avoid deadlocks and optimize decisions [4,8]. For example, every spring honeybee swarms make a complex collective decision to select a suitable location for settling a new colony. This life-or-death choice is made by a few hundred of the oldest bees in the swarm – the *scout bees*. After searching a large area, these scouts bring alternatives back to the swarm, each of them working to influence the collective decision of the group through body vibrations. Referred to as a “waggle dance”, these vibrations encode the direction and distance to possible colony sites. In addition, these dances can encode “stop signals” that inhibit other dancers. This enables closed-loop feedback control with both excitation and inhibition.

Thus, just like networked neurons, swarming honeybees comprise a closed-loop dynamic system of distributed units working in parallel, each individual bee supporting those that favor a similar alternative, while inhibiting those that promote a differing alternative. The decision is reached when a sufficient quorum emerges for the chosen alternative. In this way, a collective intelligence comprised of a few hundred honeybees is able to select among dozens of possible colony sites spread over 30 square miles, evaluating each with respect to multiple criteria. Remarkably, the bees usually arrive at the decision that best satisfies their needs [9]. This is because the decision is not produced at by a simple vote, which would favor the most popular answer, but instead through a real-time negotiation in which many options are considered in parallel, the participants pushing and pulling in synchrony until a solution emerges that optimizes group satisfaction. It is this distributed emergent process that the UNU platform aims to enable among groups of networked human users.

III. ENABLING HUMAN SWARMS

To harness the collective intelligence of online groups, a human swarming platform known as UNU was developed. Modeled after the decision-making processes of honeybee swarms and neurological brains, the UNU platform enables groups of networked users to answer questions as a unified dynamic system. And like natural the analogs, these artificial human swarms were designed to allow large numbers of participants to work together in real-time to (a) integrate noisy evidence, (b) weigh competing alternatives, and (c) converge on final decisions through a synchronous competition among multiple sub-populations.

Because we humans can’t *waggle dance* like honeybees or produce activation signals like neurons, a novel user interface had to be developed to allow participants to convey the unique direction and magnitude of their own personal intent with respect to a set of alternatives. In addition, the interface had to be crafted to allow user to perceive and react to the changing system in real-time, thereby closing a feedback loop around the full group. Simply put, the connective infrastructure for swarm-based decision making, which evolved over millions of years in honeybees, had to be enabled artificially for human users by designing a specialized software interface.

System Design: the platform allows large numbers of distributed users to login to a central server from their own local PC or tablet. At the start of each decision, all participants are simultaneously presented with a question along with a set of possible answers. The swarm of users answers the question by collaboratively moving a graphical puck to select among the provided alternatives. Each alternative is displayed as a graphical target positioned equidistant from the starting location of the puck. The puck is modeled as a physical system with a defined mass, damping and friction. Each user provides input with a graphical magnet controlled by their mouse or touchscreen. By positioning their magnet relative to the puck, each user can impart his or her own personal intent as a unique force to be applied to the puck (Fig. 1). Each user’s unique input is referred to as a User Intent Vector.



Fig 1. A human swarm comprised of user-controlled magnets collaborate in synchrony to move a graphical puck as a unified collective intelligence.

The input from each user is not a discrete vote or bid, but a continuous stream of vectors that can vary freely over the decision process. Because the full population of users can adjust their intent at every time-step during the decision, the puck moves, not based on the input of any individual, but based on the dynamics of the full system. This results in a real-time *physical negotiation* among the members of the swarm. With everyone pushing and pulling at the same time, the group collectively explores the decision-space and converges upon the most agreeable answer.

It should be noted that users can only see their own magnet during the decision process, but cannot see the magnets of others users. Thus, although participants can view the puck’s motion in real time, which represents the emerging will of the swarm, they are not influenced by the specific breakdown of support across options. This inherently limits social biasing. For example, if the puck slows due to an emerging deadlock, the participants must evaluate their own willingness to shift support to alternate options without knowing the distribution of support that caused the deadlock. This promotes honest introspection rather than reflexive support of large factions. It should also be noted that after each decision is over, users can view a replay that shows all the magnets. This allows users to reflect on how their personal contribution combined with others to produce the final answer that emerged.

It should also be noted that although the participants in natural swarms contribute in real-time, it takes finite time for information to propagate across members. In the artificial

human swarms herein, the momentum of the puck, as defined by a mass parameter, enables a time-constant for information propagation. It has been observed that without momentum, convergence on decisions is hindered. We believe momentum acts as low-pass filter, removing noise (i.e. jitter) from the collective motion of the puck, which is likely a consequence of participants reacting to changes at slightly different rates.

