

A Framework for Trust based shared Economy

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Abstract - *Network formation on trust and trustworthiness needs to be sustainable for any online trust based economy. It is important to have a matching game within our program in order to match up the most compatible individuals. Similar individuals can have higher levels of trust at the start of the relationship and thus have lasting partnerships. However, we must also create a network structure that allows us to single out more trustworthy individuals in the network; so that people have more access to these individuals in the network.*

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1 Introduction

Let us start by establishing some nomenclature. There are individuals who are strictly consumers, making up members of some set C where $c_i \in C$ will denote a prototypical member. Some individuals are providers of services and goods, as members of set P where $p_j \in P$ and p_j denotes a prototypical member. Without loss of generality, P and C may contain corporate members as well as private citizens. There are individuals who are members of overlapping C and P denoted $C \cap P$. A subset of P denoted by X will denote elite members, X_k , who are established businesses¹. A matchmaking, aggregation, and tracking platform is proposed to interface members of C to P . The aggregation API will solicit interested consumers and suggest pertinent providers. A central component of this system is to assign a *trust* scoring metric to members of C . By analogy to FICO² score, our scoring metric will consist of several components.

A consumer, C_i , is an existing member of group X , that individual will be assigned a kernel value, K , trust value of 1 for their basic trust value. A set of attributes A will be separately presented to each p_j and c_i where each attribute a is assigned a weight; important, neutral, unimportant. Thus, if someone is looking for a service, our system would inquire attributes of interest from c_i for preference elicitation and initial matching. This is at the core our aggregation component. Once the service is rendered, c_i would rate the service for feedback and suggested improvements for p_j . Lexicographic analysis³ of inquiry and feedback will be used to fine tune attribute selection as well as postmortem rating of services. For example, if someone wants to loan an automobile from a provider, we can check the credibility of c_i by parsing various data from individual i 's Facebook, Twitter, LinkedIn, and Google+. All major shared economy sites include reviews. This can be used as one of major attributes for computing trust. Individuals report values for their attributes with a value vector denoted as V . This is separate from their attribute weight vector W . The second component of the score is $T = \sum WV$. Thus, each p_j composes a trust score T for each c_i . Each trust score is used by each provider in determining quality of their potential consumer. Each consumer will be offered a trust score based on their personal weights, ω . This value differs from the trust score generated. The trust score is used as a feedback to

¹ Such as Airbnb.com and Justshareit.com

² The FICO mortgage score is between 300 and 850. Higher scores indicate lower credit risk. FICO was founded in 1956 as Fair, Isaac and Company by engineer Bill Fair and mathematician Earl Isaac.

³ Lexicology is the part of linguistics which studies words, their nature and meaning, words' elements, relations between words, word groups and the whole lexicon.

consumers as well as a list of providers recommendations. Upon lexicographic analysis of the feedback of consumer i , the third component of the trust score, L is generated.

2.0 Lexicographic Analysis

Lexicographic analysis is the part of linguistics, which studies words, their nature and meaning, words' elements, relations between words, word groups, and the whole lexicon. Lexicographic inquiry is used to fine tune attribute selection as well as postmortem rating of services. For example, if someone wants to loan an automobile from a provider, we check their credibility by parsing various data from individual's Facebook, Twitter, LinkedIn, and Google+ feeds. A collection of feeds can then be analyzed for their content to gather a measure of trustworthiness. We are able to determine positive and negative sentiment related to the individual's driving ability, trustworthiness, etc. This is accomplished by lexicographic analysis⁴. We created a metric that allows us to determine an individuals choices based on their observed lexicographic feeds. One way to approach the lexicographic measurement is to count the proportion of words that usually have a positive connotation and the proportion of words that have a negative connotation. This is a common analytic strategy for lexicographic analysis, as seen in (Golder and Macy, 2011). Following Golder and Macy (2011), we determine if there is positive or negative sentiment in each feed. Thus, we understand if a sentence is positive, negative, or neutral about an issue and to which grouping these sentiments are affiliated, e.g. car, truck, housing, etc. By investigating a person's feeds; we are able to determine what type of company or product these

people would likely select. We are also able to see if they are receptive to suggestions for use of future products. In order to measure positive and negative statements within Twitter, we first need to identify the number of positive and negative words in each feed. We use a simple counting method when checking the positive and negative words⁵. Once we have the word counts, we multiply the negative word count by negative one in order differentiate between the positive and negative statements. Next, we determine the word structure of each feed. We then aggregate the composition of each feed to get an overall emotional measurement of each issue. The emotional responses can range from negative to positive. Thus we are able to explore how individuals *feel* about specific issues. Take the status update for the following example:

Joe is not trustworthy. He cannot be trusted.

For this example, we have two negative words (i.e., not and cannot) and two positive words (i.e. trustworthy and trusted). Therefore, the overall composition of this examples does not reflect well upon Joe. Leading us to believe that this person feels that Joe is not trustworthy giving us a score of -2; only for this example. Therefore, we would see a numerical value of negative one for use of automobiles. Next, we need to sum over all instances where Joe is mentioned or mentions trustworthiness or automobiles. Thereby, giving us Joe's overall trust score in equation 1.

$$L = \sum_{i=1}^n t_i \forall i, L \in [-\infty, \infty] \quad (1)$$

⁴ Lexicology is the part of linguistics which studies words, their nature and meaning, words' elements, relations between words, word groups and the whole lexicon.

