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# Massively collaborative problem solving: new security solutions and new security risks

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## Abstract

We present the initial discoveries from an investigation of massively collaborative problem solving (MCPS) assembled from two independent projects attempting to foster large scale distributed collaboration to solve complex problems, including those relevant to local and national security. Two preliminary investigations for a DARPA Small Business Innovative Research (SBIR) program are discussed herein. Instead of a linear approach to problem solving, in which many people are asked to perform a similar task until consensus is reached, the described problem solving environments encourage deep reasoning to emerge by combining small contributions from many individuals to solve dynamic and previously unsolved problems. The environments encourage problem solvers to decompose a complex problem into parts so that it can be solved by a community with diverse skills and experiences. Social consensus then plays a role in crafting the aggregate solution. However, as the number of collaborators goes up, the number of disruptive attempts by malicious individuals to derail the solution may also increase. We discuss potential applications of MCPS for security and intelligence, and system security issues MCPS must address.

## Introduction

Many current social computing applications focus on one of three strategies: the distribution of a single task to many people (e.g., GalaxyZoo, Foldit, Games with a Purpose), the utilization of humans as a distributed sensor network (e.g., Ushahidi, Layar) or a winner-takes-all approach to problem solving (e.g., Innocentive, One Billion Minds). In these strategies large populations may be tapped, however each emphasizes individual solutions rather than collaborative solutions in which people coordinate to accomplish a task larger than a single person can solve. This is analogous to a parallelized software program in which a single function call is farmed out to multiple processors. While this social computing model has inspired numerous productive solutions, we believe that a richer model could give rise to unprecedented capabilities in secure, goal-directed behavior. Such a model consists of a limitless variety of function calls that may provide new capabilities leading to a solution. More concretely, we believe such a model should delegate a variety of deep reasoning meta-tasks, such as concept reformulation, abstraction, decomposition, and fusion, all in service of higher level reasoning goals to humans. In addition, the output from one human task should serve readily as the input to another human task in a collaboration workflow. In general, we seek to evolve from the current model of “flat”

distributed cognition to one of “deep” distributed cognition, in which a cognitive model can benefit from “function calls” to humans for any tasks that transcend current machine capabilities.

Such an approach to distributed problem solving has the potential to address two key desiderata associated with security: problem secrecy and robustness to manipulation. Generating problem abstractions by stripping away confidential problem details may sufficiently preserve fundamental conceptual relationships, thereby permitting resolution while protecting the source issue from unclassified solvers. Similarly, problem decomposition (particularly in concert with abstraction), could isolate unclassified sub-problems from classified problems, allowing unclassified sources to contribute knowledge or reasoning to a classified problem. Decomposition also affords an advantage with respect to bias or overt manipulation. Without an understanding of how solutions to sub-problems fuse together to compose high level solutions, it would be exceedingly difficult to manipulate a particular sub-problem solution in order to coerce a particular outcome.

Many problems with far-reaching consequences remain unsolved, even though the conceptual knowledge necessary to solve them resides in our populace. This paper looks at architectures for problem solving environments based on mutual deep collaboration. The environments organize large groups of people and facilitate a well-conceived workflow that faces four key challenges: 1) mediate the flow of information among humans toward a practicable solution; 2) motivate and retain participation on a massive scale; 3) resist surreptitious manipulation; and 4) obtain specialized knowledge when needed.

In this paper, we first describe the two problem solving environments studies undertaken for DARPA's Phase I SBIR program called “Massively Distributed Problem Solving”<sup>a</sup>. Critical Insights in MCPS culled from both projects are discussed first, followed by details on the PARCEL project approach by SIFT, LLC and the ePluribus project by Management Sciences, Inc.

The paper then discusses two complementary issues related to techno-social predictive analytics. First, we describe some applications in security and intelligence that would benefit from massively collaborative problem solving, including how such a framework can leverage citizens to increase situation awareness and responsiveness to significant events. If a nation uses these tools for local and national security, one must also protect the system and knowledge from malicious behavior and misuse. We discuss how to ensure security in highly collaborative and possibly open environments.

### **Critical insights**

In this section, we discuss the critical insights that have guided research and development, culled from the two approaches.

#### **A workflow for crowdsourcing complex problems**

A primary goal for MCPS is to enable a problem solving process that transfers to a distributed environment, is easy to understand, and is flexible to many types of problems and problem solvers. Simply extending existing collaborative problem solving or crowdsourcing paradigms may not maximize the value that each contributor brings to the solution, since each contributor has unique strengths and weaknesses. MCPS requires new approaches that take advantage of participation on a massive scale, leveraging the crowd's diversity and unique cognitive abilities to address the scope of large-scale

problems. For example, existing crowdsourcing paradigms for problem solving (such as Stack Overflow, a website for crowdsourcing solutions to computer programming issues[1]) only allow individuals to provide and evaluate competing answers to discrete questions. However, complex problems involve multiple sub-problems that people with diverse expertise can solve independently. A MCPS framework should enable groups to take on problems too difficult to solve as an individual.