In Fig. 2 below, an example question is shown as it would appear simultaneously on the screens of all users in the swarm. In this particular trial, a swarm of 90 users was asked to grapple with a politically charged question likely to inspire diverse opinions: “What should be Congress’s top priority?” This was presented along with six answer options. The choices can be supplied by the asker of the question or, when using “suggestion mode”, can be provided by members of the swarm. Allowing members of the swarm to provide the answer options mimics the process of scout bees, which are known to supply destination options for their colony.

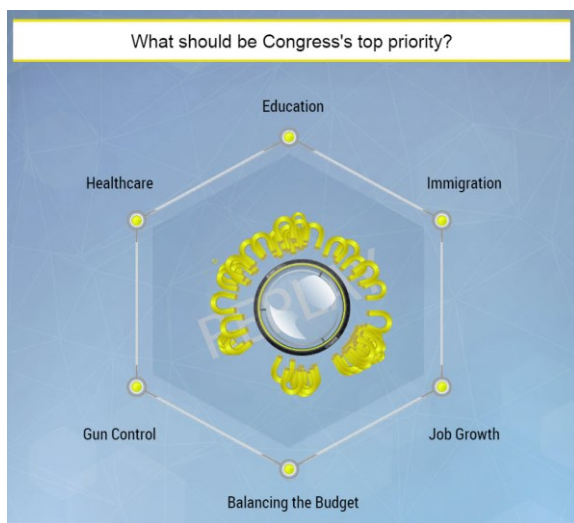


Fig 2. A replay snapshot of a human swarm answering a question.

After the question and choices are displayed to all members of the swarm, the puck appears at the center of the screen. Users are then given a 3,2,1 countdown to coordinate the start of the session. The swarm quickly springs into action, working in synchrony to guide the puck to a preferred answer. The decision process is generally a complex negotiation, with individuals shifting their support numerous times to break deadlocks or defend against options they disfavor. When a user pulls towards one option in the answer set, a component of their force also acts to impede the motion of the puck towards competing options. In this way, users don’t only add support a preferred solution when pulling towards it, but also suppress solutions they don’t prefer. This enables the dual process seen in natural swarms and neurological brains wherein individual agents are enabled to both excite and inhibit [4], thereby reducing the chances of a deadlock.

Over the past 18 months, hundreds of human swarms have been observed answering thousands of questions in this way [10,11]. If a group happens to be in substantial agreement from the start of the question, favoring one option strongly over all the others, the puck moves smoothly to that answer. But, if two or more options have significant support – as is

true of most questions worth posing to a group – the swarm performs a complex negotiation as a unified system, with individual users often changing their strategy multiple times during the decision. Most users begin by pulling towards the option they prefer most, but adjust if the puck starts moving towards an option they greatly dislike, shifting the angle of their input so it changes from pulling towards a preferred option to defending against a disliked option, and then adjusting again to pull toward their preference. With all users making such dynamic changes in parallel, the swarm explores the decision space until it converges on an answer that optimizes the collective satisfaction of the full population.

It’s important to note that users don’t just vary the direction of their input in real-time, but also the magnitude. The closer a user positions their magnet to the puck the stronger it pulls, as a real magnet would behave. Because the puck is always in motion, users need to continually move their magnet so that it stays close to the puck. This is significant, for it requires all users to be actively engaged during the real-time decision process. If they stop adjusting their magnet to the changing position of puck, the distance grows and their applied force wanes. Thus, just like bees executing a waggle dance or neurons firing activation signals, the networked users in an artificial human swarm must continuously express their changing preferences throughout the decision process or lose their influence over the final outcome.

Post testing interviews with participants suggest that the requirement that all users provide continuous and active influence on the puck is quite significant. Users with high conviction in favor of an outcome report being more vigilant in maintaining maximum force on the puck over time. Conversely, users who have lower conviction (because they are torn between multiple options or because they know they lack information about some options) report being less vigilant in maintaining maximum force over time. In this way, the swarming interface allows users to express their changing support during a collective decision, not just by indicating the direction of support but also by expressing a unique level of conviction. In addition, users report that when torn or ambivalent, they tend to be more flexible in shifting support to avoid deadlocks than if they have strong conviction in favor of a particular outcome. We believe this dynamic allows the swarming process to optimize the overall satisfaction of the group with consideration of their varying levels of conviction.

