SEW-ing a Simple Endorsement Web to Incentivize Trustworthy Participatory Sensing

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***Abstract*—Two crucial issues to the success of participatory sensing are (a) how to incentivize the large crowd of mobile users to participate and (b) how to ensure the sensing data to be trustworthy. While they are traditionally being studied separately in the literature, this paper proposes a Simple Endorsement Web (SEW) to address both issues in a synergistic manner. The key idea is (a) introducing a social concept called *nepotism* into participatory sensing, by linking mobile users into a social "web of participants" with *endorsement* relations, and (b) overlaying this network with investment-like economic implications. The social and economic layers are interleaved to provision and enhance incentives and trustworthiness. We elaborate the social implications of SEW, and analyze the economic implications under a Stackelberg game framework. We derive the optimal design parameter that maximizes the utility of the sensing campaign organizer, while ensuring participants to strictly have incentive to participate. We also design algorithms for participants to optimally "sew" SEW, namely to manipulate the endorsement links of SEW such that their economic benefits are maximized and social constrains are satisfied. Finally, we provide two numerical examples for an intuitive understanding.**

***Index Terms*—Nepotism, crowdsourcing, human-centric computing, web of participants, social networks, altruism, beneficiary effect, witness effect.**

I. Introduction

The booming smartphone industry has stimulated participatory sensing as a new sensing paradigm which primarily harnesses the sensors on handheld mobile devices to perform sensing tasks that were traditionally done by wireless sensor networks or that were not even possible. It features pervasiveness, large scale and low cost, and has hence found a wide range of applications in transportation [1], [2], environment [3], lifestyle [4], healthcare [5], and so on.

However, whether participatory sensing will be viable critically depends on two key issues: *incentive* and *trustworthiness*. The former refers to providing motivation for the public crowd to participate in the sensing campaigns and the latter refers to ensuring participants to contribute good quality sensing data; in essence, both issues arise from the fact that data is crowdsourced from the general public. While there is a sizable body of prior work [6]–[14] dedicated to addressing these two issues (usually separately), a common feature of these studies is that participants are treated *individually*—there is no explicit interaction among participants.

In this paper, we take a new, social-economic approach by (a) exploiting the incumbent *social* relationships among mobile users and (b) overlaying investment-like *economic* relationships over the social linkages, to provision and enhance both incentive and trustworthiness in a synergistic manner. Precisely, we propose a Simple Endorsement Web (SEW), a *web of participants* in which participants *endorse* one another, out of two sources of motivation: economically, they aim to maximize their own economic benefit by (optimally) selecting whom to endorse and whom to be endorsed by; socially, they are driven by *nepotism* which is a notion that we first incorporate into crowdsourcing (which subsumes participatory sensing) and is elaborated below.

In the vast literature, humans are commonly assumed to be either *selfish* (self-interested) or *altruistic* in general. Taking a somewhat conservative, but more realistic view, we would rather think of people to be *nepotic* [15]: humans do help one another but such benevolence is often confined to a particular group of people whom they actually care about. This group may consist of their families, some friends, colleagues, bosses, and even their favorite celebrities. In the context of participatory sensing, we particularly note that nepotism may potentially constitute a strong source of motivation by forming an ideology of "working for others and especially your cared ones". Indeed, it has been widely evidenced in both real life and the literature that people often work harder for their loved or cared ones than for themselves alone; psychologically, from doing so, they can develop a sense of nobleness as opposed to merely being egoistic [16].

Furthermore, we identify and exploit another impact of nepotism in addition to providing incentive: enhancing *trustworthiness*. The underlying rationale is that, although a participant might generate fake or noisy data, either by sabotage or by mistake, he tends to refrain from doing so if (a) such conducts may be witnessed by other people and especially his acquaintances, and/or (b) his cared ones have to bear the consequences, such as compromised benefit. Such a *witness effect* and *beneficiary effect* have the potential to incentivize participants to improve the *quality* of their contribution. Psychologically speaking, nepotism helps inculcate a sense of *responsibility* and *accountability* in participants to achieve more trustworthy participatory sensing systems.

On the other hand, solely relying on these social implications derived from nepotism puts the stakeholder at risk, as social linkages are implicit, intangible, and less binding, and are challenged by weak social ties. Therefore, we overlay this social endorsement web with explicit and tangible economic relations, where participants invest in one another and harvest returns like stakeholders.

These constitute the first main contribution of this paper: we design SEW which incorporates both the social and the economic elements, as will be presented in Section III.

The second main contribution is a formal analysis of the economic implications of SEW as presented in Section IV. Under a Stakelberg game framework, we solve the best-response contribution strategy for each participant which leads to the Nash equilibrium. We also derive in closed form the optimal design parameter for SEW that maximizes the utility of the sensing campaign organizer. Moreover, we show that SEW strictly satisfies *individual rationality* (IR) which means that participants strictly have incentive to participate in the campaign.

Our third main contribution is answering the key question of how to optimally "sew" SEW. That is, how each participant manipulates the endorsement links by deciding whom to endorse and whom to be endorsed by, such that his economic benefit is maximized while his social preferences are simultaneously satisfied. Section V fulfills this purpose by providing each participant with algorithmic solutions which automate the "sewing" process and thereby significantly simplify the operation of SEW.

Section VI illustrates the above optimal-decision making algorithms and evaluates our analysis of economic implications using two numerical examples. Section VII concludes.

II. Related Work

In September 2012, LinkedIn rolled out an endorsement option for its users to endorse and recognize the *skills* of their professional connections [17]. However, there is no actual commitment involved or consequence to be borne, and therefore users can perform the action arbitrarily. As a result, LinkedIn endorsement has been quoted to be "way too easy" [18] and received an overwhelming volume of criticisms [19]. In contrast, SEW ties participants closely with explicit and tangible economic benefit as well as corroborated social implications, and as such endorsement hereof is not an arbitrary decision but involves rigorous strategy optimization.

Incentive design has been extensively studied in economics and recently attracted substantial attention from the participatory sensing research community. Lee and Hoh [6] proposed a dynamic-pricing based incentive scheme using reverse auctions, in which participants bid their desired prices to sell their sensing data to the campaign organizer. Yang et al. [7] studied two incentive models: a platform-centric model where the platform allocates a total reward to users in proportion to their planned sensing times, and a user-centric model where each user declares a set of tasks to complete together with his desired payment, after which the platform will select a set of users to perform the tasks and pay them with no lower than their declared payments. Koutsopoulos [9] designed an auction in which users declare their unit costs and the service provider (organizer) determines users' participation levels (e.g., data sampling rates) as well as their payments in order to minimize total payment subject to a given quality of service. Luo and Tham [8] proposed a market-based incentive scheme using a demand-and-supply model, in which participants are not only data suppliers but also service consumers who demand information service provisioned from processing the contributed data. Luo et al. [10] designed an incentive mechanism based on all-pay auctions with a contribution-dependent prize; the model is tailored to accommodate realistic participatory sensing contexts such as uncertain population size, unknown user types, and risk aversion