### **Motivating contributors**

Collective problem solving presents many challenges for acquiring and maintaining a community of problem solvers (henceforth called *Solvers*) who show enthusiasm for the proposed problems and provide high quality solutions. A collective problem solving tool will need to appeal to contributors with the appropriate skills, experiences, creativity and insight. An MCPS environment must answer several questions than any potential solver will ask before contributing [2]:

1. Why should I participate?
2. What mechanisms are in place that allow me to progress on my own?
3. Why would I convince my friends to participate?
4. How am I rewarded for participation?

Motivating humans to contribute presents new twists on the scientific method for solving problems, and nothing could dampen motivation more than poor security causing solvers to lose credit for their efforts or not obtain rewards they deserve. Solving motivation for MCPS will cross boundaries into the social sciences, marketing and human factors.

### **Addressing “wicked” problems**

Many problems have dynamic, ill-defined natures that introduce difficulties to the solution process. While solving, new issues may arise that change the definition and significance of a problem. These problems, often called “wicked” [3], present a particular challenge to problem solving tools. Hard to define problems are difficult to solve and verify. Solvers may not even recognize a valid solution because it may not present itself with a clear completion stage. For example, one may analyze the effects of a potential solution, which may induce continued diagnosis of the dynamic situation. Also, at any point, one may select a potential solution and act on it, which may change the observed behavior and induce new hypotheses. Examples of wicked problems include forming a national immigration policy, addressing crime and violence and encouraging democracy in authoritarian regimes [4].

### **Embracing subjectivity and diversity**

Each solver brings their set of unique experiences to problem solving. As a result, there may be multiple viable solutions to a problem. By opening the process to a greater number of individuals, we increase the diversity of how problems and solutions are explored; as the number of stakeholders increases, the community’s goals may become contradictory. A problem with no clear definition, nor a single optimal solution can be classified as subjective. MCPS should address subjective problems by enabling significant diverging opinions to emerge.

Used correctly the convergence of diverse skills and backgrounds can prevent the group from getting stuck looking at problems from the wrong perspective (functional fixedness) which can prevent forward progress by a single individual. For every field of endeavor, there are many related fields populated by people familiar with their fundamental concepts, but perhaps not their problem-specific knowledge. MCPS can leverage these people we call “near experts” to evaluate solutions and innovations using their domain knowledge. Near experts represent a large portion of potential recruits from which to harness the power of crowdsourcing. In addition, MCPS frameworks should leverage creative and analytical diversity by providing interfaces and activities that suit particular dispositions, availabilities and moods.

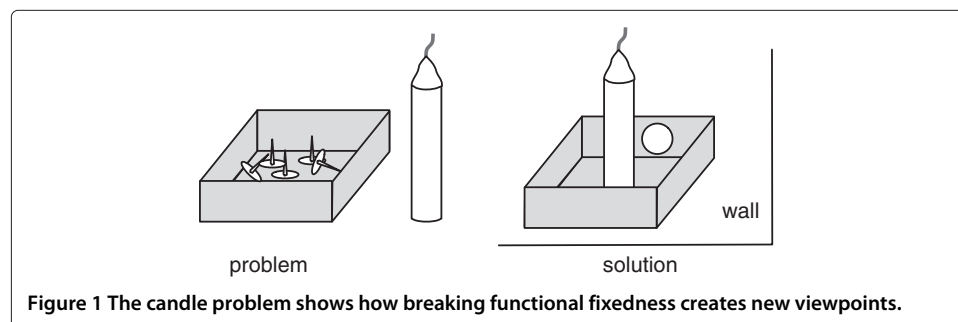
### Technology to create an “eureka” moment

When working on a problem, humans can have an “eureka” moment when they glimpse the problem solution. An eureka moment typically occurs when people combine facts in a new way to solve a problem. Continuous education loads more facts into participants’ minds and may increase the chance of an eureka moment. Technology can also increase the chance of an eureka moment by explicitly managing the juxtaposition of facts presented to the solvers. More eyes on a problem increases the chances of uncovering key insights, especially if technology presents the problems in new contexts. Because of this, technological solutions that continuously teach solvers new facts and combine those facts in new ways can improve the chances of an eureka moment. Technology may increase the odds of this, but insight only occurs in the human mind.

Consider the concept of functional fixedness described by Duncker [5]. He describes a puzzle problem involving a candle, a box of tacks and a book of matches. The solver must affix the candle to a wall and light it, as in Figure 1. Duncker found that people solved the problem much faster when the tacks were taken out of the box. When the tacks were in the box, participants only saw it as a box for holding tacks, as opposed to a shelf for the candle. MCPS technology can “take the tacks out of the box” to create different viewpoints on problems.

### Protecting against adversarial behavior

Any system that offers rewards must address individuals that aim to exploit weaknesses in the system to gain more rewards. For instance, in social media, popularity is the measure of success. In some cases people or brands will buy social media followers to appear more popular [6]. In MCPS, it is possible that an individual problem solver could use such methods to make their solution seem more popular than it actually is in the



community, eclipsing better solutions. When designing a framework for MCPS, security to detect and prevent gaming the system becomes critical for long-term success. Some have suggested inserting a “control” problem with a single verifiable solution to detect improper behavior; or to introduce market mechanisms that are less prone to exploitation [2].

