Studying the Reality of Crowd-powered Healthcare

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Abstract

The emergence of crowd-powered systems has grown immense interest in diverse areas in recent years. Crowdsourcing being a public model is hard to apply for many applications where trust, security or private information are involved. Healthcare, especially the diagnosis of diseases, is one such challenging area where crowdsourcing has recently found useful implementation. CrowdMed is an online platform that used the power of the crowd for solving medical diagnosis tasks. We analyze the CrowdMed platform and highlight some interesting outcomes and pose some open problems.

Introduction

The prospects of crowdsourcing is evident from the recent reality and have been well supported by appropriate mechanism design (Kittur et al. 2013). Earlier attempts in this direction were motivated by time-limited tasks and timed competitions (Tang et al. 2011). Simultaneously, efforts have been made to understand the behavior of crowds in real-life systems. Crowdsourcing tasks are performed publicly in exchange for payments. Therefore it becomes risky to solve personal problems or secured issues through such models. However, this is now becoming possible with robust design models (Kittur et al. 2013). Unfortunately, there is a lack of comprehensive study to understand more real-life systems successfully employing the power of crowds. It is a hard challenge to manage the increasing crowd latency and outstripping demands. Here, we analyze a specialized crowdsourcing environment, known as CrowdMed (Cro 2014) that posts medical diagnosis problems to be solved by crowd workers. CrowdMed is a crowd-based online support to the patients who simply weren't getting any conclusive diagnoses from the healthcare system. Various novel telehealth systems have emerged that are enabled by social networking platforms (Han et al. 2013). Healthcare4Life (HC4L) is one such recent online tool that targets at senior patients (Dhillon, Wünsche, and Lutteroth 2013). But CrowdMed is the first unique platform to use the power of crowd to provide medical diagnosis (Cro 2014).

Related Works

The convergence of information and communication technologies supporting telehealth systems and applications are provably cost-effective and efficient. In fact, healthcare systems based on mobile devices are already in use (Medhi et al. 2012). The largest number of efforts in this area has been in using PDAs as the platform for data collection for clinical research, disease records like very recently for Ebola, sexual behavior survey, etc. On the other hand, crowd-powered healthcare is a relatively recent concept. CrowdMed is one such successful model that claims approximately 80% of the diagnosis or solution suggestions to be accurate, or in many cases they are at least close to a correct diagnosis or cure. Therefore, studying CrowdMed and understanding its behavior is of immense importance.

Preliminaries

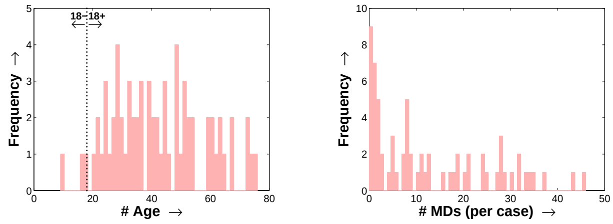
Let us first introduce some basic terminologies that will be required to discuss about CrowdMed.

- **Case:** A case is a problem for the crowd workers to be solved. This is simply a task.
- **Patient:** The person who posts (or for whom it is posted) the medical problem for crowd-powered diagnosis is a patient. A patient is simply a requester.
- **Medical detectives (MDs):** The person who submits the diagnosis in response to a patient is an MD. An MD is simply a crowd worker.
- **Reward:** A reward is the money that is paid for successful completion of the case. This is simply the incentive.

In CrowdMed, the cases are posted by the patients (or on behalf of them) to be taken by the MDs, may be experts or non-experts. The MD providing the best solution bags the reward.

Dataset Details

CrowdMed is a privately accessible platform where the data is available to the registrants (as a patient or MD) only. We collected information about 68 cases (until March 2014) from CrowdMed that involve 30 male and 38 female patients (sex ratio $\sim 3 : 4$). We collected the information about the patient details including sex, age, ethnicity, country, state, case age (when the symptoms began) in months, the major symptoms, case history, medicines administered, brief lifestyle, etc. Details like number of MDs, payout and reward amount related to each case were collected. Fig. 1(a) shows the distribution of ages of the patients. Interestingly, there are patients who are not adults.



(a) (b)

Figure 1: (a) The age distribution (min = 9, max = 76, mean = 42.21, median = 40) of the patients. (b) The distribution (min = 0, max = 46, mean = 12.88, median = 8) of the number of MDs involved per case.

Preliminary Results

To study the power of collaborative efforts we have gathered the count of MDs involved per case. Fig. 1(b) shows the distribution of count of MDs per case that closely pursue a power-law distribution. We observed that critical cases have involved more number of MDs.

To study the demography of the patients, we have plotted their geographic locations on the world map. Fig. 2 shows an interesting fact that the patients mostly belong to the northern part of USA, with limited exceptions in France, UK and UAE. This gives a highlight that it is still not popular to the people of underdeveloped countries. However, it is motivating to note that the result is not biased by the count of Internet users (Group 2012). The popularity is growing slow possibly because medical diagnosis is still a sensitive issue to the people.

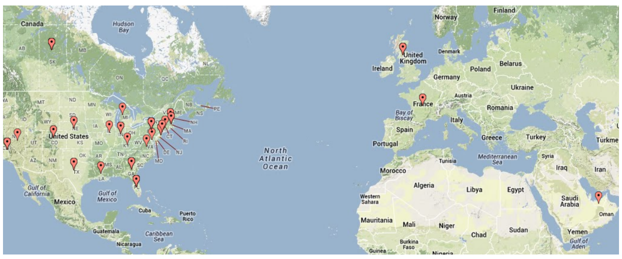


Figure 2: The global distribution of the patients in CrowdMed shows a bias towards North America.

After studying the case histories we observed that most of the cases are very old (cases ages have a minimum value of 4 months and maximum 625 months with a mean and median of 90.15 months and 37 months, respectively). The patients have possibly posted the problems as open cases after long years of frustration. That is why the case ages are too large. Certainly, it is a psychologically tough decision to publicly post health problems. This highlights that there are still many issues, like trust and truthfulness, which are required to be handled carefully in crowd-based models.

Discussion

The results from CrowdMed establish that it has a discriminative pattern mainly because it deals with a sensitive issue like medical diagnosis. The cases are handled with robust models to remove spammer MDs. Some of the demographical analyses also highlight about a very specialized involvement of the crowd volunteers. Whether the sustainability of such a system depends on the power of collaborativeness is also a matter of further analysis. We observed a balanced use of collaboration and competition that might be the reason of success of such models. As the cases involve specialized people, and they might compete to one another's feedback, the truthfulness of diagnosis becomes high. However, how to draw the attention of more workers remains an interesting problem.

Conclusion

In this paper, we studied a real-life scenario of crowdsourcing that involves general crowd to solve medical diagnosis problems. We studied a novel and interesting collaborative-competitive pattern in a crowdsourcing platform. Through a systematic analysis, we found that this crowdsourcing platform has a discriminative pattern and there is immense scope of further analysis of the dynamic behavior of such real-life environments.

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