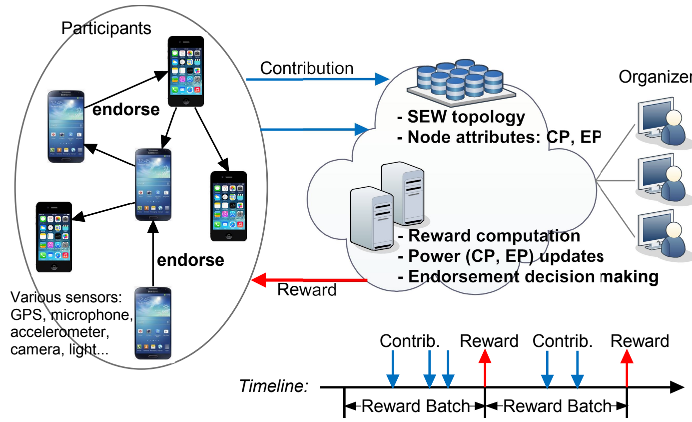


Figure 1: A SEW-based participatory sensing system.

of users. All these prior studies treat participants individually, whereas SEW links them together to take advantage of the *mutual influence* among users.

For general networked systems, Lottree (lottery tree) [20] was proposed as an incentive scheme to recruit users. It arranges users in a tree according to who (a parent node) has recruited whom (child nodes), and conducts a lottery where a user gets higher chance to win if he has recruited more users. SEW differs significantly from Lottree firstly in its graph structure instead of a tree. Second and more importantly, each branch in Lottree is determined at the time a user joins the tree (and henceforth fixed permanently), and the user is given no room to choose his parent node; on the contrary, SEW allows participants to manipolate or "sew" the endorsement web based on their respective contribution and endorsement performance, thereby permitting flexibility and strategy optimization. Third, SEW formally embodies the idea of "working for your cared ones" which is absent in all related prior work.

To address the trustworthiness issue in participatory sensing, Wang et al. [13] took a maximum likelihood estimation (MLE) approach to discover truth from multiple observations. It assumes that most users will submit multiple different reports for the same object and some users will repeat the same report multiple times, neither of which is assumed by SEW. Also, it deals with binary reports only whereas SEW handles general cases. [14] proposed a trust framework to find candidate participants for sensing tasks, by evaluating the suitability of candidates using information published on social media, such as expertise and education background, which is clearly different from this work. [11] and [12] made an attempt to tackle the issue by using Trusted Platform Module (TPM) which involves hardware modification; in addition, the trustworthiness thereof refers to protecting data integrity against malicious users, which is not the quality of data in the general sense.

III. Design of SEW

A SEW-based participatory sensing system is depicted in Fig. 1 with an operational timeline. SEW is application-agnostic and works with any type of sensor readings (scalar, vector, etc.) and modalities.

A SEW is a directed graph (or simply digraph) $\mathcal{W} = (\mathcal{N}, \mathcal{E})$ that consists of a set $\mathcal{N}$ of participants and a set $\mathcal{E}$ of endorsement links, where a link $(i, j) \in \mathcal{E}$ represents that i endorses

j for some $i, j \in \mathcal{N}$. A participant may take the role of (a) a *contributor*, who submits sensory data from his smartphone to a central server via a mobile app, or (b) an *endorser*, who endorses contributors, or (c) both. Each participant can endorse, and be endorsed by, multiple participants except himself.

A. Endorsement Setup and Revocation

SEW requires bilateral agreement when setting up endorsement: one participant i must initiate a "Request To Endorse" (RTE) or "Request to Be Endorsed by" (RBE) message to another participant j, and the endorsement is only set up if j approves the request. This is an asynchronous non-blocking process: all requests will be queued up until the requested participant approves or rejects the requests. On the contrary, revoking endorsement is unilateral: either i or j can terminate their endorsement relationship without seeking approval from the other party.

B. Power Transfer

Each participant possesses two power attributes:

- *Contribution Power* (CP): a number indicating the participant's contribution performance, earned through making contributions.
- *Endorsing Power* (EP): a number indicating the participant's endorsement performance, earned through endorsing other contributors.

A key feature of SEW is that EP is *transferable*: an endorser i automatically lends his EP, in an amount of $\frac{EP_i}{|\mathcal{N}_i^{out}|}$, to *each* of his endorsed contributors who are collectively denoted by $\mathcal{N}_i^{out}$. That is (and as a result), each contributor k automatically receives from his endorsers, who are collectively denoted by $\mathcal{N}_k^{in}$, a *borrowed power* of

$$BP_k = \sum_{i \in \mathcal{N}_k^{in}} \frac{EP_i}{|\mathcal{N}_i^{out}|}. \tag{1}$$

Power transfer takes effect in a reward scheme described below.

C. Reward Scheme

Participants who make contributions will receive reward as per *batches*: depending on the application, a batch can be a preset period of time (as in Fig. 1), a geographic region, a spatiotemporal combination of both, or a specific number of submissions. Upon collecting a batch of contributions from participants $\mathcal{N}_c$, the server determines a reward for each contributor $k \in \mathcal{N}_c$ according to the following reward function:

$$r(k, \mathbf{q}, \mathbf{CP}, \mathbf{W}) := \frac{q_k^\alpha [CP_k(1 + w_k)]^\beta}{\sum_{j \in \mathcal{N}_c} q_j^\alpha [CP_j(1 + w_j)]^\beta} R \tag{2}$$

or r_k in short. A contributor k then accrues to his CP as per

$$CP_k \leftarrow CP_k + r_k. \tag{3}$$

In (2), $\mathbf{q} = (q_1, ..., q_m)$ is a quality vector in which $q_k \geq 0$ is the quality[1] of sensing data sent by contributor k, $\mathbf{CP} = (CP_1, ..., CP_m)$ is the CP vector, $\mathbf{W} = (w_1, ..., w_m)$ is a vector of power-transfer coefficients in which w_k characterizes how much power was transferred from k's endorsers to k, such that $CP_k(1+w_k)$ is k's effective power in competing for the reward. A possible form of w_k is[2]

$$w_k = \frac{BP_k}{BP_k + CP_k}. \tag{4}$$

The two elasticity indexes $\alpha, \beta \in (0, 1]$ allow the campaign organizer to prioritize between the (intrinsic) sensor quality and the (extrinsic) contributor credibility connoted by his power, and R is the constant total reward for the current batch.

Upon joining the sensing campaign, a participant will have his CP and EP initialized as an insignificant positive value.

