The Curse of Competitive Crowd Intelligence

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Abstract

In this paper, we aim to understand the impact of introducing competitiveness in crowd intelligence by studying a real-life crowd-powered environment. In a competitive environment, tasks are solved with competing interests of the crowd. Such an environment has rarely been studied under real-life observations, albeit much is known about the behavior of collaborative crowd-powered systems. The limited studies to gain insights about competitive crowd intelligence mainly involve specialized crowd (like coders or professionals). Here we study a competitive crowdsourcing environment, which is an older version of Flightfox, involving non-specialized people as crowd workers. It is a platform to launch contests for finding the best itineraries through crowdsourcing. We analyze this crowdsourced data, comprising about thirteen thousand contests completed within a duration close to two years, to investigate the guiding force of competitive crowd intelligence. We analyze the global competitive behavior of the system through network analyses. Overall, we gain some important insights about the deplorable effect of competitiveness in controlling the sustainability of such systems.

Introduction

Crowdsourcing has become a useful model to promote teamwork at an enormous scale by using the online workers. It has led to promising applications both in academics and industry due to its distributed and united power of problem solving (Brabham 2013; Kittur et al. 2013). The working behavior of any crowd-powered system can be either collaborative, where the problem is solved collectively by the crowd, or competitive, in which the problem is solved with competing interests. Recently, researchers have started to understand the real-life behaviors of collaborative (Ipeirotis 2010; Ross et al. 2010) and competitive crowdsourcing (Boudreau, Lacetera, and Lakhani 2011; Tang et al. 2011) environments. Earlier attempts to study competitive crowdsourcing cover specialized crowds working for design, innovation, etc. But, the behavior of crowd intelligence is expected to change when the crowd workers are no more specialized people.

There are limited approaches to evaluate the underlying reality of crowdsourcing systems involving general people. Earlier attempts are focused on time-limited tasks and timed competitions (Tang et al. 2011). Simultaneous efforts are made to understand the behavior of crowds in real-life systems. Ipeirotis studied Amazon Mechanical Turk to understand the patterns of real-life collaborative crowd-powered systems (Ipeirotis 2010). Similarly, real behaviors of competitive crowdsourcing environments have also been studied in recent years (Boudreau, Lacetera, and Lakhani 2011). But the analyses with competitive crowdsourcing are limited to innovation problems involving specialized experts (or coders). Researchers have tried to realize the demography of the participating crowd and their changing behavior (Ross et al. 2010). Understanding the variations in crowd workers' motivations (competence, enjoyment, connectedness, social orientation, etc.) have been studied well in recent times (Gerber, Hui, and Kuo 2012). How mechanism designs can motivate the crowd to work (or volunteer) is also of current interest (Kittur et al. 2013). Even then there is a lack of comprehensive study to understand more real-life systems successfully employing the power of competing crowds.

The current paper analyzes a competitive crowdsourcing platform involving non-specialized crowd. Flightfox is a platform to launch contests for finding the best itineraries through crowdsourcing. Flightfox had a competitive model earlier but it has recently switched to a collaborative model. With an intention to discover what might went wrong with the competitiveness model in Flightfox, we analyze the previous contests' data from Flightfox. We also aim to understand the competence and reliability of such competitive crowdsourcing environment. Yang et al. have already carried out network level analysis on the interactions between the tasks and the contestants in Taskcn.com, further extending it to the winner level (Yang, Adamic, and S. 2008). We also carry out network study for realizing the global effect of competitive crowd intelligence.

Working Principle of Previous Flightfox Model

For realizing the effect of competitiveness on crowd intelligence, it is important to first understand how Flightfox works. Flightfox is a crowdsourced platform to find out the most suitable itinerary for a flyer (Fli 2013). In Flightfox, the flyers are the passengers availing flights. In the previous model of Flightfox we analyze, worldwide contestants, termed as experts, compete to find the best flights, accommodation, tours and more. To accomplish this, primarily a flyer launches a contest with the desired itinerary and preferences. The experts, who can freely participate in any of the contests, contend to search out the best (in terms of cost, time, etc.) itinerary for a flyer. The system works because booking travel is complicated, the search results are not necessarily consistent, and experts have a material competitive advantage. We formally introduce the basic terms used in Flightfox below.

