Innovation Via Human Computation

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Abstract. Successful innovation has a distinct and crucial human element. Scaling innovation successfully requires encompassing and harnessing the knowledge of groups of individuals to provide outcomes greater than any one individual could achieve on their own. This set of innovating individuals can be thought of as a network – an innovation network of people and ideas – interacting, collaborating, innovating as one. Maximizing and optimizing the outcomes from such an innovation network demands machine mediation to help facilitate, filter, distribute information, and engage the network in the innovation process. To provide a functioning computational system for true innovation at scale requires approaches for modeling and incorporating people's behaviors, trust, emergent crowd wisdom, social ties, rewards. In this chapter we examine some of these key challenges and future opportunities to creating intelligent cooperative systems that incorporate human computation to generate productive crowd innovation.

1 Introduction

This chapter considers the means by which many people can work together to generate new ideas that have practical value. A familiar example of such a process is "brainstorming", where people build off of each other's ideas. Network technology and social collaboration have allowed us to improve traditional brainstorming so that more people can contribute ideas and work together more effectively irrespective of time asynchronicity or geographical distance. This chapter describes the techniques we have found to be instrumental for achieving innovation on an organizational scale.

Innovation, the introduction of new methods, solutions, products, is important to today's global business growth. Innovative products enjoy 70% higher margins than 'me-too' products [1]. However, successful innovation at scale in today's enterprise environments is a complex and elusive process, especially as one tries to capture productive innovation in a large enterprise, where the internal culture, behaviors, and goals interact in sometimes unpredictable and changeable ways.

The collective wisdom of a crowd through the aggregation of information in groups has long been recognized as a powerful decision-making approach [2]. Applying this approach to maximize outcomes from the innovation process makes intuitive sense. However, doing so productively requires intelligent approaches to understanding the innovation network and its interactions, the engagement with innovation that is occurring in order to help maximize outcomes, and to ensure that a healthy mix of collaboration and participation is happening.

Spigit is a collaborative innovation Software-as-a-Service (SaaS) platform that enables social collaboration for enterprises at scale. The platform and its usage within Spigit customer contexts, large Fortune 500 enterprises seeking to establish effective innovation for growth within their businesses, has enabled numerous observations and insights that advance the state of collaborative innovation.

We have found that there are several key elements to a healthy innovation network, that all must be modeled and nurtured in a collaborative system in order to ensure optimal results. In this chapter we examine several of these elements in turn, and provide insight into current and future models and approaches for encompassing these elements in a collaborative innovation system.

In Section 2 we examine the innovation network itself – what it consists of, its typical characteristics that build the foundation for an intelligent collaborative system around it. In Section 3 we discuss the role of engagement in innovation, and how to model and measure it. In Section 4 we examine the role of social recognition in crowd innovation – how it manifests and what behaviors and structures in the network support it. We continue in Section 5 by examining future aspects we are exploring to maximize the process of innovation through intelligent systems, and then conclude in Section 6 with a summary.

Please note that the mathematical expositions in this chapter are provided in order to reinforce the concepts for math-literate readers, but math is not required to understand the concepts herein. Readers may skip the formal expositions and still be confident about being able to follow conceptually.

2 Modeling The Innovation Network

An innovation network is a complex network of people and ideas, which can be represented as a graph consisting of vertices/nodes and edges/links. A vertex represents a person or idea in the network, and an edge represents some sort of connectivity between two vertices. One can think of an innovation network as a social

graph with an additional layer of idea nodes integrated into it. In essence, the network consists of people, ideas, and the interactions between them.
Let the crowd 'C' be represented by a graph $G = (V,E)$ where $V = \{v_1, v_2, \ldots, v_n\}$ and $E = \{e_1, e_2, \ldots, e_m\}$ where n is the number of nodes and m is the number of edges.

In a typical *social* graph, people are the nodes and edges represent relationships between nodes, with the graph depicting the structure of how people are 'related' to one another through their relationships.

In an innovation network, nodes are not only people, but also ideas, and edges are not only the typical *person-to-person* connections, but also *person-to-idea* connections, capturing explicitly the additional interactions that occur on an idea by a person: an up vote, a down vote, comment, review, market trade, view, sharing with a friend, testimonial, workflow task, etc.

In this way in an innovation network, the ideas serve as connection hubs - connecting people nodes that otherwise would not be interacting or connected in a typical social network. What is interesting is that both traditional social networks as well as innovation networks exhibit small world properties – clustering and short paths [3, 5]. The difference is that in a social network the clustering occurs between people, and in an innovation network the clustering happens around ideas. The idea layer brings the network together, with idea clusters that act as magnets to bring people together across the far reaches of the network.

Adding ideas as nodes to the network is a key aspect to scaling innovation, as otherwise the typical social clusters tend to magnify existing silos (groups of people that interact only with one another) act as silo magnifiers as a network forms and operates in an enterprise – counteracting the diversity desired for healthy collaborative innovation. Next let's examine how to assess the health and engagement of the innovation network.