Revenue Sharing: Power transfer enables participants to act like stakeholders investing their EP in one another. Conversely, each participant would expect a return of investment (ROI), for which we introduce a revenue sharing scheme as follows. In addition to r_k, SEW allocates certain *appreciation power* (AP) for each contributor and redistribute it among all his endorsers, as an appreciation of their endorsements. Specifically, $AP_k = \rho_k r_k$ will be allocated, where

$$\rho_k := \left(\frac{w_k}{1 + w_k}\right)^\beta, \tag{5}$$

for contributor k to redistribute to k's endorsers such that each endorser $i \in \mathcal{N}_k^{in}$ receives a share $\eta_{ik}\rho_k r_k$, i.e.,

$$EP_i \leftarrow EP_i + \sum_{k \in \mathcal{N}_i^{out}} \eta_{ik}\rho_k r_k, \tag{6}$$

where the summation is due to the multiple contributors that endorser i may be endorsing, and η_{ik} is the revenue sharing ratio defined as

$$\eta_{ik} := \frac{EP_i}{|\mathcal{N}_i^{out}| BP_k} \tag{7}$$

which indicates the power that endorser i lends to contributor k (i.e., $\frac{EP_i}{|\mathcal{N}_i^{out}|}$) relative to k's total borrowed power (i.e., BP_k).

Ultimately, a participant in SEW has *multiple sources of income*: reward r_k as a contributor (cf. (3)) and multiple shares of AP as an endorser (cf. (6)).

D. Power Redemption

CP and EP are redeemable in monetary terms. For each reward batch, the system determines two *exchange rates*, x_c and x_e, to convert each participant's CP and EP earned in this batch, into monetary values, respectively. These are then deposited into participants' respective private accounts for them to cash out anytime. The optimal exchange rates are determined in Section IV.

Operational considerations: Since power redemption follows the same cycle of batches (e.g., hourly), the system has the flexibility to reinitialize power attributes (CP and EP) at the end

[1]Quality in this paper bears general semantics; it could be accuracy, resolution, timeliness, relevancy, etc., depending on the specific application and sensor modality. It could also be as sophisticated as a cumulative metric that accommodates multiple contributions from the same participant. A detailed discussion can be found in [21].

[2]In accordance with intuition, we only require w_k to be an increasing and concave function in BP_k and satisfy $w_k(0) = 0$. Most of our results hold in principle regardless of the specific form of w_k, while we use (4) mainly for calculating numerical results. One merit of using (4), though, is that it caps w_k below 1 and therefore prioritizes CP over BP, which concurs with our philosophy that contribution is the *bread and butter* of participatory sensing while endorsement is an *auxiliary* instrument.

of any batch, without being concerned about any unredeemed power. Thus the system can keep participants' track records up-to-date, for example by associating a *sliding window* (in the size of, say, a week or month) with each participant so that only his most recently earned power is recorded whereas old record is nullified. This also benefits recruiting new participants, because otherwise newcomers will face the challenge of competing with overly powerful veterans.

E. Social Implications

We summarize two social implications from SEW design.

Beneficiary effect: The revenue sharing scheme essentially renders endorsers *beneficiaries* of their endorsed contributors. This promotes a sense of nobleness in contributors as they are now working altruistically rather than egoistically, which potentially constitutes a strong source of motivation (for both contribution quantity and quality). In addition, this beneficiary effect may also motivate participants to recruit their cared or loved ones to join as their endorsers (beneficiaries), thereby expanding the participant pool.

Witness effect: The system can choose to inform endorsers of their endorsed contributors' contribution performance or even the content of contribution (subject to privacy settings). This essentially associates each contributor with *witnesses* who may as well be his acquaintances, thereby inculcating a sense of accountability and responsibility in the contributor, which mitigates producing fake data and fosters trustworthiness.

IV. Optimal Contribution and Reward Strategies

This section analyzes the economic implications of SEW. The problem is stated as follows. At the beginning of each reward batch, the organizer announces two exchange rates x_c and x_e to be used to respectively convert CP and EP earned in this batch into dollar values. Each participant i chooses a quality q_i to contribute for this batch, where $q_i = 0$ indicates not to contribute. The problem is thus to determine (a) x_c and x_e for the organizer, and (b) q_i for each participant, in order to maximize their respective utilities.

A. Game Formulation

We model the above problem as a *Stackelberg game*, where the *leader* is the organizer who takes the first move—announces exchange rates—and the *followers* are the participants who take the second move—determine contribution qualities. All are players who aim to maximize their respective utilities. The utility of the organizer is defined as

$$u_0 = x_0 \log(1 + \sum_{k\in\mathcal{N}} q_k) - x_c R - x_e \sum_{k\in\mathcal{N}} \rho_k r_k \tag{8}$$

where $x_0 > 0$ is exogenously given which converts user contributions to the real cash value perceived by the organizer, the log term reflects the diminishing marginal return from the aggregate user contribution,[3] R is the total reward for all contributors (to accrue to their CP), and $\sum_k \rho_k r_k$ is the total AP to be redistributed to all the endorsers (to accrue to EP).

[3] Alternatively, $\sum_k \log(1+q_k)$ can be used in place of $\sum_k q_k$, yet the problem remains the same in principle.

The utility of a participant i consists of two components, one gained from contributing and the other from endorsing:

$$\text{Contributing}: \quad u_i^c = x_c r_i - c_i(q_i), \tag{9}$$

$$\text{Endorsing}: \quad u_i^e = x_e \sum_{k\in\mathcal{N}_i^{out}} \eta_{ik}\rho_k r_k. \tag{10}$$

In (9), $c_i(\cdot)$ is the individual cost function of i, assumed to be increasing and satisfies $c_i(0) = 0$ and $c_i''(q_i) \geq 0$. In (10), we assume that endorsement does not incur perceivable cost. Thus, a participant i's utility is

$$u_i = u_i^c + u_i^e = x_c r_i - c_i(q_i) + x_e \sum_{k\in\mathcal{N}_i^{out}} \eta_{ik}\rho_k r_k. \tag{11}$$

B. Equilibrium Analysis

To solve for the equilibrium of the Stackelberg game, we use *backward induction*. Supposing that x_c and x_e are given, we analyze the Nash equilibrium strategy q_i^* for each participant i.

To prioritize contribution (bread and butter) over endorsement (auxiliary instrument), we assume $x_c > x_e$. To simplify notation, let $P_i := CP_i(1+w_i)$. To simplify analysis, let $\alpha = \beta = 1$. First, expand (11) as

$$\begin{aligned} u_i &= x_c R \frac{q_i P_i}{\sum_{j\in\mathcal{N}} q_j P_j} - c_i(q_i) + x_e R \sum_{k\in\mathcal{N}_i^{out}} \eta_{ik}\rho_k \frac{q_k P_k}{\sum_{j\in\mathcal{N}} q_j P_j} \\ &= R\frac{x_c q_i P_i + x_e \sum_{k\in\mathcal{N}_i^{out}} \eta_{ik}\rho_k q_k P_k}{\sum_{j\in\mathcal{N}} q_j P_j} - c_i(q_i), \end{aligned}$$

where $j \in \mathcal{N}$ is equivalent to $j \in \mathcal{N}_c$ since $q_j = 0$ indicates no contribution. Letting $Q_0 := \sum_{j\in\mathcal{N}\setminus\{i\}} q_j P_j$ and $Q_i^{out} := \sum_{k\in\mathcal{N}_i^{out}} \eta_{ik}\rho_k q_k P_k$, we have

$$\begin{aligned} u_i &= R\frac{x_c q_i P_i + x_e Q_i^{out}}{Q_0 + q_i P_i} - c_i(q_i), \\ \frac{\partial u_i}{\partial q_i} &= P_i R \frac{x_c Q_0 - x_e Q_i^{out}}{(Q_0 + q_i P_i)^2} - c_i'(q_i), \\ \frac{\partial^2 u_i}{\partial {q_i}^2} &= -2P_i^2 R \frac{x_c Q_0 - x_e Q_i^{out}}{(Q_0 + q_i P_i)^3} - c_i''(q_i). \end{aligned}$$