A *contest* is a travel proposal, along with a list of preferences, launched in a competitive crowdsourcing environment for the search of best itinerary. The preferences given along a contest can be of different types. But they are mainly restricted to cost, time and number of layovers. A *flyer* is a passenger (availing flights) who launches a contest along with the preferences. *Experts* are the contestants who compete in a contest. Although the term 'expert' is used to represent a crowd worker in Flightfox, however they do not literally represent an expert. In fact, these experts are general crowd that makes this platform unique to be studied for understanding crowd intelligence. The *winner* is the expert who achieves to provide the best itinerary and gets the finder's fee (wins). The winning itinerary is the best travel proposal that simultaneously optimize most of the preferences sought. These Flightfox terms will be used throughout the paper as defined above.

Dataset Collection

The crowdsourced projects in the previous Flightfox environment were posted as open contests with posted finder's fee (Bhattacharyya 2013). On obtaining (searched by the competing crowd) a satisfactory cost for the itinerary, the contest is closed and the finder's fee is paid. We crawled the Flightfox website to access data from $13,056$ contests that are still open or have already been closed, finished or awarded between December 2011 and August 2013. We downloaded the contest pages in html format for extracting the required data. We collected the details about source, destination, best fare found, travel type, number of competing experts, finder's fee paid (or to be paid), etc. from these contests.

Basic Terminologies and Definitions

In this section, we introduce some terminologies that will be used hereafter and include some necessary definitions. A network $N = (V, A)$ is defined with a set of nodes $V = \{v_1, v_2, \ldots, v_{|V|}\}$ and a set of arcs $A : (v_i, v_j)$ $(v_i \neq v_j, \forall v_i, v_j \in V)$, which connect these nodes. Generally, we discard self-loops or parallel arcs from a simple network and consider it to be undirected. Whenever a network is called directed, we distinguish between the two arcs (v_i, v_j) and (v_j, v_i) $(\forall v_i, v_j \in V)$.

A subnetwork $N' = (V', A')$ is a part of the network $N = (V, A)$ such that $V' \subseteq V$ and $A' \subset A$. Again, by the term induced subnetwork we restrict A' to include only the comprehensive set of arcs existing within the nodes of V' in N. A network $N = (V, A)$ is bipartite if the node set of N can be segregated into two disjoint subsets $V_1, V_2 \in V$ $(V_1 \cap V_2 = \phi)$ such that $A \subseteq V_1 \times V_2$. This can also be extended to define a k-partite network.

To better understand the global view of crowd intelligence, we model a crowd-powered system as a network. The tasks that are crowdsourced and the workers who tackle them get involved in a large scale connectivity. This can be best visualized as a network. For our purposes, we define different forms of crowdsourced networks as follows.

Definition 1 *A* competitive crowdsourced network *is defined as a triplet* $(\mathcal{C}, \mathcal{E}, \mathcal{A})$*, where* $\mathcal{C}$ *and* $\mathcal{E}$ *denote the set of contests and experts, respectively, and* $\mathcal{A} \subseteq \mathcal{C} \times \mathcal{E}$ *represents a set of arcs between the contests and experts.*

An arc in a *competitive crowdsourced network* indicates which expert is involved in which contest. Thus it represents the competitive interactivity between the experts. Now if we exclude the experts from the network who were not able to win the contests, then we have a different form of the network as follows.

Definition 2 *A* winner crowdsourced network *is defined as a triplet* $(\mathcal{W}, \mathcal{C}, \mathcal{A})$*, where* $\mathcal{W}$ *and* $\mathcal{C}$ *denote the set of winners and and contests, respectively, and* $\mathcal{A} \subseteq \mathcal{W} \times \mathcal{C}$ *represents a set of arcs between the winners and contests.*

An arc in a *winner crowdsourced network* indicates which expert is the winner of which contest.

Definition 3 *A* competitive flyer network *is defined as a triplet* $(\mathcal{C}, \mathcal{F}, \mathcal{A})$*, where* $\mathcal{C}$ *and* $\mathcal{F}$ *denote the set of contests and flyers (who launches a contest), respectively, and* $\mathcal{A} \subseteq \mathcal{C} \times \mathcal{F}$ *represents a set of arcs between the contests and flyers.*

It basically represents the global relationships between the crowd workers and the flyers. An arc in a *competitive flyer network* indicates which expert is linked to which flyer via participating in a contest (launched by that flyer).