Observations and post-testing interviews also reveal that human swarming yields consistent outcomes regardless of the spatial placement of answer options. For example, if two highly favored options are placed on opposite sides of the puck’s starting position, the swarm will fall into an early deadlock as it grapples between them. Conversely, if the two highly favored options are placed on the same side of the puck’s starting position, the swarm will not fall into an early deadlock, but instead move the puck towards those two highly favored options. Still, a deadlock will emerge as the puck approaches midpoint between the two favored options. In this way, the swarm explores the decision space, which can have alternate layouts, but arrives at the same outcome. A similar robustness has been observed in honeybee swarms, which are known to decide upon optimal nesting locations regardless of the order in which candidate sites are discovered and reported by scout bees [9].

Referring again to Fig. 2, the default layout used by the platform is a set of six alternatives in a hexagon pattern. The hexagonal configuration was chosen because according to social-science research, people are efficient decision-makers when presented with up to six options, but suffer from increasing “choice-overload” inefficiencies when confronted with larger sets [12]. To enable swarms to consider larger sets of answers, the system employs an iterative approach, presenting users with a series of six-option subsets of the full answer pool, then pitting the winner of each subset against each other. This allows a final answer to emerge from a large set of options. The one exception are answers that fall on a continuum, for example when selecting a value from 0 to 1,000. To support such questions, the platform allows users to position the puck on a continuous scale. This enables swarms to collectively decide upon quantities, prices, percentages, odds and other numerical values within pre-defined ranges.

An example of a scale-based question is shown in Fig. 3. In this example, a swarm of users was asked to decide upon the fair price of a movie ticket on a scale from \$0 to \$25. When using this type of layout, the puck starts at the center of the scale and can be moved smoothly in either direction. In these types of collective decisions, the swarm generally overshoots the final answer, then reverses the direction of the puck, oscillating in narrower and narrower bands as all the users adjust their pulls in parallel. An answer is chosen from the continuous range when the puck settles upon value for more than a threshold amount of time (e.g., 3 seconds).

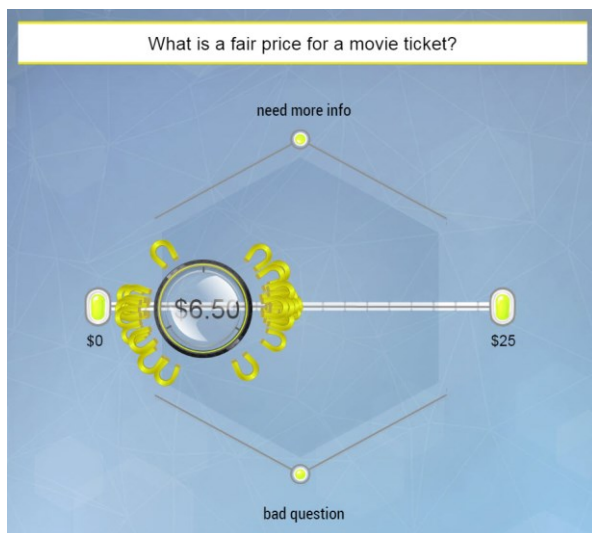


Fig 3. A sample scale-based layout for human swarming

Time Pressure: whether selecting from a set of discrete choices or from a continuous scale, each swarm of users are given a time limit of **60 seconds** to arrive at an answer. After this time, the decision process ends, deemed a failed attempt. This time pressure was implemented for two reasons. First, it imparts a Prisoner’s Dilemma upon the group as time runs out, driving individuals to be less entrenched in the support of answers that seem unlikely to be agreed upon. The objective is to drive flexibility, increasing the chance that the swarm will converge on common ground. Second, social-science research indicates that people are more likely to express honest and

selfless answers when responding under time pressure. Conversely, people are more likely to be influenced by pre-held biases and selfish interests as time increases [13]. Because the goal of this swarming platform is to express the collective intelligence of a population, capturing honest and selfless input facilitates finding the true group intent.

Data Collection: to support research into human swarming, a database stores the User Intent Vectors for all members of the swarm at continuous time-steps across each decision. The vectors are stored every 0.25 seconds, starting from the moment the puck is free to move, and ending when an answer is chosen by the group. Although the raw data is very useful, of particular interest is the study of how sub-populations within the swarm form and dissolve, each vying for a favored alternative while inhibiting disfavored options. We refer to each sub-population as a *faction* and have developed a technique called “faction analysis” to track and visualize the dynamics of sub-populations during each decision process. This is a particularly useful for identifying if and when a sufficient quorum forms and if it lasts long enough to drive the puck to a collective decision.