We note that $x_e Q_i^{out} < x_c Q_0$ because (a) $\eta_{ik} \leq 1$ and $\rho_k < 1$, (b) $\mathcal{N}_i^{out} \subseteq \mathcal{N} \setminus \{i\}$, and (c) $x_e \leq x_c$. In addition, since $c_i''(q_i) \geq 0$, thus $\frac{\partial^2 u_i}{\partial {q_i}^2} < 0$ and u_i is strictly concave. Therefore, the maximizer of u_i can be uniquely determined using the first-order condition to be

$$\tilde{q}_i = \sqrt{\frac{R}{P_i t_i}\left(x_c Q_0 - x_e Q_i^{out}\right)} - \frac{Q_0}{P_i}$$

where $c_i(q_i)$ is instantiated by $c_i(q_i) := t_i q_i,\ t_i > 0$, a commonly used linear cost model. As a participant will not contribute if $\tilde{q}_i \leq 0$, the *best-response* strategy of i, denoted by $\hat{q}_i(q_{-i})$, is thus

$$\hat{q}_i = \begin{cases} 0, & \text{if } x_c Q_0 - x_e Q_i^{out} \leq \frac{Q_0^2 t_i}{P_i R}; \\ \sqrt{\frac{R}{P_i t_i}\left(x_c Q_0 - x_e Q_i^{out}\right)} - \frac{Q_0}{P_i}, & \text{else.} \end{cases} \tag{12}$$

Given the best-response strategy (12), the Nash equilibrium $\mathbf{q}^* = (q_1^*, ..., q_{|\mathcal{N}|}^*)$ can be computed using either a simplicial method [22] or a differentiable homotopy [23].[4]

The above analysis holds regardless of whether there will be any endorsement setup or revocation in the current reward batch, because the system can choose to effect topology changes only at the end of each batch. Also, the analysis assumes that all the participants' CP, EP and BP are anonymously known to each participant,[5] which is clearly feasible in a real system and is not privacy-intrusive.

C. Organizer Utility Maximization

While the preceding subsection deals with the follower stage of the Stackelberg game, this subsection deals with the leader stage to determine the optimal exchange rates x_c and x_e such that the organizer's utility u_0 is maximized.

We assume without loss of generality that $x_e = \epsilon x_c$, $0 < \epsilon < 1$. Plugging r_k (2) into (8), we reformulate the organizer's problem as

$$\text{maximize: } x_0 \log(1+\sum_{k\in\mathcal{N}} q_k^*) - x_c R\big(1+\epsilon\sum_{k\in\mathcal{N}} \rho_k \frac{q_k^* P_k}{\sum_{j\in\mathcal{N}} q_j^* P_j}\big)$$

where we note that q_k^* is a function of x_c. This optimization problem can be solved using standard methods such as Newton's method [24]. In order to obtain explicit expressions, consider a homogeneous reference model where all players have the same CP, EP, cost function $t \cdot q$, and each player endorses d^{out}, and is endorsed by d^{in}, other players. It is easy to prove that $d^{out} = d^{in}$,[6] and thus the Nash equilibrium can be expressively written, according to the best response (12), as

$$q_i^* = \frac{R}{n^2 t}[(n-1)x_c - \rho x_e], \quad \forall i \in \mathcal{N}, \tag{13}$$

where $\rho = \frac{EP}{2EP+CP}$ and $n = |\mathcal{N}|$. Note that (13) does not depend on d^{in} or d^{out} because each player has $BP = d^{in} \cdot \frac{EP}{d^{out}} = EP$. Therefore, the organizer's utility is

$$u_0 = x_0 \log\big(1 + \frac{n-1-\epsilon\rho}{nt} x_c R\big) - (1+\epsilon\rho)x_c R$$
$$\Rightarrow \frac{\partial u_0}{\partial x_c} = \frac{x_0 \frac{n-1-\epsilon\rho}{nt} R}{1 + \frac{n-1-\epsilon\rho}{nt} x_c R} - (1+\epsilon\rho)R,$$
$$\frac{\partial^2 u_0}{\partial {x_c}^2} = -\frac{x_0 (\frac{n-1-\epsilon\rho}{nt})^2 R^2}{(1 + \frac{n-1-\epsilon\rho}{nt} x_c R)^2} < 0.$$

Therefore, u_0 is strictly concave in x_c. However, since $u_0|_{x_c=0} = 0$, it must be satisfied that $\frac{\partial u_0}{\partial x_c}|_{x_c=0} > 0$ for u_0 to have positive values. This leads to

$$x_0 > \frac{nt(1+\epsilon\rho)}{n-1-\epsilon\rho}. \tag{14}$$

[4]Simplicial methods solve a non-linear equilibrium problem by solving a piecewise linear approximation of the problem. On the other hand, a differentiable homotopy exploits the differentiability structure that is present in games. Both algorithms have been shown to converge to Nash equilibrium for a generic n-person game.

[5]To elaborate, the set of power attributes of all the users are commonly known, but users are not able to associate any particular user with his power attributes, except that each endorser knows his endorsed contributors' respective power attributes (which is reasonable and natural). In any case, user identities are not disclosed without user permission.

[6]In a digraph, the total outdegree $|\mathcal{N}|d^{out}$ equals the total indegree $|\mathcal{N}|d^{in}$.

Now we can apply the first-order condition to obtain the unique maximizer of u_0, as

$$x_c^* = \frac{x_0}{(1+\epsilon\rho)R} - \frac{nt}{(n-1-\epsilon\rho)R} \tag{15}$$

which achieves the organizer's maximum utility

$$u_0^* = x_0\big[\log\frac{x_0(n-1-\epsilon\rho)}{nt(1+\epsilon\rho)} - 1\big] + \frac{nt(1+\epsilon\rho)}{n-1-\epsilon\rho}. \tag{16}$$

D. Incentive for Participation

Given that the organizer achieves the maximum utility, it is of interest to know if participants have incentive to participate. This requires satisfying *individual rationality* (IR), which means that the expected utility of each participant must be nonnegative at equilibrium.

To this end, we calculate u_i at the equilibrium for all i, using (11) with the results obtained from Section IV-C, and obtain with some algebraic manipulation that

$$u_i = \frac{1+(n+1)\epsilon\rho}{n^2} x_c^* R \tag{17}$$

which is strictly positive. This proves that SEW (strictly) satisfies IR; in other words, participants strictly have incentive to participate.