3 Innovation Network Engagement

For the innovation process to yield maximal results, the innovation network must be engaged and active. In an innovation network, it is not enough for the network to simply grow in number of nodes (ideas and people) to signal a healthy network as Metcalfe's law supposes for standard communication networks [4]. Metcalfe's law makes a variety of assumptions on the type of structures in the network. Most real world complex networks are not homogeneously linked by similar types of edges. In an innovation network, the actual activity across nodes - in this case edge formation around idea nodes - must emerge and remain strong for optimal innovation results.

But how does one assess the engagement and activity growth or decline in an innovation network? Surely it ebbs and flows and changes over time. Thus having a computation that can serve as the engagement thermometer enables insight into the relative productiveness of the crowd at each moment in time.

We have created a model for measuring engagement in terms of the entropy of the innovation network [5]. In our case, we define entropy as a measure of message activity flux. Entropy is calculated as a function of the probability frequency distributions of the incoming and outgoing messages, which represents the entropy in the activity over the network. And in this way we can translate the activity occurring over a network in terms of message exchange as a measure and prediction of the ongoing engagement of the network.

The engagement of a node is calculated in terms of the incoming and outgoing message entropy, which is the entropy of the incoming and outgoing probability distributions associated with a particular node. The measure of uncertainty is actually the information content in a distribution. Thus the entropy of an incoming and outgoing message probability distribution measures the information content in these distributions. The cumulative incoming and outgoing message entropies of a network are calculated as the summation of all the individual incoming and outgoing node entropies. Thus, the incoming entropy (1) and outgoing entropy (2):

$$H^{in} = \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} * x_{ij} \log\left(\frac{1}{x_{ij}}\right) \qquad (1)$$

$$H^{out} = \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} * y_{ij} \log\left(\frac{1}{y_{ij}}\right) \qquad (2)$$

Where x_{ij} is the incoming message distribution, y_{ij} is the outgoing message distribution, and $a_{ij} = 0$ if i and j are not connected, and $a_{ij} = 1$ if i and j are connected.

Finally, the total value of a network is calculated as a weighted measure of the incoming and outgoing entropies of the network. Thus, the value V is represented as a function of weighting variable α as in Eq. 3. The variable α allows for weighing the incoming and outgoing network entropies.

$$V(\alpha) = \alpha H^{in} + (1-\alpha) H^{out} \qquad (3)$$

As it turns out, some of the structural features of a network indicate a disposition towards good engagement/cumulative entropy [5]: high total number of active links, high clustering coefficient, low average shortest path length, and many connected components. Thus with this model, we can quickly assess not only the current engagement level of an innovation network, but also whether that network is predisposed towards engagement growth or decline – and thus recommend adjustments to optimize.

One of the aspects that plays strongly towards engagement growth is social recognition. In Section 4 we now examine a model for recognition in an innovation network, and how it interplays with engagement.

4 Social Recognition and Rewards in Crowd Innovation

One of the key behavioral aspects that drives good engagement in an innovation network is *social recognition*. This is due to the fact that social recognition is in reality an important motivator. Going back to Maslow's hierarchy of needs [6] we can see that the 'esteem' layer of needs encompasses accomplishment, social status, attention, recognition needs.

Thus a key element to achieving good engagement in an innovation network is some way to model and externalize this esteem layer for social recognition. We have developed a model for reputation in an innovation network that captures in essence what the crowd thinks of an individual's contributions and interactions. We base this on the 'reaction' edges (votes and comment sentiment) to that person's idea nodes and comment edges in the innovation network.

However, it is not enough to simply look for volume of these edges signaling popularity – this would be a very shallow measure that does not over time scale to provide the motivational behavior desired, as one can quickly understand that simply soliciting volume of positive votes and comments on your ideas provides high reputation, artificially bringing everyone with any sort of activity on their contributions to the same level. We must be more intelligent about those who are positively reacting to an individual's contributions and factor in other measures as we incorporate their reactions into a reputation measure.

Key factors that we have found crucial to a more accurate and effective reputation measure are: decay over time, slower movement at the tails of the permissible range for the reputation score, continued engagement, reputation of the rater, and ability of the rater to discern good ideas from bad [7].

The first key aspect to this model is that an individual's actual rating on an idea or comment (R^A) is not taken at face value, but an effective rating (R^E) is computed from it. The modulation factors of reputation of the rater (m_1), discernment of the rater (m_2), how recently the rating happened (m_3) all contribute to the effective rating as in Eq. 4:

$$R^E = m_1 * m_2 * m_3 * R^A \qquad (4)$$

The discernment of the rater is a measure of how skilled the rater is at finding the best ideas. For this, we use the Wisdom of the Crowds (WoC) principle [2] that tells us that the aggregated judgment of a number of individuals is closer to the answer than any of the 'best' individual estimates. And thus with this principle the crowd always comes up with the true value of an innovation. Thus, in this model, we predict the discernment of the rater based on: the history of the voter to side with the crowd, and the evidence about the idea in terms of what the crowd thinks.

