Crowdsourcing Participation Inequality: A SCOUT Model for the Enterprise Domain

Osamuyimen Stewart
IBM Research
1101 Kitchawan Road
Yorktown Heights, NY
011+1-914-945-1137
ostewart@us.ibm.com

David Lubensky
IBM Research
1101 Kitchawan Road
Yorktown Heights, NY
011+1-914-3261
davidlu@us.ibm.com

Juan M. Huerta
IBM Research
1101 Kitchawan Road
Yorktown Heights, NY
011+1-914-9453378
huerta@us.ibm.com

ABSTRACT
In large scale online multi-user communities, the phenomenon of 'participation inequality,' has been described as generally following a more or less 90-9-1 rule [9]. In this paper, we examine crowdsourcing participation levels inside the enterprise (within a company's firewall) and show that it is possible to achieve a more equitable distribution of 33-66-1. Accordingly, we propose a SCOUT ((S)uper Contributor, (C)ontributor, and (OUT)lier)) model for describing user participation based on quantifiable effort-level metrics. In support of this framework, we present an analysis that measures the quantity of contributions correlated with responses to motivation and incentives. In conclusion, SCOUT provides the task-based categories to characterize participation inequality that is evident in online communities, and crucially, also demonstrates the inequality curve (and associated characteristics) in the enterprise domain.

Categories and Subject Descriptors
H.1.2 [**User/Machine Systems**]: Human factors, Software psychology H.5.3 [**Group and Organization Interfaces**]: Computer-supported cooperative work, web-based interaction

General Terms
Design, Human Factors

Keywords
Crowdsourcing, online community, incentives, motivation

1. INTRODUCTION
Crowdsourcing is generally described as a web-based activity that harnesses the creative contributions of a diverse large network of individuals (the crowd) through an open call requesting for their participation and contributions [3, 4, 7, 8, 12, 13, and 14]. After the open call is issued, there are various views on crowd response or composition in terms of participation and contribution. Nielsen [9] based on existing works [5, 15] has analyzed the phenomenon of 'participation inequality' in online communities and advocates a general 90-9-1 rule: (a) 90% of users are 'lurkers' (i.e., they read or observe, but don't contribute), (b) 9% of users contribute from time to time, but other priorities dominate their time, (c) 1% of users participate very often and account for most contributions (it can seem as if they don't have lives because they often post just minutes after whatever event they are commenting on occurs). Based on this, participation inequality is deemed to be a function of human behavior and one that is almost impossible to overcome [9]. This presents a major challenge for crowdsourcing inside the enterprise (within a company's firewall) due to serious time constraints and work pressures that greatly inhibit employees' participation and coupled with the fact that motivation and incentives are different from the public domain [11]. Thus, the only real choice is in how online crowdsourcing communities inside the enterprise can shape the inequality curve's angle differently from the 90-9-1 distribution. This is the issue addressed in this paper.[1] We argue for a SCOUT (Super contributor, Contributor, OUTlier) framework wherein 33% are the (OUT)liers who do very little, 66% are the (C)ontributors who provide moderate contributions, and 1% are the (S)uper contributors who offer super effort. This is based on empirically motivated crowd categorization from quantifiable (measurable) task-based or effort-level features pertaining to the quantity of contributions and responses to motivation, correlated with attitudes towards incentives.

Crowdsourcing based on enterprise data from employee participation in translation tasks provides the background for our research, conducted inside a multinational company (IBM) with about 400,000 employees spread over 160 countries. We developed the community to help us with the data collection effort required for improving statistical machine translation algorithms, by harnessing the linguistic skills of worldwide bi-lingual employees for accomplishing the complex translation task that is typically done by professional translators. The open call to the crowdsourcing community was to help translate sentences from English to their native languages (or vice versa) including Arabic, Chinese (simplified), Chinese (traditional), French, German, Italian, Japanese, Korean, Portuguese, Russian, and Spanish. Participants are presented with text of relevant data e.g., news, technical content, history, etc., in a source language and asked to translate into a target language.

KDD-HCOMP'10, July, 25, 2010, Washington, DC, USA.