Definition 4 *A* winner flyer network *is defined as a triplet* $(\mathcal{W}, \mathcal{F}, \mathcal{A})$*, where* $\mathcal{W}$ *and* $\mathcal{F}$ *denote the set of winners and flyers, respectively, and* $\mathcal{A} \subseteq \mathcal{W} \times \mathcal{F}$ *represents a set of arcs between the winners and flyers.*

An arc in a *winner flyer network* indicates which expert wins the contest of which flyer. Most importantly, all the above networks are bipartite in nature.

We quantify the *degree of competitiveness* (η) of a contest as the ratio between the number of experts defeated and the total number of participating experts. Formally, it can be defined as follows

$$\eta = \frac{\#\text{Experts} - 1}{\#\text{Experts}}. \tag{1}$$

When the number of experts is one, η will be zero, denoting no competition. The upper bound of η is one for any finite number of experts. This score will help to formalize the additional questions like "What happens to the sustainability of the system with the power of competitiveness?", "How is the power of competitiveness related with the other factors?", etc. for the current analysis.

Results

We analyze the Flightfox data from different perspectives, however, the main goal remains to be understanding the competitive crowdsourcing environment in a better way. We first mine the data from Flightfox to explore the crowd patterns and activity for studying the impact of competitiveness. The total number of experts in the collected dataset is close to one thousand who have already competed for more than thirteen thousand contests. To determine the amount of competitiveness between the experts involved in the Flightfox contests, we prepare the frequency distribution of the number of experts (max = 22) involved per contest. The average number of experts involved in a single Flightfox contest is found to be 3.98, which is considerably high for a competition as previous research in economics highlights (Boudreau, Lacetera, and Lakhani 2011). To observe the overall pattern of competitiveness among the contests, we prepare the frequency distribution of *degree of competitiveness* (η). This distribution plot is shown in Figure 1.

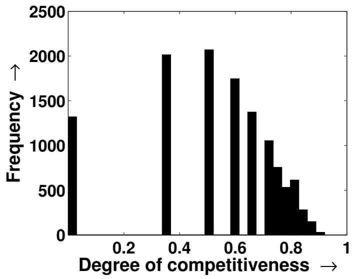
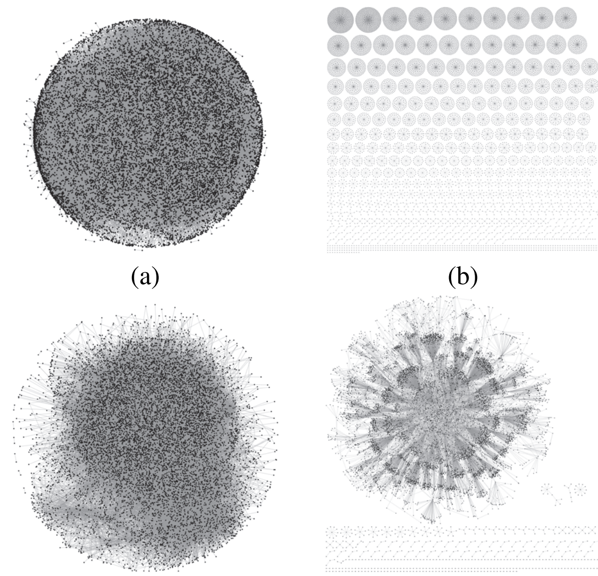


Figure 1: The distribution of the *degree of competitiveness* for the contests.

Interestingly, we observe no correlation between the number of experts and either the finder's fee ($r = 0.07$, p-value $< 1\text{E}{-}08$) or the best fare found ($r = -0.08$, p-value $< 1\text{E}{-}08$) for a particular contest, respectively. Therefore, the number of experts participated does not necessarily guarantees a better solution or deserves a better remuneration. There is also no correlation ($r = -0.06$, p-value $< 1\text{E}{-}08$) between η and the fare. So, the power of competitiveness does not appear to control the competition. The monthly average value of η has not even been changed over time although the interest in Flightfox has increased. So, it seems that the power of competitiveness does not have an influence over the sustainability of such crowdsourcing environments. This might be one of the reasons why Flightfox shifted from a competitive crowdsourcing model to a collaborative one.