V. Optimal Endorsement Strategies

To put SEW into practice, it is key to answer the question of how a participant decides on whom to endorse and whom to be endorsed by, i.e., how to "sew" the SEW.

Recall that setting up endorsement requires bilateral agreement which consists of two stages: request and approval. The major difference between the two stages is that the request stage is an "attempting" stage whereas the approval stage nails down the actual relation. Hence we focus on providing optimal solutions to the approval stage (Section V-A,V-B), yet give guidelines to the request stage.

In the request stage, a contributor who looks for endorsers should send the RBE requests to two sets of participants: (a) from a social perspective, those whom he wants to benefit by sharing his revenue with (regardless of their power values), and (b) from an economic perspective, those who can lend him the highest *prospective*[7] supporting power, $\frac{EP_i}{|\mathcal{N}_i^{out}|+1}$, in order to elevate his BP.

On the other hand, an endorser who looks for contributors should send RTE requests to two other sets of participants: (a) based on his knowledge gained from social acquaintance, those who he believes to be "good" (active and trustworthy) contributors, and (b) those $k \in \mathcal{N}$ who have the highest *prospective profitability* with respect to him, say i, defined as

$$\pi_{ik}^+ := \eta_{ik}^+ \rho_k^+ q_k^\alpha [CP_k(1+w_k^+)]^\beta, \tag{18}$$

which is self-explanatory by combining (6) and (2), and where the superscript '+' indicates the prospective version of each corresponding variable (cf. (7),(5),(4)): $\eta_{ik}^+ = \frac{EP_i}{(|\mathcal{N}_i^{out}|+1)BP_k^+}$ in which $BP_k^+ = BP_k + \frac{EP_i}{|\mathcal{N}_i^{out}|+1}$ (i.e., BP incremented by

[7]The power is called "prospective" because one can only *expect* to receive it *after* being endorsed by this requestee.

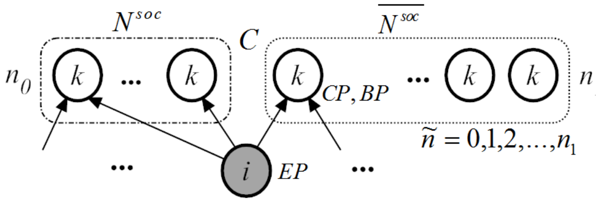


Figure 2: Endorsers' problem: illustration of formulation (19).

power lent from i), $\rho_k^+ = \frac{w_k^+}{1+w_k^+}$, $w_k^+ = \frac{BP_k^+}{BP_k^+ + CP_k}$, q_k is based on historical (e.g. the most recent) contribution.

In terms of implementation, the system can provide two sorted lists for the two prospective metrics, respectively, to facilitate participants to find candidate endorsers or contributors. They can then send RTE and RBE requests which will be queued up at their respective recipients until being acted upon (approved or rejected).

A. Optimal Decision for Endorsers

In the approval stage, an endorser checks his RBE notification queue and needs to decide which requests to approve and which to reject (ignore).

Problem statement: Given a set $\mathcal{C}$ of contributors who are soliciting for endorsement, an endorser is to determine a subset $\mathcal{N}^{out} \subseteq \mathcal{C}$ to endorse such that his economic payoff (10) is maximized, subject to the social constraint that he *will* endorse his socially preferred acquaintances in $\mathcal{C}$, denoted by $\mathcal{N}^{soc}$. To formulate, the endorser is to determine

$$\mathcal{N}_{out}^* := \underset{\mathcal{N}^{out} \subseteq \mathcal{C}}{\arg\max} \sum_{k \in \mathcal{N}^{out}} \tilde{\pi}_k, \quad \text{s.t. } \mathcal{N}^{soc} \subseteq \mathcal{N}^{out}, \tag{18}$$

where $\tilde{\pi}_k$ is the profitability of contributor k when $\mathcal{N}^{out}$, the endorser's endorsing set, is uncertain; it can be understood as $\eta_k \rho_k r_k$ as similar to (18), while its precise definition will be given shortly in (20). Here we drop the subscript i as we will be dealing with a single endorser throughout this section (V-A) and hence no ambiguity will arise. Without loss of generality, we let $\mathcal{C}$ include this endorser's existing endorsed contributors, and as such the outcome entails both setups and revocations.

To solve the problem, we reformulate it as an unconstrained problem by letting $\mathcal{N}_{out}^* = \mathcal{N}^{soc} \cup \mathcal{N}^*$ and finding $\mathcal{N}^*$ instead:

$$\mathcal{N}^* := \underset{\tilde{\mathcal{N}} \subseteq \overline{\mathcal{N}^{soc}}}{\arg\max} \sum_{k \in \tilde{\mathcal{N}} \cup \mathcal{N}^{soc}} \tilde{\pi}_k \tag{19}$$

where $\overline{\mathcal{N}^{soc}} := \mathcal{C} \setminus \mathcal{N}^{soc}$, as illustrated in Fig. 2.

To ease exposition below, denote

$$n_0 := |\mathcal{N}^{soc}|, \; n_1 := |\overline{\mathcal{N}^{soc}}|, \; \tilde{n} := |\tilde{\mathcal{N}}|.$$

The brute-force solution is: for each of the 2^{n_1} subsets $\tilde{\mathcal{N}} \subseteq \overline{\mathcal{N}^{soc}}$, calculate the sum of $\tilde{\pi}_k$ over all $k \in \tilde{\mathcal{N}} \cup \mathcal{N}^{soc}$, and then choose the maximum of the 2^{n_1} sums. This amounts to a computation time of $\sum_{k=0}^{n_1} \binom{n_1}{k}(n_0 + k) + 2^{n_1} = (n_0 + \frac{n_1}{2} + 1)2^{n_1}$, using the formula $\sum_{k=0}^{n_1} k\binom{n_1}{k} = n_1 2^{n_1 - 1}$. This signals an exponential increase of complexity which is undesirable.

Our solution is based on two key observations. First, let us express $\tilde{\pi}_k$ by referring to (18) and plugging in η_k, ρ_k, w_k, as[8]

$$\tilde{\pi}_k = \frac{q_k^\alpha CP_k^\beta \tilde{\delta}_{EP}}{CP_k + 2BP_k + 2\tilde{\delta}_{EP}} \Big(2 - \frac{1}{CP_k + BP_k + \tilde{\delta}_{EP}}\Big)^\beta \tag{20}$$