### **Classes of problems that would benefit from MCPS**

To date, there are many working examples in which the crowd can provide an evaluation, such as image tagging [7] and protein folding [8]. However, to solve problems with an unknown solution, what characteristics should the problem have to increase to improve the chance of the crowd solving it? While speculative at this stage in MCPS research, our insights are given below:

#### ***Intrinsic motivation***

Encouraging high quality contributions from a diverse population may require “casting our net wide” to find potential solvers. Monetary and gaming rewards can manufacture motivation, but we suspect that the largest crowds will arise with issues that intrinsically motivate large numbers of people such as: curing diseases, safety, creating exciting new technology, and responding to political, social and environmental crises.

#### ***New viewpoints***

MCPS is intended to take on problems that have no existing solution or may require revisiting and combining insights from various existing (and possibly unrelated) solutions. With it, the crowd brings the potential to create new processes and solutions that may diverge from current conventional wisdom. If one needs the crowd to solve a specific, testable problem such as protein folding [8], a very focused game approach with a domain-specific interface would be more effective than the general MCPS approach outlined here.

#### ***Decomposability***

The value of MCPS comes from having many eyes on many aspects of the problem. Large problems that can be decomposed into smaller, more specific sub-problems can leverage this diversity. Only a small crowd of experts may have the depth of knowledge to understand the entire scope of the original problem.

#### ***Cost of failure low***

The benefit of MCPS comes from trying many new ideas, or even looking at discarded old ideas in a new way. If the risk of applying exploratory methods exceeds the potential benefits, then traditional problem solving is more appropriate. For example, one would not crowd-source new drugs by human testing. However, MCPS can aid in the brainstorming phase, after which empirical approaches can be applied to the best candidate solutions.

### **MCPS approaches**

This section provides an overview of the two exploratory MCSP projects.

#### **PARCEL**

The PARCEL design incorporated a top-down, human-driven workflow for problem solving, organized into a five stage workflow; problem specification, problem decomposition,

knowledge capture, solution integration and reward determination. PARCEL rewards participants through a blended knowledge economy of altruism, recognition, competition and monetary rewards. The design also includes an integrated set of games to motivate, manage continuous education, foster innovation, and evaluate new concepts. Figure 2 provides an overview of the various PARCEL elements.

The first stage of the PARCEL workflow requires the problem sponsor to clearly define the target problem to ensure that solvers focus on the desired problem. The problem sponsors also lay the groundwork of common definitions and resources to solve the problem.

Next, the solvers decompose the problem specification into more manageable sub-problems. Participants can disagree on a decomposition and offer alternative decompositions, creating alternate branches to the decomposition tree. Discussion and voting tools focus effort on what participants feel provide the best avenue of success. However, participants can always explore alternatives and reap rewards if they succeed. PARCEL problem decomposition relies entirely on human inspiration, allowing overlap and competing decompositions.

The third stage captures knowledge related to the problem and stores it for the benefit of other solvers on this and future problems. PARCEL uses mind maps—also known as concept maps—to help organize information into a directed graph of knowledge [9,10]. Each concept node on the knowledge graph has a wiki page to capture detailed descriptions of the concept. The graph allows for rapid traversal of the knowledge base and viewing relationships between concepts. The separation of problem decomposition from knowledge capture enables knowledge reuse on future problems. Solvers put solutions into the knowledge base and then link them to the specific parts of the problem decomposition as partial solutions.

The fourth stage integrates the stage-three partial solutions to solve larger problems. PARCEL allows for multiple solutions, with the sponsor determining the final rewards. Integration selects a single working solution, based on evidence, from the chaotic, human-driven decomposition process.

PARCEL's final stage determines the reward payout for solvers. Since motivation depends on fair and timely accounting, PARCEL allots recognition and competition rewards throughout the problem solving process. PARCEL reserves monetary payouts for when sponsors accept a solution because only then can PARCEL understand the value of each contribution. Solvers must feel that the reward stage accurately reflects their contributions, and they must know disruptive participants cannot abuse PARCEL to unfairly earn rewards.

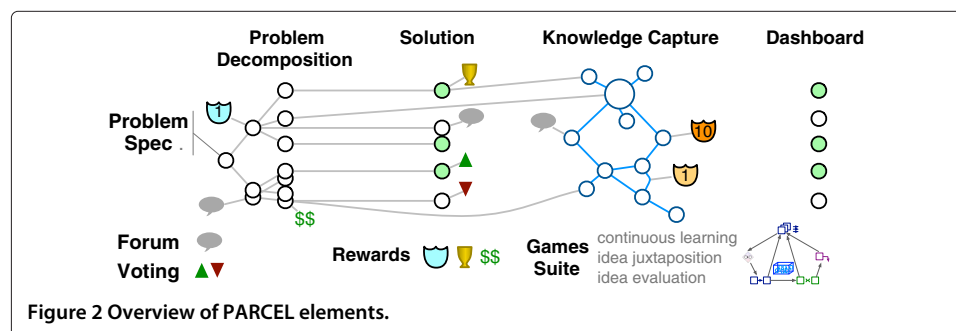


Figure 2 Overview of PARCEL elements.

### **Rewards**

Paying a massive number of solvers for small improvements quickly becomes economically unfeasible. As a result, PARCEL creates a blended knowledge economy that rewards even the smallest contributions with a combination of feedback, recognition, and fun, as well as money.