[1] Additional co-authors are: Julie Marcotte (IBM GBS), Cheng Wu (IBM Research), Andrzej Sakrajda (IBM Research)

2. THE SCOUT MODEL

As an emerging field in web-based, computer-supported cooperative work, there are very few fully developed models of crowdsourcing participation besides some foundational work [9, 14] which focus on online communities like Wikipedia, blogs, and social networking collaborations for which one can get substantial value from lurking rather than actually contributing. As far we know, there is no research that has attempted to formalize the differences in crowd behavior with respect to the *nature of the task*, beyond merely listing types of crowdsourcing [4, 7, 8, and 14]. We would like to propose an initial typology based on three relevant distinctions summarized as follows:

Collectivistic: this involves a task whereby several people are handling small parts of a larger problem (e.g., uTest) and the community exhibits the need to collaborate and network with each other using available social tools.

Individualistic: this involves a task whereby many people are contributing (individually) towards a single goal (e.g., iStockphoto) and do not need to "socialize" with each other.

Collectivistic-individualistic: a mixture of collectivistic-individualistic properties wherein the crowd is made up of subgroups who form (cooperate or collaborate) to compete against other subgroups in the quest of completing a task (e.g., 2009 DARPA experiment in crowdsourcing won by MIT[2]

Our implementation focused on the individualistic community in which the individual-participants are engaged in a translation task. This is similar to the iStockphoto community described in [3] as both of them share certain similarities: there is no need for social networking or collaboration amongst the participants.

Therefore, we propose a model of participation based on level of effort that can be measured in terms of quantity of contribution and the nature of participants' motivation (incentives). We postulate three broad categories of crowd participation: (S)uper contributors, (C)ontributors, and (OUT)liers (SCOUT):

Super contributors: This is an elite group of participants who give super effort by going above and beyond the ordinary. Super effort can be measured in terms of quantity (usually in the thousands). They are highly motivated members who participate for altruistic reasons as well as being overtly intrinsically motivated, and less concerned about the extrinsic motivation.

Contributors: This group of participants give moderate effort and contribute just enough to keep in pace to make it to the set goals for getting a prize. Moderate effort can be measured in terms of quantity (usually in the hundreds). They are heavily focused on the rewards (extrinsic motivation) and are always conscious of where they rank (at each point) relative to the reward and the end date of the task that is being accomplished.

OUTliers (crowd): This group of participants may be considered as leisurely contributors (they are not lurkers, because they do contribute). Leisurely effort can be measured in terms of quantity (usually in the teens). In terms of motivation, they appear to have enough interest in participating in the crowdsourcing community but are not sufficiently engaged to make any solid contributions.

[2] https://networkchallenge.darpa.mil/default.aspx

3. MEASUREMENT METHOD

We set out to validate the proposed SCOUT model of crowd participation by issuing an open call to the worldwide employees (about 400,000 spread over 160 countries) to join the crowdsourcing data collection effort as volunteer translators. This call was issued in the form of a "Challenge" or a "Sprint" so that whoever accumulates the most points (from translations) at the end of an announced end date will be declared as the winner and recognized with some reward. A multi-tiered incentive structure was created to test the impact of both intrinsic and extrinsic motivation in crowdsourcing [1, 2, and 6]. For enterprise-specific constraints, participants did not personally keep the monetary awards but by virtue of winning were able to give it is as charitable donation to designated charities. Individuals in the top ten with the most points in a language received the highest amount which they could donate to a charity of their choice. The next top five participants (10-15) received the second highest amount for donation to a charity, while the next five winners (15-20), rounding up the top twenty winners in the language, received the minimum award that could be donated to a charity. It is important to note that the winners were given the option of either making a charitable donation or selecting a personal award (trinkets, bags, wrist watches, etc) that they could keep.

We set up low barriers for all participants to be able to participate in this Challenge. All that was required was a simple login (using the existing employee's intranet id and password), and then a simple registration with just two mandatory steps that allows users to select the relevant language(s) and agree to the Terms and Conditions for participation.

The Challenge ran for eight weeks and during this time participants received real-time updates of their points and their relative ranking in the Challenge in terms of where they stood relative to the top 15 overall contributors. On a weekly basis, the relative ranking in each language community was sent by email to the members of a language group to know their status. A dynamic leaderboard showing real-time update of the top 15 overall contributors as well as the relative (real-time) contributions of each language were also provided.

3.1 Results

At the completion of the Challenge, the following table summarizes the contribution and overall participation.

Table 1. Summary of Challenge contributions

Activity	Totals
Words translated	2.4 Million
Sentences translated	123,646
Countries with participants	47

A total of 2.4 million words (from 123,646 sentences) were translated in eight weeks by 967 bi-lingual employees from 47 countries representing the eleven languages within the scope of the crowdsourcing translation task. Some important patterns emerge in support of the SCOUT model which we will now discuss.