Referring to Fig. 4 below, a question is shown as it was presented to a group of voters in early 2015, just after a number of Republican candidates announced their intention to seek the presidential nomination. As is true of most political questions, this inspired a range of conflicting opinions. Still, by working together as a unified swarm, the group converged on “Jeb Bush” after only 31 seconds of deliberation.



Fig 4. A human swarm selects among six presidential candidates.

While the final answer reveals the collective will of the swarm, it’s valuable to study how the decision was reached. In this case, the puck first rushed towards Marco Rubio, nearly selecting that option, but reversed course as defending factions came together and pulled the puck away. Such behavior is common in swarm-based decisions, resulting from users changing their strategy as the puck nears a choice they dislike. With all users making such changes in parallel, a complex negotiation results by which a preferred solution is converged upon by the full system. The faction analysis

shown in Fig. 5 provides a visual representation of the negotiation that yielded this particular decision.

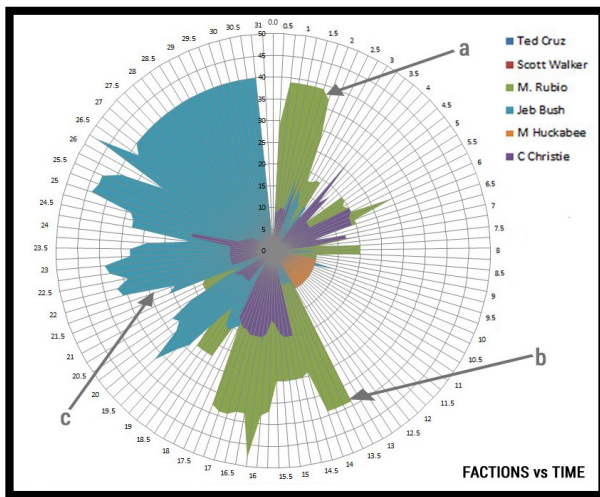


Fig 5. A sample Faction Analysis of a real-time swarm decision.

In Fig. 5, each colored area on the radial plot represents the time-varying factional support for one of the six answer options. The plot is read clockwise from the start of the question ($t = 0$ sec) until the answer is reached ($t = 31$ sec). The radial height of each colored area represents the total force applied by swarm participants pulling towards that particular option at that particular moment in time. This unique representation makes it clear even at a glance that numerous factions formed and dissolved across the decision period, reflecting a complex negotiation within the swarm.

A good way to read a Faction Analysis plot is to begin at $t = 0$ sec and scan clockwise. Doing so, we see that a faction quickly formed in support of Marco Rubio. This is the green area labeled (a) in the plot. During this time, the puck moved quickly towards the Rubio option, almost selecting it. But, because this is a real-time dynamic system, the full population of users are effected by the decision as it forms. Thus as the swarm of users sees the puck approach that option in real-time, those who were undecided often start pulling for an option, while others who may have been pulling towards alternate options, may change their strategy and defend against the emerging answer. Post-session interviews suggest that the swarming process has the unique benefit of encouraging participants to confront their true feelings as they see possible outcomes emerge before their eyes. For example, they might not have realized how strongly they felt for or against the Rubio option until they witnessed it emerging before them.

As soon as the puck started moving away from Rubio, the factional support represented by the green area (a) on the plot, quickly dissolved, and was followed by a period of negotiation and deadlock ($t = 2$ to $t = 13$), during which time no clear faction emerged. As indicated by the green area (b), another faction appeared in support of Rubio at roughly $t = 13.5$ seconds. Again the faction dissolved, and a new significant faction appeared at $t = 18$, in support of Jeb Bush. The Jeb Bush faction maintained strength for the duration of

the session and the puck reached the target and made the collective decision of “Jeb Bush”.

During post-testing interviews, participants generally express having substantial “buy in” with respect to the final answer, not necessarily because it aligns with their initial opinion, but because they actively participated in the process, having direct influence during the full decision period. They contrast this with polls where they often feel less consequential. To quantify these feelings, 48 college students who participated in swarms were given post-testing surveys. Despite the fact that each only controlled one magnet of 48 that worked together to move the puck, only 4 of the respondents of the 48 disagreed with the statement “*I felt like a consequential member of the group.*” Similarly, only 5 of the 48 respondents disagreed with the statement “*The process motivated me to find common ground.*” This is encouraging feedback, suggesting that the process of human swarming is a positive experience for users.