PARCEL rewards altruistic solvers by providing feedback that the solver's effort has led to an effective solution. Many projects have failed in the past, even though they consisted of highly motivated, altruistic individuals. If an individual donates their time for the common good, they must understand the impact of their actions and how they contribute to the overall goal. PARCEL allows solvers to quickly find some way to contribute, tailored to their available time, tracks contributions, and shows on a dashboard how an individual's efforts contribute to the overall solution progress. Too often, an individual feels that his or her efforts are being lost in bureaucratic red tape and that the final goal never gets closer. PARCEL ensures that solvers feel effective even with minimal time investment.

PARCEL creates an open-ended set of reward badges to ensure rewards are never too far out of reach. PARCEL solvers earn recognition points in a variety of ways: coordinating solutions, decomposing problems, deducing facts, fact checking, resolving conflicts between solvers, adding links, adding tags, creating solutions and integrating solutions. The recognition structure rewards different behaviors requiring diverse skills so that everyone can strive for accomplishments. MCPS solutions require a flexible rewards engine that can manage and direct participation over time.

Competition provides great motivation for many individuals, often costing the sponsor nothing but recognizing the winner. To harness this motivation factor, PARCEL creates tools to define and manage competitions between individuals or teams, creating a scoreboard from the problem visualization tool.

Money becomes an important tool in the sponsor's arsenal for challenging problems. Some required tasks may incur real costs, such as a DNA analysis, that the project must fund. A PARCEL solution must handle money as part of the knowledge economy, using it to manage interest and motivate solvers through contest prizes and monetary contracts for specific tasks. PARCEL allows sponsors to hold contests with monetary rewards for very specific challenges, much like the Netflix challenge or the X prize [11,12].

### **Games for innovation**

PARCEL includes a suite of six integrated games that help solvers contribute to the PARCEL workflow and evaluate new ideas. The games provide for continuous education and try to increase the odds of the solver having that eureka moment. These games use social elements to increase motivation and recruit new solvers. They apply ideas from the "Games with a purpose" philosophy to increase the computer's understanding of the novel concepts presented [13]. PARCEL incorporates innovations that appear useful into other games and collects metrics on the value of the innovation, based on the player's response. PARCEL increases the exposure of valuable insights and limits the exposure of insights that do not appear useful. The games work together as a suite to generate and evaluate new ideas.

PARCEL's games use the mind map knowledge representation as a way to understand and organize information into a suite of games that teach people new facts and solicit innovative ways to combine facts. Mind maps allow for games that deal with general knowledge, as opposed to a game like fold-it that creates an optimized game for specific knowledge like protein folding. This allows PARCEL games to support multiple knowledge domains.

The Constructo game allows solvers to build on the innovations of others, by breaking down a potential solution mindmap into its basic elements and injecting new concepts. The solver tries to rebuild the solution, not knowing which components have changed. The other games do the following: relationship utility evaluates the constructo results, functionym brainstorms new ways to use concepts, idea interval captures the semantic distance between concepts to control injected concepts, concept cull removes poor ideas, and think tank provides memes to recruit new solvers.

PARCEL provides a top-down workflow for solving a problem. Each solver gets a customized "to do" list when they log in to PARCEL. This list provides tasks that range from only a few minutes, such as playing a game, to more time-consuming, deep reasoning tasks. This allows solvers to contribute as much of their valuable time as they can spare. PARCEL continuously motivates solvers using social networking game memes, competition, altruistic rewards and money to ensure ongoing contributions and progress. PARCEL remains a human-driven approach, with humans finding the key insights and integrating key facts to arrive at solutions. PARCEL uses algorithms and knowledge matching to control which facts each solver sees to improve the chances of an eureka moment.

#### **ePluribus solver**

Management Science's (MSI) framework, called the *ePluribus Solver*, provides building-blocks for problem solving while encouraging the emergence of new problem-solving processes. Our objectives for the *ePluribus Solver* fit into two complementary categories, the first addressing the challenges involved in forming a tool for general problem solving, the second addressing the challenges involved in soliciting and integrating large numbers of people in the problem solving process. After defining a core set of building-blocks for problem solving and a basic incentive structure for encouraging participation, we developed a prototype application that demonstrates our approach applied to a shared situation awareness problem.

#### ***Exploring problems and solutions***

There are many theories and methodologies to problem solving, often oriented towards a particular kind of problem. However, a "Swiss-army knife" containing a full set of specialized tools from which problem solvers can select becomes impractical. Instead *ePluribus Solver* implements a core set of commonly used problem solving building blocks. Given a core set of building blocks, solvers can combine them in infinite ways to produce a workflow based on their own problem-solving processes.