3.2 Validating the SCOUT model

The resulting overall contribution by the various participants (measured in sentences) was heavily skewed consistent with the Zipf curve [10].

Table 2. Distribution of total contribution in sentences

Contributor Rank	Total Sentences
Winner (1st place)	9345
10th place	2711
20th place	2650
30th place	727
40th place	532
50th place	341
100th place	148
100++ place	Below 100

When we plot this data in Table 2 in a chart (Figure 1), we observe that a few participants have large contributions, many are in the middle, and the rest provide only small contributions.

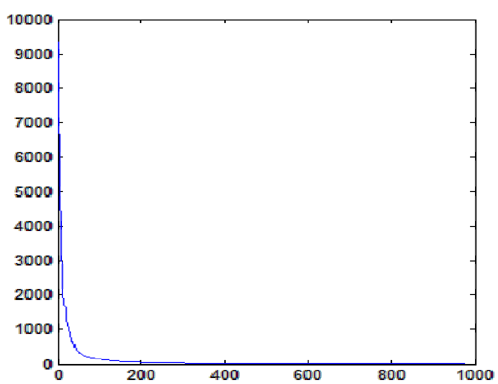

Figure 1. Plot of participant's contributions

In light of the SCOUT crowdsourcing model we are proposing, we can extrapolate some quantifiable conclusions relative to effort-level from the total contributions and surmise that:

- The top 20 contributors (out of 967) made contributions in the thousands (between 2,000 and 10,000 sentences).
- The top 20-100 contributors (out of 967) made relatively smaller contributions in the hundreds (between 100 and 700 sentences).
- The rest of the participants only made even smaller contributions in the teens (below 100 sentences).

4. DISCUSSION

We have hypothesized earlier on that crowd participation can be understood in terms of the consistent behavior of the three groups relative to their contribution (quantity) and their response to motivations (incentives). We will now discuss these respectively.

4.1 Impact of model on quantity

We can validate the SCOUT model from the relative impact of the contributions by the different crowd groups to the total effort (i.e., relative to the total number of sentences contributed).

Table 3. Impact of model on quantity

Participants	Sentences	Total data
1%	2,000-10,000	44%
66%	100-999	54%
33%	Below 100	2%

The following generalizations can be derived from Table 3: the contributions of 1% (Super Contributors) accounts for 44% of the overall contributions by the community, while the Contributors make up 54% of the total contributions and the Outliers make up the rest (which is a miniscule 2%). This approach to the crowdsourcing participation levels provides an empirical basis for better understanding how the 90-9-1 distribution rule applies in the enterprise domain. On the basis of quantity of contributions, the data points to a more equitable 33-66-1 distribution.

4.2 Impact of model on motivation

We can further validate the SCOUT crowdsourcing model by systematically examining the motivation (responsiveness to communication) of each group and then correlating the group behavior to their corresponding responses to crowdsourcing incentives. First, we present the participation trend during the eight-week period of the Challenge.

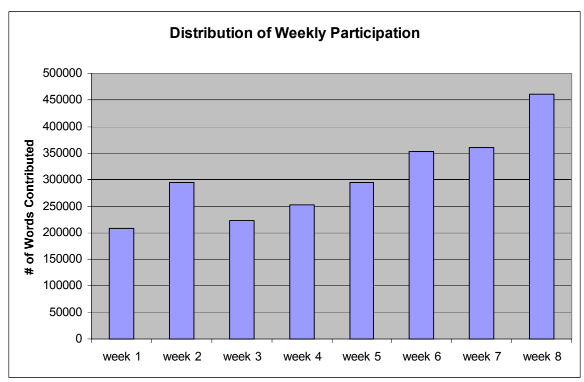

Figure 2. Weekly distribution of crowd participation

As the chart shows, aside from a slight aberration in the second week, we see a steady climb in the crowd contribution with each passing week during the Challenge. This steady trend in contribution was facilitated (triggered) via weekly communication with the crowdsourcing community: several strategies were used to communicate and interact with the participants during the Challenge including email, social media, blogs, newsletter, etc. each with varied and measurable impact on crowd response and behavior. By tracking the responsiveness by the crowd the day following each of these communications, we observe the following generalization regarding the three SCOUT groups:

Table 4. Crowd groups' response to communication

Group	% Response
Super Contributor	100%
Contributor	60%
Outliers	35%

If participation (based on the response the next day after each communication is released) is combined with the previous observation about a steady weekly increase in the contributions (Figure 2), then we can conclude that there is a hierarchy of distinctive motivation qualities that can be derived: Super contributors are highly motivated (100% response); Contributors are moderately motivated (only 60% response); OUTliers are very mildly motivated (only a meager 35% response).