IV. PERFORMANCE TESTING

To test the intelligence of human swarms, a set of pilot studies were conducted using the UNU platform. The first test enlisted a random group of users and asked them to make predictions on a verifiable event: the 2015 Academy Awards. The second test enlisted a group of random users and asked them to estimate the weight of a cow. In both tests, the results produced by the synchronous swarm were compared to an asynchronous baseline – a traditional online survey. Because polls and surveys are the most commonly used method for expressing “the wisdom of crowds”, these studies allowed us to compare asynchronous crowds with synchronous swarms.

Prediction Study Setup: To test the ability of human swarms to make predictions, a group of users were asked to predict the winners of the 2015 Academy Awards [11]. A population of 48 individuals participated online, each filling out a traditional survey to predict the top 15 award categories. This provided baseline predictions for individuals working in isolation. To test swarming, a seven person sub-population of the full group was selected at random and instructed to make the same predictions as a swarm using the UNU platform. These individuals were networked over standard internet connections to a central server. The only interaction these individuals had with other members of the sub-population was through the swarming interface. Review of the poll results from these seven individuals confirm that they were typical performers on the written poll.

Prediction Study Results: The poll results across the full baseline of 48 users revealed that individual respondents, on average, achieved 6 correct predictions across the top 15 award categories (40% success). When looking at the most popular prediction across the population, as is the most common “*Wisdom of Crowds*” method of data aggregation, the group achieved 7 correct predictions across the top 15 award categories (47% success).

When working as a unified swarm, the sub-population of seven individuals achieved 11 correct predictions across the top 15 award categories (73% success). In other words, a sub-group that was only 15% the size of the full population had a success rate that was nearly double when working together as synchronous system. Furthermore, the unified swarm made more correct predictions than 47 of the 48 participants on the

poll. This is a promising result and speaks to the potential for real-time swarming to harness the wisdom of online groups.

As a point of reference, experts at the New York Times made similar predictions for the 2015 Academy Awards. These experts possessed far deeper knowledge than the novice members of our study. These experts likely also invested more than 60 seconds for each prediction made. Still, the New York Times Blog made predictions that yielded only 55% success.¹ In other words, a group of novices, working together as a human swarm, made predictions that surpassed industry experts. Although not conclusive, this pilot study suggests that human swarming may be a means of achieving expert-level insights from groups of non-experts.

Estimation Study Setup: In 1906, Francis Galton ran the classic “Wisdom of Crowds” study at an English fair where farmers held a weight-judging contest for a large ox. A total of 787 people submitted their best guess of the weight. Galton computed the statistical average. It came out to 1,198 pounds. The actual weight was 1,197 pounds. While the vast majority of guesses were way off, the crowd’s statistical average was remarkably accurate. Over a century later, National Public Radio duplicated this classic study by asking their listeners to estimate the weight of a cow from a photo posted online.² This is a more difficult challenge, for a photo is harder to judge than direct viewing. They received 17,205 guesses. Because the photograph and massive set of data were made available by NPR, this modern study was chosen as a baseline for a comparison of estimations by crowds and swarms.

To assess the ability of human swarms to make intelligent estimations, a group of 49 users were selected at random and asked to view an online photograph of the cow used in the NPR study. They were then asked to predict the cow’s weight in pounds. Users first worked as individuals by entering their prediction into an online survey. Users were then asked to estimate the weight of the cow by working together as a swarm. This estimation was performed by users collectively moving the graphical puck first on a hexagon layout that provided six ranges of values, then on a continuous scale of values that allowed a fine selection to the nearest 5 lbs.

Estimation Study Results: Looking first at the polling results, the statistical average of the 49 individual predictions made was 1,137 lbs. This was off by 16.1% from the true weight of the cow (1,355 lbs). Those same users, when working together as a human swarm, predicted the weight of the cow to be 1,250 lbs. This was off by only 7.7% from the true weight of the cow. In other words, the same set of users were more than twice as accurate when their predictions were made synchronously as a system as compared to their predictions made asynchronously as a statistical average. This supports the idea that synchronous human swarming can be more effective than asynchronous polling when harnessing the collective intelligence of groups.