To construct a set of building blocks for problem-solving we consulted several sources, including research on generalized problem-solving tools developed in early Artificial Intelligence systems [14-16], cognitive models for learning and development [17-19], and empirical studies of problem-solving methods [20-22]. We also formed use-cases for types



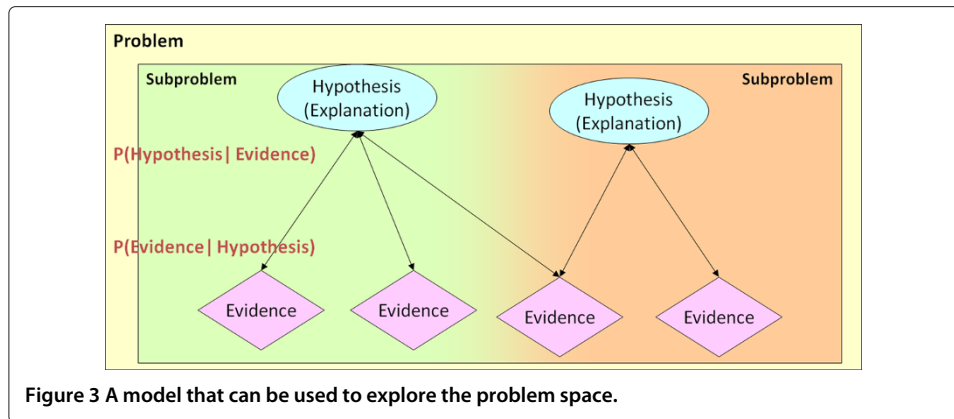


Figure 3 A model that can be used to explore the problem space.

of MCPS problems. We discovered that at a high level, all problem-solving processes involve one or both of the following two stages: (1) describing the current understanding of the problem, and (2) describing a desired outcome and working towards a solution.

The first phase of problem-solving involves a diagnostic approach to understanding a situation that manifests as observable behaviors or events. In this stage, the problem-solver attempts to formulate hypotheses for the observed behavior and in the process may seek out additional evidence to support or eliminate competing hypotheses. This process involves the complementary reasoning methods of abduction [23] and deduction [24]. The scientific method exemplifies this approach. We refer to this stage of problem solving as *exploring the problem space*.

The complementary high-level stage of problem solving is a goal-oriented process of affecting a desired outcome. For example, one may set forth parameters for a solution and seek out a solution that addresses these parameters. This stage may involve selecting and taking actions that could modify the observed behaviors or affect their underlying causes. Means-end analysis provides an example of this technique. [14]. We refer to this stage of problem solving as *exploring the solution space*.

Figure 3 illustrates a model containing the building blocks for exploring the problem space including nodes for evidence and hypotheses. This model specifies a Bayesian network which allows us to represent abductive and deductive reasoning. The equation  $P(\text{Hypothesis} | \text{Evidence})$  shows abduction, or inferring a hypothesis from observations. In other words, the equation represents the likelihood of a hypothesis given some evidence. Deduction uses the complementary equation  $P(\text{Evidence} | \text{Hypothesis})$  to compute the likelihood of evidence given a hypothesis. The problem space can also be split into multiple subproblems, each of which may be addressed by different hypotheses.

The ePluribus approach to exploring the problem space can be compared to Richard Heuer Jr's *Analysis of Competing Hypotheses (ACH)* approach in which an analyst compares a number of hypotheses by listing and elaborating on how available evidence contributes to the hypotheses [25]. ACH analyzes intelligence information. ACH may become cumbersome to complete for a large matrix, in which each piece of evidence is applied to each hypothesis. In contrast, ePluribus provides a flexible approach to make connections only between related hypotheses and evidence. Connections also may be made between hypotheses and pieces of evidence. In some cases evidence may become hypotheses when the evidence itself is in question.

### **Prototype problem**

The primary research objective of the first *ePluribus Solver* prototype was to evaluate its ability to form a collective solution from multiple perspectives. *ePluribus* asked solvers to describe a situation that was shown to them in pictures using only a few characters or words. Each solver could interpret the picture differently and provide a unique description. Then contributions were peer-evaluated for quality and accuracy and combined to form a story. This addresses how a community might get word out about a situation if communication resources were somehow constrained, such as occurred in the Egyptian Revolution [26].

The prototype problem addresses the problem-solving process of exploring the *problem space*. The images represented observations, or *evidence*, and the descriptions represented *hypotheses* describing what was going on. Forming a shared situation awareness relates to many practical, real-life situations, such as diagnosing the cause of bank failure or describing the effects of a natural disaster.

### **ePluribus incentive structure**

In hopes of appealing to a diverse community of problem solvers and encouraging involvement at multiple levels of the problem solving process we consulted Dr. Riley Crane at MIT's Human Dynamics laboratory. Dr. Crane provided general guidance and helped design an initial incentive structure that defines how individuals earn *Unums*, or points, by joining *ePluribus* and contributing to the collective story.

The objective of the *ePluribus* prototype was to demonstrate a viable incentive structure while maintaining simplicity. The prototype's problem-solving process was composed of two phases, the first called *Describe* and the second called *Compose*. The *Describe* phase was equivalent to brainstorming in which *ePluribus* elicited hypotheses about a set of images depicting an event from the human solvers. The describe phase solvers chose to do one or two tasks: 1) *Contribute to Story*: in which they describe one or more images and 2) *Be the Judge*: in which they evaluate the descriptions that other individuals submitted.

In the *Compose* phase individuals "invested" in the top descriptions. In the process, individuals formed their personal story by combining their preferred descriptions. After the second phase, *ePluribus* combined the top five descriptions according to amount invested into them to form the "collective story." In all phases of the game, individuals could earn points, called *Unums*, for various tasks that contributed towards forming the collective story.