where $\tilde{\delta}_{EP} := \frac{EP}{n_0 + \tilde{n}}$ in which $n_0 + \tilde{n}$ is the prospective number of contributors to endorse. From this, we observe that AP_k^+ does not depend on a chosen $\tilde{\mathcal{N}}$ per se but the *cardinality* of $\tilde{\mathcal{N}}$, as well as k's other attributes (q_k, CP_k, BP_k) which are *independent* of $\tilde{\mathcal{N}}$. Hence, we can equivalently write AP_k^+ as $AP_k^+(\tilde{n})$ and, for each k, obtain all its $n_1 + 1$ values (since $\tilde{n} = 0...n_1$) regardless of the 2^{n_1} possible subsets $\tilde{\mathcal{N}} \subseteq \overline{\mathcal{N}^{soc}}$. The second observation is drawn from finding the maximum of all the $\sum_{k \in \tilde{\mathcal{N}} \cup \mathcal{N}^{soc}} AP_k^+$, each being a sum over all possible k's, for a fixed $\tilde{n}$. Finding this "local" maximum (as compared to the "global" maximum which is among all $\tilde{n} = 0...n_1$) involves calculating and comparing all the $\binom{n_1}{\tilde{n}}$ combinations of contributor k's AP_k^+, leading to a complexity of $\binom{n_1}{\tilde{n}}(\tilde{n} + n_0)$. However, a more efficient way is to take advantage of the fact that the local maximum must be achieved by the $\tilde{n}$ contributors with the largest AP_k^+ among all the n_1 contributors, and to find these $\tilde{n}$ largest values we can use a highly efficient *partial sorting* [25] algorithm with complexity $\Theta(n_1 + \tilde{n}\log\tilde{n})$ [26], which results in a much lower overall complexity $\Theta(n_1 + \tilde{n}\log\tilde{n}) + \tilde{n} + n_0$.

The pseudo-code of our solution is given by Algorithm 1. It acts on behalf of an endorser to decide his optimal portfolio of contributors to endorse, given his socially preferred acquaintances $\mathcal{N}^{soc}$ specified by himself as input. Iterating over all $\tilde{n}$ and in each iteration, the algorithm first calculates AP_k^+ for all the requesting contributors and divide them into two lists, $\mathcal{L}^{soc}$ and $\overline{\mathcal{L}^{soc}}$. Next, it finds the largest $\tilde{n}$ elements in $\overline{\mathcal{L}^{soc}}$ using our adapted version of partial quicksort [26] which is asymptotically the fastest partial sorting algorithm. These largest $\tilde{n}$ elements are then summed together with all the n_0 elements of $\mathcal{L}^{soc}$, which is the local maximum. The global maximum is then obtained by comparing all the local maxima.

Algorithm 1 Endorser's decision: Constructing the optimal portfolio of contributors

Input: $\mathcal{C}$, $\mathcal{N}^{soc}$
Output: $\mathcal{N}_{out}^*$
$\mathcal{N}^* \leftarrow \emptyset$, $Y_{max} \leftarrow \sum_{k \in \mathcal{N}^{soc}} AP_k^+|_{\tilde{n}=0}$
for $\tilde{n} = 1 \rightarrow n_1$ **do**
  Compute $AP_k^+(\tilde{n})$ for all $k \in \mathcal{C}$ using (20)
  $\mathcal{L}^{soc} \leftarrow \{AP_k^+(\tilde{n}) | k \in \mathcal{N}^{soc}\}$,
  $\overline{\mathcal{L}^{soc}} \leftarrow \{AP_k^+(\tilde{n}) | k \in \overline{\mathcal{N}^{soc}}\}$
  $\mathcal{L}^{ind}$ = `PartialQuickSort`$(\overline{\mathcal{L}^{soc}}, 1, n_1, \tilde{n})$
  $Y_{\tilde{n}} \leftarrow \sum_{i=1}^{n_0} \mathcal{L}^{soc}[i] + \sum_{i=1}^{\tilde{n}} \overline{\mathcal{L}^{soc}}[i]$
  if $Y_{\tilde{n}} > Y_{max}$ **then**
    $Y_{max} \leftarrow Y_{\tilde{n}}$
    $\mathcal{N}^* \leftarrow \mathcal{L}^{ind}[1..\tilde{n}]$
  end if
end for
return $\mathcal{N}^* \cup \mathcal{N}^{soc}$

[8] If k is an existing contributor, BP_k will be replaced by $BP_k - \frac{EP}{|\mathcal{N}^{out}|}$, i.e., as if he were a "new" contributor not endorsed by the endorser.

Function 2 `PartialQuickSort(`$\mathcal{L}$, $left$, $right$, k`)`

Output: $\mathcal{L}[1..k]$ stores the largest k numbers (unordered) of $\mathcal{L}$, and $\mathcal{L}^{ind}[1..k]$ their corresponding indexes (pseudo-code for the latter is omitted for being nonessential)

```
if right > left then
    pNew ← Partition(L, left, right)
    if pNew > left + k then
        PartialQuickSort(L, left, pNew − 1, k)
    else if pNew < left + k then
        PartialQuickSort(L, pNew + 1, right, left + k − pNew − 1)
    end if
end if
return L^ind
```

Function 3 `Partition(`$\mathcal{L}$, $left$, $right$`)`

Output: $pvtNew$ which satisfies that $\mathcal{L}[left..pvtNew\text{-}1] > \mathcal{L}[pvtNew] \geq \mathcal{L}[pvtNew..right]$

```
pvt ← SelectPivot(L, left, right) //select an index between left and right, either randomly or using the median
pVal ← L[pvt]
swap L[pvt] and L[right] //move pivot to the end
pvtNew ← left
for i = left → right − 1 do
    if L[i] > pVal then
        swap L[i] and L[pvtNew]
        pvtNew ← pvtNew + 1
    end if
end for
swap L[pvtNew] and L[right]
return pvtNew
```

Proposition 1. *The asymptotic average complexity of Algorithm 1 is* $\Theta(n_1^2 \log n_1)$.

Proof: The computation time of lines 3 and 4 are both $\Theta(n_0 + n_1)$, and that of line 6 is $\Theta(n_0 + \tilde{n})$. At line 5, `PartialQuickSort` has an asymptotic average complexity of $\Theta(n_1 + \tilde{n} \log \tilde{n})$ [26]. Therefore, the overall complexity of Algorithm 1 is asymptotically

$$\begin{aligned} T = &\sum_{\tilde{n}=1}^{n_1} \Big(2(n_0 + n_1) + (n_1 + \tilde{n} \log \tilde{n}) + n_0 + \tilde{n} \Big) \\ = &3n_1(n_0 + n_1) + \frac{n_1(n_1+1)}{2} + \sum_{\tilde{n}=1}^{n_1} \tilde{n} \log \tilde{n}. \end{aligned}$$

To solve the last term, we use the Euler-Maclaurin formula (21), where B_i's are the *Bernoulli numbers* ($B_{1,2,\ldots} = -\frac{1}{2}, \frac{1}{6}, 0, -\frac{1}{30}, 0, \frac{1}{42}, 0, \frac{1}{30}, \ldots$). The solution is derived in (22) where C and C' are constants ($C = \log A_0$ where $A_0 \approx 1.28$ is the Glaisher-Kinkelin constant). Thus,

$$\begin{aligned} T = &\frac{1}{2} n_1^2 \log n_1 + \frac{13}{4} n_1^2 + \frac{1}{2} n_1 \log n_1 + \\ &(3n_0 + \frac{1}{2}) n_1 + \frac{1}{12} \log n_1 + O(\frac{1}{n_1^2}) + C. \end{aligned}$$