To further study whether competitiveness has any global impact on the environment, we carry out a deeper network level analysis. We construct two separate networks between the contests and the experts and winners. As can be seen from the Figs. 2(a-b), winners have a unique pattern irrespective of the fact that there is a high competitiveness among the participating experts. The difference between these two networks is interesting from the perspective of neighborhood density (see Table 1). A higher neighborhood density signifies a larger effect of the neighboring nodes. On the other hand, the networks between the flyers and the experts and winners are also constructed. These are shown in Figs. 2(c-d). Here also, the same pattern of competitiveness is observed and competitiveness does not appear to influence the participation of flyers or the selection of the winners. We claim this because the competitiveness does not appear to uniformly distribute over the winners. The density of a bipartite network denotes the ratio between the number of existing edges and the total number of edges possible. The number of components represents the count of connected components in the networks. Interestingly, 113 common flyer-expert pairs are found in these networks, highlighting reliability of the experts over the flyers while participating in the contests.



(a) (b) (c) (d)

Figure 2: Visualizing the (a) competitive crowdsourced network, (b) winner crowdsourced network, (c) competitive flyer network, and (d) winner flyer network of Flightfox.

Network parameters	Values
# Total nodes	13014
# Contest nodes	11947
# Expert nodes	1067
# Edges	38601
Density	0.003
Avg. # neighbors	5.932
Avg. path length	3.937
# Components	10
Diameter	10
Radius	1
Network heterogeneity	6.776

Network parameters	Values
# Total nodes	12557
# Contest nodes	11947
# Winner nodes	610
# Edges	11947
Density	0.002
Avg. # neighbors	1.903
Avg. path length	1.987
# Components	610
Diameter	2
Radius	1
Network heterogeneity	6.159

Table 1: The parameters observed in the bipartite competitive crowdsourced network (left) and winner crowdsourced network (right) of Flightfox. The values are approximated up to three decimal places.

Network parameters	Values
# Total nodes	11036
# Flyer nodes	10121
# Expert nodes	1067
# Edges	37789
Density	0.003
Avg. # neighbors	6.848
Avg. path length	3.629
# Components	8
Diameter	9
Radius	1
Network heterogeneity	6.162

Network parameters	Values
# Total nodes	10640
# Flyer nodes	10121
# Expert nodes	610
# Edges	11834
Density	0.002
Avg. # neighbors	2.224
Avg. path length	5.177
# Components	190
Diameter	14
Radius	1
Network heterogeneity	5.652

Table 2: The parameters observed in the bipartite competitive flyer network (left) and winner flyer network (right) of Flightfox. The values are approximated up to three decimal places.

To verify whether there is any collaborative interest among the competing experts, we collected data about the discussions they participated during the contests. Interestingly, the distribution of the discussions posted against the contests (see Fig. 3) follows a heavy tail as observed in many occasions involving human dynamics (Barabási 2005). On analyzing the data, the average number of discussions posted is found to be 2.19. So, it is found that there is a motive to approach toward collaboration even being in a competitive environment. As a whole, this highlights the disadvantage of competitiveness in crowd-powered systems and emphasize the superiority of collaboration.

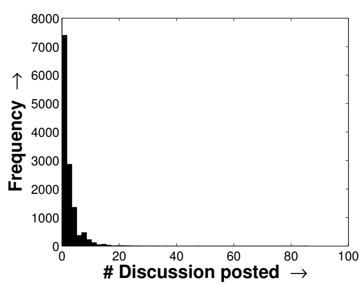


Figure 3: The distribution of the number of discussions posted for the contests.

Concluding Remarks

In this paper, we study a real-life scenario of competitive crowdsourcing that involves general crowd to solve flight fare challenges. Through a systematic analysis, we find that competitive crowdsourcing has some limitations that promote collaboration. The results from the contests of Flightfox establish that competitive crowdsourcing has a discriminative pattern than any other crowd-powered system. The competitive behavior possibly guides the global interaction pattern among the crowd workers. Interestingly, there is a clear trade-off between the interests of the flyers and the experts from the perspective of competitiveness. Flyers gets benefitted from more competitive behaviors, however, this can reduce the success rates of an expert. It seems that there exists an interdependent relation – success lies in the power of crowd and also in the demand of crowd. Still there are issues that might change our views. It is hard to ensure whether the same person is competing with different names as experts. Thus manipulating the number of experts might enhance the chance of winning for a specific expert. Many such conflicting scenarios may arise in a competitive environment. In fact, the literature has generally recommended against the free entry into contests (Boudreau, Lacetera, and Lakhani 2011). Many of the other factors including the sustainability of such systems appear to be independent of the power of competitiveness, although a comprehensive analysis is required to strongly ensure this. We believe there is immense scope of further analysis of the dynamic behavior of such real-life environments.

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