The final part of the Phase I incentive structure forms the basis of a solutions market in which market forces determine the top hypotheses or solutions. Market based approaches have been shown to reduce subjectivity and encourage consensus because one must consider the likelihood of consensus when selecting which solutions to invest in [27]. The Phase I investment mechanism worked as follows:

1. Individuals could invest their *Unums* into one or more of the top ten descriptions
2. The top five descriptions according to investment composed the collective story
3. Once the *Compose* stage was completed, the investments were redistributed to the investors using each descriptions' return on investment, based on the description's popularity.

The final reward mechanism in the *ePluribus* prototype was a raffle in which the number of *Unums* each individual earned was equivalent to the number of “raffle tickets” that they held. A winner was then drawn from the solvers for a single prize. This design has numerous benefits for simplicity, including avoiding maintaining a monetary equivalent for the *Unums* and providing an incentive for non-leaders to contribute [2].

### **Aggregation**

In the *ePluribus* prototype the final aggregated story is formed by simply combining the top rated contributions. In general, *ePluribus* aggregation algorithms will utilize peer and expert evaluation to guide how to select and combine components to form a final solution. A complex problem, such as forming situation awareness about a large-scale threat, will likely have multiple components with contributors working specifically on individual components. In turn each sub-component may be broken into other components or sub-tasks. Aggregation will occur in a bottom-up fashion in which the best representation (according to peer review and expert oversight) of each component will be combined. There may be cases in which there is no convergence on a single solution. For example two solutions may have strong support. In this case the aggregator may show alternate solutions or solution paths to a final result. For example, in [28] a population was partitioned into groups of consensus before aggregation occurred, resulting in potentially diverging solutions for different groups.

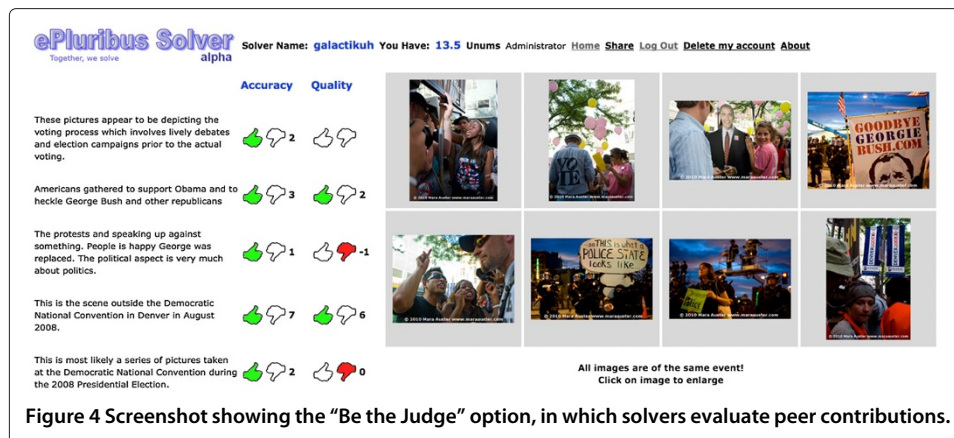
### ***ePluribus* prototype**

During the *Describe* phase, *ePluribus* users who chose the *Contribute to Story* option were presented with a random subset of eight images. *ePluribus* prompted the user to describe what was going on in the pictures, possibly including what the pictures had in common. This process was intended to simulate the diagnostic process of forming a hypothesis for one or more observations. By describing random subsets of images, people would in theory describe the whole story - from the high level summary to the specific details.

Figure 4 shows a screenshot of the *Be the Judge* option. Solvers clicked on the “thumbs up”/ “thumbs down” icons to provide their evaluations for the given criteria (*accuracy* and *quality*). The judgment earned the solver a small amount of *Unums* to encourage participation in this important aspect of the game.

During the *Compose* phase the top ten descriptions from the *Describe* phase were shown. The solver selected one or more descriptions to compose her version of the collective story. The solver could then invest *Unums* she had earned in the selected descriptions. The top five descriptions composed the collective story. The descriptions were ordered such that the phrase describing the greatest number of images was first. This was intended for simplicity and to put the most general statement first.

The *ePluribus* prototype went “live” in August 2010 at <http://www.epsolver.com> for a two-week experiment. An advertisement was created in *Facebook*. A “HIT” was also created using *Mechanical Turk* to pay workers to sign up and use *ePluribus*. Fifty users were solicited, contributing 40 different descriptions and 329 evaluations. The following



paragraph is the “collective story” from the experiment describing the images in Figure 4. The story is composed of descriptions submitted by five different people.

This is the scene outside the Democratic National Convention in Denver in August 2008. Americans gathered to support Obama and to heckle George Bush and other republicans. These pictures appear to be depicting the voting process which involves lively debates and election campaigns prior to the actual voting. Highlighting the delineation between the parties yet embracing the Constitution individuals rallied in Denver to convince people to Vote. The riot police were out in full gear as the sun set on the street protest. Although the crowd was peaceful the powder keg had potential.