Since $n_0 = |\mathcal{N}^{soc}| < \infty$, i.e., a socially preferred acquaintance set is finite, T belongs to both $O(n_1^2 \log n_1)$ (i.e., $T \leq n_1^2 \log n_1 \cdot C_1$ for some C_1) and $\Omega(n_1^2 \log n_1)$ (i.e., $T \geq n_1^2 \log n_1 \cdot C_2$ for some C_2). Hence, $T = \Theta(n_1^2 \log n_1)$. ■

B. Optimal Decision for Contributors

A contributor checks his RTE queue and decides which requests to accept or reject. Making this decision is relatively easier than an endorser's as in the preceding Section V-A, because accepting more endorsers will only *increase* the contributor's BP and hence w_k, and eventually his reward r_k. However, the definition of η_{ik} (7) implies that increasing a contributor's BP will *dilute* each of his endorsers' *individual* share of appreciation power. Therefore, a contributor is subject to two social constraints: (a) ensuring that among the requesting endorsers, his *preferred beneficiaries*—which we denote by $\mathcal{N}^{bnf}$—are accepted, (b) ensuring a subset $\mathring{\mathcal{N}}^{bnf} \subseteq \mathcal{N}^{bnf}$, which contains those who are more "intimate" to him, to enjoy a revenue sharing ratio of at least η^{min}. To draw an analogy, one can think of $\mathcal{N}^{bnf}$ as the contributor's relatives and $\mathring{\mathcal{N}}^{bnf}$ as his family. Similarly, here we drop subscript k for brevity as we are dealing with a single contributor only.

Now, denote the requesting endorsers by $\mathcal{D}$, and similar to Section V-A, let $\mathcal{D}$ include his existing endorsers. Further, define $\delta^+_{EP,i} := \frac{EP_i}{|\mathcal{N}_i^{out}|+1}$.[9] The problem can be formulated as:

$$\text{Determine} \quad \mathcal{N}^*_{in} := \arg\max_{\mathcal{N}^{in} \subseteq \mathcal{D}} \sum_{i \in \mathcal{N}^{in}} \delta^+_{EP,i} \tag{23}$$

$$\text{s.t.} \quad \mathcal{N}^{bnf} \subseteq \mathcal{N}^{in},$$

$$\frac{\delta^+_{EP,j}}{\sum_{i \in \mathcal{N}^{in}} \delta^+_{EP,i}} \geq \eta^{min}, \quad \forall j \in \mathring{\mathcal{N}}^{bnf}. \tag{24}$$

The inequality (24) can be understood by noting that $BP = \sum_{i \in \mathcal{N}^{in}} \delta^+_{EP,i}$.

The key idea of our solution is to convert the problem into a standard combinatorial optimization, *knapsack problem*. Notice in (24) that the smallest $\delta^+_{EP,j}$ in $\mathring{\mathcal{N}}^{bnf}$ determines the upper bound of the total BP, and furthermore, the total BP is lower bounded by all the $\delta^+_{EP,i}$ from $\mathcal{N}^{bnf}$. Following this, the solution is given by Algorithm 4, in which the `knapsack` procedure has a variety of available solution algorithms, e.g. the Lua Knapsack solution [27]. In the case of $BP^{cap} < 0$, there is no solution and the contributor needs to either decrease η^{min} or shrink his beneficiary set $\mathcal{N}^{bnf}$ or $\mathring{\mathcal{N}}^{bnf}$.

Algorithm 4 Contributor's decision: Constructing the optimal portfolio of endorsers

Input: $\mathcal{D}$, $\mathcal{N}^{bnf}$, $\mathring{\mathcal{N}}^{bnf}$, η^{min}

Output: $\mathcal{N}^*_{in}$

```
Compute δ+_{EP,i} for all i ∈ D
δ^min_EP ← min_{j ∈ N̊^bnf} δ+_{EP,j}
BP^all ← δ^min_EP / η^min
BP^cap ← BP^all − Σ_{i ∈ N^bnf} δ+_{EP,i}
if BP^cap ≥ 0 then
    return N^bnf ∪ Knapsack(BP^cap, δ+_{EP,i}|_{i ∈ D\N^bnf})
else
    return Nil
end if
```

[9]When i is k's existing endorser, $|\mathcal{N}_i^{out}|$ will be replaced by $|\mathcal{N}_i^{out}| - 1$, i.e., as if he were a "new" requesting endorser of the contributor.

$$\text{Euler-Maclaurin formula}: \sum_{i=a}^{b} f(i) = \int_a^b f(x)\,\mathrm{d}x + \frac{f(a)+f(b)}{2} + \sum_{i=1}^{\infty} \frac{B_{2i}}{(2i)!}\Big(f^{(2i-1)'}(b) - f^{(2i-1)'}(a)\Big) \tag{21}$$

$$\text{Let } f(x) = x\log x \Rightarrow \sum_{\tilde{n}=1}^{n_1} \tilde{n}\log\tilde{n} = \int_1^{n_1} x\log x\,\mathrm{d}x + \frac{n_1\log n_1}{2} + C' + \frac{\log n_1 + 1}{12} + O(\frac{1}{n_1^2})$$

$$= C - \frac{n_1^2}{4} + \frac{n_1(n_1+1)}{2}\log n_1 + \frac{\log n_1}{12} + O(\frac{1}{n_1^2}) \tag{22}$$

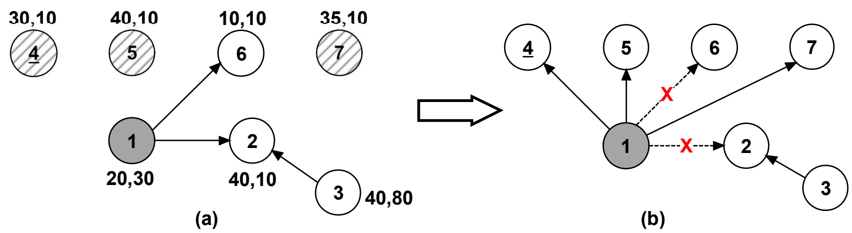


Figure 3: Illustration of the evolution of a SEW. The tuple beside each node indicates (CP,EP) of the associated node. Nodes 4,5,7 sent requests to be endorsed by node 1 who is the decision maker. The solid lines indicate endorsements and dotted lines indicate revocations.

VI. Evaluation

To derive an intuitive understanding, we illustrate the sewing process and our analysis using two examples.

A. Evolution of SEW

See Fig. 3(a) for an initial SEW, where node 1 has received three RBE requests to endorse nodes 4,5,7, while it is already endorsing nodes 2 and 6. Hence, the whole set $\mathcal{C} = \{2,4,5,6,7\}$. Suppose node 4 is node 1's "socially preferred acquaintance". To make the optimal decision, node 1 simply tells the mobile app (which implements Algorithm 1) that $\mathcal{N}^{soc} = \{4\}$ and the program will run and give the outcome, which is depicted in Fig. 3(b). It shows that nodes 2 and 6 lose the competition while nodes 5 and 7 win (besides node 4 who is a sure winner).