As for the NPR study, they collected asynchronous data from an astonishing 17,205 users. The statistical average of their predictions was 1,287 pounds, only 5% off from the true weight of the cow. This poll result was more accurate than the human swarm, but the difference in predictions is surprisingly small considering the extreme difference in population size. The swarm of 49 users working in synchrony, produced an estimation that was only 37 pounds different than the prediction made by 17,205 polled respondents. This suggests

that swarms are potentially more efficient than crowds, producing strong results with a fraction of the population size. Future studies are required to determine optimal swarm size.

V. DISCUSSION AND CONCLUSIONS

Are swarms smarter than crowds? The pilot studies suggest that although polling a large crowd is a powerful means for capturing the average views of a population, without real-time feedback control, polling cannot enable groups to explore a decision-space and find common ground. In fact, polling is generally “polarizing,” for by capturing the isolated opinions held by members of a group, polls and votes highlight the preexisting difference in a population while providing no direct means for bridging those differences. As a result, polling can foster entrenchment, even when the participants have flexibility among various options.

Swarms, on the other hand, bring groups together, enabling all the participants to negotiate in synchrony, adapting as decisions emerge before them in real-time. The members of a swarm don’t express static views, but continually assess and reassess their own unique convictions with respect to each of the possible outcomes, weighing their personal confidence and preferences. With all participants doing this in parallel, the swarm can quickly converge on solutions that reflect the collective will of the group. We believe this is why swarms are able to efficiently capture a group’s collective wisdom.

Of course we must also ponder why the group’s collective wisdom, once captured, yields results that are more accurate than those generated by the majority of individual participants. Observations and post-testing interviews suggest two possibilities: (a) *knowledge mixing* and (b) *heuristics mixing*. With respect to the former, when participants have incomplete knowledge with which to make a decision, the swarming process seems to enable the group to fill the gaps in each other’s knowledgebase such that the full system can reach an intelligent decision. This was most apparent when predicting the 2015 Academy Awards. None of the participants reported having seen all the films and most reported having seen only a select few. And yet, when working together as unified swarm, the group was able to fill in the gaps and make accurate predictions.

With respect to heuristics, it is well-known in economics and psychology that when individuals are confronted with decisions involving many alternatives, each with numerous attributes to evaluate, they resort to simplified heuristics as a way to keep the process manageable. In the case of the Academy Awards, some users relied on the “media buzz” around certain films, while others drew upon their perceptions of box-office success, the acclaim of well-known actors or directors, or their own personal enjoyment of the film. While no single heuristic would have likely yielded an accurate result -- as each is an overly simplified method by which to make the prediction -- the swarming process allowed the group to combine their heuristics with positive results. This may be because swarming enabled the users to not only combine their individual heuristics, but also weight their input based on their own personal confidence and conviction.

Because of the potential of human swarming to enable groups to merge their knowledge and heuristics, swarming likely offers the greatest benefit when groups make complex decisions on topics where individual knowledge is limited and

where the decision involves multiple options, each of which having multiple attributes that impact favorability. Not surprisingly, this is exactly the type of problem for which swarming evolved in honeybees. When honeybee swarms choose a new colony site, they consider an average of 24 different locations, each evaluated with respect to at least six independent attributes. Despite the complexity of the decisions involved, honeybee swarms have been documented as making nearly optimal decisions most of the time [9].

Going forward we aim to evaluate if human swarms can achieve similarly optimal outcomes when confronted with complex decisions. Of particular interest is whether the decisions produced by human swarms result in greater group satisfaction than decisions reached by traditional votes and polls. In addition, to support the study of human swarming, we have made the UNU platform available to all academic researchers who wish to run their own swarming experiments. To request access, visit: www.unanimousai.com.

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FOOTNOTES

¹ <http://carpetbagger.blogs.nytimes.com/2015/02/19/oscars-2015-the-carpetbaggers-predictions/>

² <http://www.npr.org/sections/money/2015/08/07/429720443/17-205-people-guessed-the-weight-of-a-cow-heres-how-they-did>

Louis Rosenberg received B.S., M.S. and Ph.D. degrees from Stanford University. His doctoral work in human-computer interaction was sponsored by the USAF Armstrong Labs and produced the *Virtual Fixtures* platform (1992), the first immersive Augmented Reality system. Rosenberg then founded Immersion Corporation, a public virtual reality company focused on advanced human interfaces. More recently, he founded Unanimous A.I. a human-computer interaction company focused on harnessing collective intelligence by enabling online human swarms.