While we did not compare the collective story to stories written by a single person for quality, we note that the final collective story was a combination of five descriptions from five people, even though several people had submitted multiple descriptions. A full-featured version of ePluribus for general problem solving will be developed in a Phase II program.

### Lessons learned

Some conclusions drawn from the first *ePluribus* experiment:

- Investing in complete stories resulted in a slightly different story than simply combining the top five descriptions according to their individual evaluations. This implies that the manner in which the descriptions were combined was relevant to the story’s perceived quality.
- The *ePluribus* approach to evaluation biased contributions submitted earlier because later submissions did not have enough time to accrue as many points as earlier contributions. This implies that ensuring uniform exposure of elements may be necessary.
- The *ePluribus* prototype required users to provide an email address and accept a license. These requirements are barriers to entry for users who are reluctant to sign up for a new application.
- *Facebook* advertising resulted in a small number of recruits. The advertisement may not have captured enough people’s attention, highlighting the importance of engaging interfaces and traditional marketing that plays to people’s motivations.

- Our *Mechanical Turk* efforts were significantly more successful, acquiring about 30 new users. This may be because an explicit incentive was given or *Mechanical Turk* workers are already familiar with, and perhaps enjoy contributing to crowdsourcing efforts. It is difficult to quantify in this experiment the importance of financial incentives and hence this introduces a potential research topic. The quality of *Mechanical Turk* contributions is often high even though they are paid very little to contribute.

Note: No personal information was collected and all involvement was voluntary, online and anonymous through *Mechanical Turk* and Facebook Advertising.

## **Intelligence and security**

### **Massively collaborative problem solving for security and intelligence**

The ePluribus and PARCEL frameworks address problems that benefit from contributions by many distributed individuals, including defense and security. The first ePluribus prototype focused on forming situation awareness from multiple perspectives. ePluribus can leverage “sneakers on the ground” citizen observers who can provide a wealth of information and help form situational awareness. We provide two hypothetical situations in which security and intelligence problems can leverage citizen observers using ePluribus.

#### ***Forming intelligence reports from distributed fragments***

The first scenario illustrates a crowd sourced approach to forming shared situation awareness in which groups of individuals with increasing expertise take on the Joint Director of Labs (JDL) fusion levels [29]. Imagine a situation in which American coalition forces cannot embed intelligence agents into a village. However, a number of locals have cooperated with the American forces and agree to provide their observations. Each individual “observer” may present an incomplete view of the event based on their limited perspective. Many observers do not have the depth of knowledge to add meaning to the observations. However MCPS tools can integrate the non-expert observers with experts possessing sufficient knowledge to make relevant inferences.

These remotely located experts will evaluate the observations. They will interpret the situation at a high level and in detail and share their interpretations with their peers, which may in turn be evaluated by other experts. Stories describing the event, its origin and its impact will emerge from the collective through a collaborative process of revision, evaluation and selection. Remote solvers may discover relationships between seemingly disjointed pieces of information that reveal important patterns of behavior and contribute to high-level intelligence. For instance a piece of graffiti may look innocuous upon observation but become suspicious when observed at multiple polling locations. In this manner, ePluribus will allow US coalition forces to combine fragmented contributions from citizen observers with their own high-level reasoning to construct a comprehensive, high quality intelligence report.

Using distributed contributors increases redundancy, reduces risk to the contributors, and improves the security of information. If each individual only contributes a small amount of information then the capture, loss or deception of a single person will be less detrimental to the mission than a significant contributor. The classification of the aggregated report may increase as experts add more information. While personnel clearances

can protect a specific document, a MCPS system must balance between sharing facts with the crowd to foster insights and ensuring that classified information is not released. In the described scenario, observations would be carefully partitioned from their interpretation and information synthesis would occur at higher classification levels.

#### ***Reducing false positives with citizen observers***

In homeland security, the ability to respond to threats often begins with awareness of important indicators. One could imagine a situation in which citizens submit photos and information about situations they find to be suspicious. While this increases the awareness, some of the data collected may be irrelevant or explainable as non-threatening.

ePluribus can distribute the collected observations to a larger group of solvers to encourage more objectivity, and explore a variety of possible interpretations, selecting only the high-grade interpretations to share with higher level analysts. Collaborative interpretation also incorporates a broader expertise base not present in a small group of analysts, such as cultural expertise, helping to eliminate possible misinterpretation of signals.

#### ***Incentives***

Security and defense MCPS environments that consider providing incentives to their citizen solvers may wish to avoid financial incentives. Instead, altruistic rewards - such as pointing out how their contributions improve the stability in their city or increase the safety of their troops may be more appropriate. These kinds of rewards can result in greater satisfaction while discouraging "gaming" the system (for example by providing false information for financial gain). However, stopping and adversary from injecting deceptive information requires additional safeguards, such as Byzantine fault tolerance [30].

#### ***Security for massively collaborative problem solving***

A secure MCPS system must address the issues discussed below.