To verify the result, Table I provides a sanity check where three candidate sets are evaluated, and the underscored numbers indicate the social node 4. Different values of $\tilde{\pi}_k$ are computed according to (20). We can see that the set {4,5,7} is the most profitable (i.e., generates the highest revenue) for node 1 and is therefore selected. In fact, the three candidate sets shown in Table I are the highest three among all the $2^4 = 16$ candidate sets.

Table I: Selecting from different combinations of contributors

Candidate Sets	$\tilde{\pi}_k$	$\sum_k \tilde{\pi}_k$
$\{k \mid \underline{4},5,7\}$	$\{\underline{7.5}, 8, 7.78\}$	23.3
$\{k \mid \underline{4},5,6,7\}$	$\{\underline{6}, 6.31, 4.28, 6.18\}$	22.8
$\{k \mid 2,\underline{4},5,6,7\}$	$\{1.9, \underline{5}, 5.22, 3.75, 5.12\}$	21.0

We remark on two intuitions. First, it is *not* true that "the more people you endorse, the better off you will be". Second, it is worth noting that, node 2 is not selected although it has the *highest* CP among all the nodes. While one can calculate $\tilde{\pi}_2 = 1.9$, the intuitive reason is that node 2 is endorsed by node 3 which is a very powerful node with $EP_3 = 80$, and hence node 3 will grab a significant share of revenue generated by node 2, leaving node 1 in a disadvantaged position.

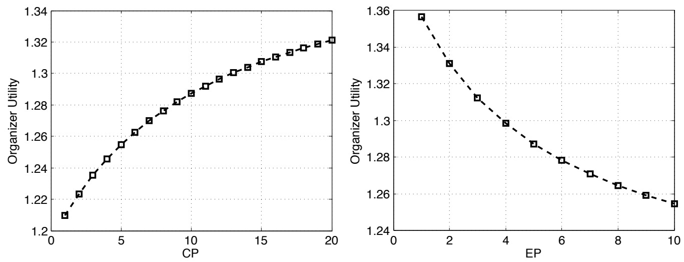
B. Economic implications

In line with the analysis in Section IV, we examine the organizer's utility as well as the participants' contribution quality in equilibrium, with respect to participants' three attributes: CP, EP, and unit cost. The case is based on the reference model thereof, instantiated by the parameters enumerated in Table II.

Table II: Parameters used in evaluation

Parameter	Value
No. of participants	100
Range of CP; Default CP	[1, 20] (step size: 1); 10
Range of EP; Default EP	[1, 10] (step size: 1); 5
Range of unit cost t; Default t	[0.01, 0.5] (step size: 0.025); 0.1
Others	$R = 1$; $x_0 = 1$; $\epsilon = 0.5$; $\alpha = \beta = 1$

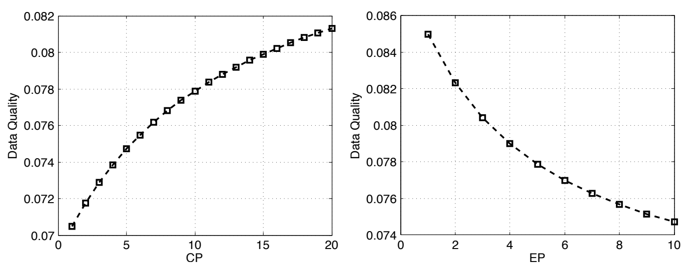
We first plot the organizer's utility u_0^* versus the participants' CP and EP in Fig. 4, according to (16). We follow the convention that the X-axis parameter takes its "Range" as in Table II while the other two parameters take their "Default" values as also in Table II. Fig. 4(a) and (b) demonstrate a sharp contrast: u_0^* is increasing and concave in CP but is decreasing and convex in EP. Although this could be explained by examining the first and second-order derivatives of u_0^* with respect to CP and EP, an intuitive understanding is of more interest. For this purpose, note that the organizer gains utility from revenue (contribution) and loses utility from cost which consists of a fixed reward R for contributors and a variable AP for endorsers (depending on how much power they lend to contributors). When CP is higher, contributors rely more on themselves and less on endorsers in competing for the reward, and as a result less AP will be allocated. Therefore, the organizer has more budget to increase the exchange rate x_c so that $x_c R$ values more. Since x_c is announced beforehand, participants are incentivized to contribute with higher quality, leading to a higher organizer's utility (partially due to the reduced AP as well). Mathematically, the above can also be interpreted as: $CP \uparrow\Longrightarrow \rho = \frac{EP}{2EP+CP} \downarrow\overset{(15)}{\Longrightarrow} x_c \uparrow\overset{(13)}{\Longrightarrow} q \uparrow$. The concavity is partially due to the diminishing marginal return from aggregate contributions (cf. (8)). Conversely, when EP is higher, more AP has to be allocated, which adds to the cost of the organizer; in the meantime, x_c and hence q also drop for the similar reason above. Consequently, the utility u_0^* decreases.



(a) Impact of CP. (b) Impact of EP.

Figure 4: Organizer's utility u_0^* versus CP and EP.

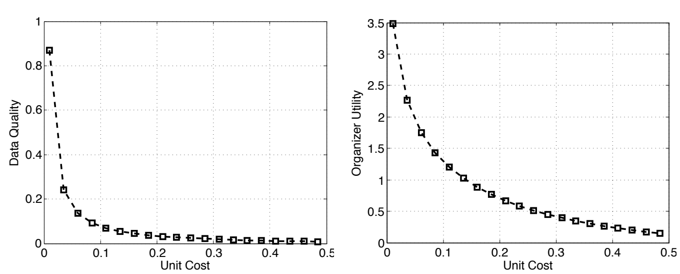
Next, we examine the relation between equilibrium contribution quality q^* and CP (resp. EP), as shown in Fig. 5. The trends coincide with Fig. 4 and the explanation has been provided above.



(a) Impact of CP. (b) Impact of EP.

Figure 5: Contribution quality q^* versus CP and EP.

Lastly, we examine how unit cost affects organizer's utility and participants' contribution quality in equilibrium, by plotting (13) and (16) in Fig. 6. The results conform to the intuition that higher cost drags down contribution quality (Fig. 6a), resulting in the organizer's declining utility (Fig. 6b).



(a) Contribution quality q^*. (b) Organizer's utility u_0^*.

Figure 6: Impact of unit cost on q^* and u_0^*.

VII. Conclusion

To the best of our knowledge, this is the first work that explores nepotism in the context of networked computing; unlike prior work which treats users individually, SEW links them together as a "web of participants". Nepotism is a key concept that reflects humans' multi-facet complexity rather than pure rationality or altruism, and this paper explores it as a potentially strong source of motivation for trustworthy crowdsourcing.

This work also represents the first effort to formulate and interweave social and economic elements together into participatory sensing: social motivation is reinforced by palpable economic benefit while economic return is complemented by social recognition.

While SEW themes around participatory sensing in this paper, the core idea is applicable to human-centric networked systems in general, including crowdsourcing, peer-to-peer, and recommendation systems.

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