These two are defined by Event C (the hypothesis) = rate with the crowd. Event I (the data/evidence about the value of the idea) = the cumulative crowd sentiment about the idea. Then the overall sentiment about an idea is computed as follows:

$$P\left(eventI\right) = \frac{upRatings - downRatings}{totalRatings} \qquad (5)$$

Now we can compute the probability of the hypothesis i.e. rating with the crowd given what the crowd is thinking about the idea. This probability is modeled using Bayesian inference as in Eq. 6,

$$p = P(C \mid I) = \frac{P(C) * P(I \mid C)}{P(I)} \qquad (6)$$

where $P(C|I)$ is the posterior probability which we are calculating. $P(C)$ is the prior probability – the probability of the person voting with the crowd, i.e. the person's history of voting for the good idea. $P(I|C)$ is the likelihood – the probability of the idea being a good/bad idea given the rater rates with the crowd. P(I) is the data/evidence about the idea, the probability that the idea is good/bad given the voter votes with/against the crowd respectively, given by Eq. 7:

$$P(I) = P(I|C) * P(C) + P(I|{\sim}C) * P({\sim}C) \qquad (7)$$

The overall probability p thus becomes the discernment of the rater – how probable is it that this rater tends to rate with the wisdom of the crowd, and becomes m_2 in our effective rating computation, to modulate the rating according to how discerning this rater is.

The sum of the effective ratings is then coupled with continued engagement e of the individual, a decay factor d over time and a tail velocity v that slows movement at the tails to define the overall reputation of an individual at time t:

$$R_t = d * R_{t-1} + \sum_{1}^{n} R_n^E * v * e \qquad (8)$$

And in this way, we have a reputation measure that serves as a social recognition metric that goes much beyond simple volume of positive ratings to provide a reputation measure that elicits the engagement behaviors desired, and is robust to gaming as the innovation network grows.

5 Future Work on Innovation Network Optimality Factors

Several additional factors are key to ensuring productive and effective scaling and operation of an innovation network. Modeling and incorporating *trust* is one such factor. Finding particular *innovation personae* in the network and the optimal groupings and makeup of these personae in well-functioning innovation networks is another. And *emergent cooperation* and the factors and conditions necessary in the network to ensure cooperation grows rather than shrinks is a third important future area for exploration.

Network trust has been studied in social network and general collaboration contexts [8,9]. We have also observed various trust behaviors that impact innovation network engagement, such as more readily-given trust in smaller innovation networks than in larger ones. In future work we will examine whether the traditional trust behaviors such as preference similarity [10] and frequent and regular communication [11] are also the same factors the engender trust in an innovation network, and/or what additional trust metrics exist in the innovation context.

We have also observed that typical healthy innovation networks have a mixture of behavioral personae (innovation behavior types), for example innovators (skilled at creating good ideas), and discerners (skilled at finding good ideas of others). And that the mix of innovators and discerners remains fairly constant as the healthy innovation network scales. In future work we will explore additional personae that contribute to an especially healthy innovation network, such as creative collaborators, action-takers, etc., and in what contexts are they most effective and necessary, in order to be able to recommend innovation team groupings for optimality.

And finally, studies about emergent cooperation in social networks show that certain conditions favor cooperators over defectors in a network, ensuring that cooperation grows rather than shrinks [12]. We will also examine as part of future work whether these conditions are also sufficient and necessary in innovation networks, and how the cost/benefit scenario can best be modeled to achieve emergent cooperation in innovation.

6 Summary of Human Computation in Innovation

Successful innovation has a distinct and crucial human element. Scaling innovation successfully requires encompassing and harnessing the knowledge of groups of individuals to provide outcomes greater than any one individual could achieve on their own. To provide a functioning computational system for true innovation at scale requires approaches for modeling and incorporating people's behaviors, trust, emergent crowd wisdom, social ties, rewards.

In this chapter we have examined how to model the innovation network as a social network layered with ideas that brings the social clustering across the network rather than in social silos. We have examined the role of engagement in an innovation network, and how it can be modeled and measured with a network entropy approach, as well as how to find structural indicators of whether a network is predisposed towards high or low engagement. We have also examined the crucial role of social recognition in an innovation network, and how to model reputation in such a way that it elicits desirable interaction behaviors, is robust to gaming, and scales as the network grows. And finally we examined the additional aspects of trust, emerging cooperation, and personae that are additional future key elements to incorporate into optimal innovation network models and approaches.

By modeling and incorporating these key factors into an intelligent human-machine computation system, the innovation network is positioned best to harness the knowledge of the group, and produce optimal innovation results.

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