**Information flow** represents getting the right knowledge to the right people at the right time, with no other unexpected information flows. If an entity could stop the flow of information they could delay or inhibit innovation. For example, in PARCEL the network of games manages the exposure of ideas to the solver population. Ideas with merit get more exposure spreading the idea further. A malicious solver could mark good ideas as poor to prevent their being seen. However, in the face of tens of thousands of solvers such an attack has almost no impact. If PARCEL chooses solvers randomly for the dissemination of an idea, even a large subgroup trying to suppress an innovation could only reduce the exposure an innovation gets, not eliminate it. Rather than a random dissemination, PARCEL would attempt to maximize its benefit by sharing the innovation with experts and near experts in the target knowledge domain. In fact, a workable radical idea that bucks the status quo could easily be suppressed by experts who myopically assume it will never work. To combat this, PARCEL only limits exposure, never removing an idea without human review.

Malicious solvers could degrade the system by introducing solutions that seem plausible on the surface, but by design, do not work. Since the majority of solvers are novices for

a specific topic, even a meritless idea could spread. The extant spread of pseudo-science serves as a prime example. Such a flood of information-poor contributions could easily de-motivate experts, greatly reducing the efficacy of the problem solving environment. MCPS can protect from this type of attack by having a formal process that removes an idea from consideration, when experts determine the idea hampers further progress. The removal requires sufficient documentation so that solvers can learn why the idea does not work.

Thus, a sponsor-driven “executive function” could serve to weed out distracter ideas that an automated process might miss. In general, combating against information flow attacks involves a combination of strategies that leverage the respective strengths of humans and machines to simultaneously protect unpopular ideas that might contain merit and attenuate popular noise.

**Proper motivation** ensures people stay engaged in the problem solving process. If the system hands out rewards unfairly, solvers will feel their efforts are wasted and stop contributing. Traditional security concerns controlling confidentiality, availability and integrity with appropriate protection technology for each. However, MCPS require an additional property of equitability. Secure systems incorporate specific rules to prevent “cheating” for a specific context. For example, today we consider a person’s email private, but there was a time when it was simply another file in the system. A human decided that email was private and hard coded the policy into the operating system. MCPS must define equitability policies to address questions like: who contributed a key idea when there may have been thousands of contributors?

A MCPS should create a set of rules to calculate rewards. The PARCEL study learned that a flexible reward engine remains critical to shift solver focus to critical areas. A flexible reward engine should have a stable core of rules to ensure fairness over time. For example, a monthly contest should not remove prior received rewards. Ideally even partially earned rewards should remain untouched by new rules. Overall if the new rules are additive, drawing from their own reward pool they will not conflict with prior contests. The identification of flexible rules that maintain equitability over time remains an interesting research pursuit.

**Resisting surreptitious manipulation** refers to preserving the integrity of data, a well studied area of computer security. Most approaches concentrate on preserving integrity. However, MCPS requires evaluating new contributions with unknown integrity. To illustrate, software cannot determine if a solver’s contribution to an idea was an improvement or not. A MCPS solution must preserve the integrity of each individual’s contribution and provide an accurate history of modifications and additions, like a version control system. This prevents malicious individuals from manipulating contributions of others to degrade the idea. MCPS can engage solvers to help police and track the provenance of ideas. Technology can link related ideas and humans can confirm the origins of ideas. A collaborative environment means multiple eyes can watch for malicious manipulation.

**Obtaining specialized knowledge** becomes a critical factor in the success of any MCPS system. A solution, or even a partial solution may represent valuable intellectual property. People may maliciously submit proprietary information or attempt to capitalize on

knowledge in the MCPS system for their own personal gain. The MCPS environment must ensure that any solutions found by MCPS are used for the intended purposes the solvers signed up for.

Legal procedures provide one secure way to protect the solution by ensuring that any contributions remain open source. The MCPS must then detect and remove any proprietary entered by solvers. However, quite likely the MCPS will reinvent technology held as proprietary by some organization. When this happens the solvers must simply find an alternative solution. One simple alternative is acquiring the license rights to use the proprietary information.

## Conclusion

In this paper we have laid the groundwork for developing first-generation MCPS systems and delineating the conceptual space. We have also discussed some potential applications of MCPS to security and intelligence. We invite the reader to consider how applying a more collaborative and decomposable approach to crowdsourcing might be appropriate for a particular challenge with which he or she is confronted.

Since we propose to open national security issues to a larger, more diverse community, we must not neglect system security in pursuit of exciting new features. In many cases, new security tools will not need to be invented, but simply applied appropriately. MCPS platforms utilized by large communities could solve far-reaching problems that improve the safety, health and lives of global citizens. However, the excitement of building a social computing platform for solving problems on the edge of human capabilities should not overshadow the importance of a solid security foundation. Without a secure foundation, problem solving efforts may be upstaged by the new problems they introduce.

## Endnote

<sup>a</sup>This research was funded by DARPA contracts N10PC20061 and N10PC20060.

### Competing interests

The authors declare that they have no competing interests.

### Authors' contributions

KG developed the ePluribus Solver approach. DT developed the PARCEL approach. PM developed the SBIR topic description. All authors read and approved the final manuscript.

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Received: 14 November 2011 Accepted: 7 March 2012

Published: 22 August 2012

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doi:10.1186/2190-8532-1-12

**Cite this article as:** Greene et al.: Massively collaborative problem solving: new security solutions and new security risks. *Security Informatics* 2012 **1**:12.

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