The foregoing analysis is significant not only because it confirms the validity of the three SCOUT groups, but it also provides the basis for examining another contrastive behavior relative to the incentives (awards). At the end of the Challenge, the winners were asked to pick one option: either to make a charitable donation or select a personal award (trinket, wrist watch, etc). The following table summarizes how the groups responded:

Table 5. Group behavior regarding incentives

Group	% Response
Super Contributor	95% donation to charity
Contributor	55% donation to charity
Outliers	n/a

Based on these percentages of the preferences selected by the winners, we see that only 5% of the Super contributors chose personal awards. This can be taken as indicative of a key characteristic of this group: they participate for mainly altruistic reasons. By contrast, 45% of the Contributor category selected personal awards, thus confirming that majority of the members of this group participate for extrinsic reasons.

5. CONCLUSION AND FUTURE WORK

While there are many challenges with crowdsourcing participation inside the enterprise, however, we have observed a more equitable 33-66-1 distribution different from the 90-9-1 rule. This offers great hope for the future of crowdsourcing inside the enterprise. On the basis of quantitative and empirical evidence with respect to contribution levels and the nature of motivation, we formalized three components of the SCOUT model of crowd participation: (S)uper Contributors are the 1% who consistently give super effort in terms of quantity and are driven mainly by altruism (intrinsic reward); (C)ontributors are the 66% who provide moderate effort in terms of quantity and are mainly driven by extrinsic reward; and OUT(liers) are the 33% that only provide low-level effort not sufficient for receiving an award. In the future, we will attempt to replicate the SCOUT model outside of the firewall, in the public domain, to see if the approach of using quantifiable effort-levels will yield similar results.

6. REFERENCES

[1] Blumler, J.G. 1979. The role of theory in uses and gratifications studies. *Communication Research,* 6,(1), 9-36

[2] Bonaccorsi, A. and Rossi, C. 2004. Altruistic individuals, selfish firms? The structure of motivation in open source software. *First Monday,* 9, (1),

[3] Brabham, D.C. 2008a. Moving the crowd at IStockphoto: The composition of the crowd and motivations for participation in crowdsourcing application. *First Monday,* 13, 6

[4] Brabham, D.C. 2008b. Crowdsourcing as a model for problem solving: an introduction and cases. In *Convergence: International Journal of Research into New Media Technologies,* 14, (1), 75-90

[5] Brothers, L. Hollan, J., Nielsen, J., Stornetta, S., Abney, S., Furnas, G., and Littman, M. 1992. Supporting informal communication via ephemeral interest groups. In *Proceedings of ACM Conference on Computer-supported Cooperative Work, CSCW '92,* 84-90

[6] Hars, A. and Ou, S. 2002. Working for free? Motivations for participating in open source projects. In *International Journal of Electric Commerce*, 6, (3), 25-39

[7] Howe, J. 2006. The rise of crowdsourcing. *Wired,* 14, 6, http://www.wired.com/wired/archive/14.06/crowds.html (June, 2006)

[8] Howe, J. 2008. *Crowdsourcing: Why the Power of the Crowd is driving the Future of Business*. Random House Publishers

[9] Nielsen, J., 2006. Participation inequality: Encouraging more users to contribute. http://www.useit.com/alertbox/participation_inequality.html [accessed May 3, 2010]

[10] Nielsen, J., 2006. Zipf curves and website popularity. http://www.useit.com/alertbox/zipf.html [accessed May 3, 2010]

[11] Stewart, O., Huerta, J., Sader, M., Sakrajda, A., Marcotte, J., and Lubensky, D. 2009. Designing crowdsourcing for the enterprise. SIG KDD HCOMP Workshop, (June 2009)

[12] Surowiecki, J. 2004. *The Wisdom of the Crowds: Why the many are Smarter than the few and how Collective Wisdom Shapes Businesses, Economies, Societies, and Nations.* Doubelday, New York

[13] Surowiecki, J. 2005. *The Wisdom of Crowds.* Anchor

[14] Viitamaki, S. 2008. The FLIRT model of crowdsourcing: planning and executing collective customer collaboration. MA thesis: Helsinki School of Economics.

[15] Whittaker, S., Terveen, L., Hill., W.C., and Cherny, L. 1998. The dynamics of mass interaction. In *Proceedings of ACM Conference on Computer-supported Cooperative Work, CSCW '98,* 257-264