⁵ Golder and Macy's Twitter study used the lists of positive and negative words that are part of the Linguistic Inquiry and Word Count (LIWC) project. However, we found similar dictionary that's freely available thanks to Neal Caren at University of North Carolina, Chapel Hill.

3.0 Trust Scoring

We compute a simple measure of trust in equation 2.

$$\text{Trust} = K + T + L \quad (2)$$

Apart from trust score value, an individual who has multiple profiles on social networking sites will be assigned a social presence value. The social presence indicates a potential for dissemination of word of mouth information that is a crucial source of PR value for providers. Social scoring algorithm for an individual i:

1. Social (i) = 0, which is the default value
2. For an individual i, collect social network links to i, E(i).
3. For each social network sn of i, these include connections from Twitter, Facebook, LinkedIn, and Google+.

Therefore, we can compute the social value of individual I using equation 3.

$$\text{social}(i, \text{sn}) = \text{social}(i, \text{sn}) + \rho \sum_{j=0}^n \frac{\text{social}(j)}{L(j)} \quad (3)$$

Here n is the number of ties, j is one of i's ties. ρ is the propensity coefficient for i's network. Page rank = 0.85, which represents the normalized score.

4. The normalized score is computed with equation 4.

$$\text{Social}(i, \text{sn}) = \frac{\text{score}(A)}{|\text{sn}|} \quad (4)$$

4.0 Literature Review

In this section, we will review recent literature on trust based networks and matching games. Cagno and Sciubba (2008) ran laboratory experiments where friendship networks are generated endogenously within an anonymous group. Their experiment builds on two phases in sequence: a network

formation game and a trust game. Cagno and Sciubba (2008) found that in those sessions where the trust game is played before the network formation game, the overall level of trust is not significantly different from the one observed in a simple trust game; in those sessions where the trust game is played after the network formation game we find that the overall level of trust is significantly lower than in the simple trust game. Hence surprisingly trust does not increase because of enforced reciprocity and moreover a common social history does affect the level of trust, but in a negative manner. Where network effects matter is in the choice of whom to trust: while we tend to trust less on average those with whom we have already interacted compared to total strangers, past history allows us to select whom to trust relatively more than others. Cagno and Sciubba (2008) show us that there is an importance in how we build trust within a network of individuals. We will see that later work solidifies the understanding of network formation on trust and trustworthiness needed to sustain an online trust based economy.

More recent work in (Di Cagno and Sciubba, 2010) investigated the impact of network formation on trust and trustworthiness. Again they ran laboratory experiments where, in sequence, networks are generated endogenously within an anonymous group and subjects play a trust game. The experimental design includes two main treatments and a baseline: in the baseline subjects play a trust game with no networks being formed, in treatment NT the network building phase precedes the trust game, and in treatment TN the network game is played at the end. This allows us to identify the two main factors through which networks impact on trust and trustworthiness: information accrued to subjects through social interaction (when this occurs first) and reputation (when it follows). Di Cagno and

Sciubba (2010) found that in NT, the overall level of trust is lower but offers are directed to more trustworthy recipients. A common past history matters in determining whom to trust (information value of networks). In TN, continuation play enforces higher levels of trust and trustworthiness (reputation and enforced reciprocity). Profits that subjects make in the trust game are higher in the presence of social interaction, and significantly so when network formation informs the decision of whom to trust. This shows that it is important to have a “matching game” within our program. So that like individuals can have higher levels of trust at the start of the relationship. However, we must also create a network structure that allows to single out more trustworthy individuals so that people have more access to these individuals in the network. (i.e. broadcast these individuals as “users of the week” that show who has the highest ranking or who is the most trustworthy).

(Cannatelli and Antoldi, 2012) describes how the role of network facilitator, played by a third party institution, may substantially contribute to the development of trust among SMEs involved in a strategic alliance. (Cannatelli and Antoldi, 2012) give empirical evidence that is presented by a longitudinal analysis of a case history. The case study focuses on eight international-oriented SMEs located in an industrial district in Northern Italy that built up a formal network called ‘I-Style Partners’. Two rounds of in-depth interviews were carried out with firm leaders and facilitator’s managers involved in the strategic alliance over a three-year period. Their paper contributes to theory generation suggesting a three-stage process model in which a network facilitator may enhance inter-organizational trust by constituting in turn a substitute of alliance members’ perceptions of ability, integrity and benevolence. Thus giving need to a their party to

vouch for the trustworthiness of network members.

Karlan et al. (2009) builds a theory of trust based on informal contract enforcement in social networks. In their model, network connections between individuals can be used as social collateral to secure informal borrowing. They define network-based trust as the largest amount one agent can borrow from another agent and derive a reduced-form expression for this quantity, which is then use in three applications:

1. Predict that dense networks generate bonding social capital that allows transacting valuable assets, whereas loose networks create bridging social capital that improves access to cheap favors such as information.

2. For job recommendation networks, it is shown that strong ties between employers and trusted recommenders reduce asymmetric information about the quality of job candidates.

3. Using data from Peru, Karlan et al. (2009) show empirically that network-based trust predicts informal borrowing, and we structurally estimate and test our model.

Tams (2012) advances propositions regarding the structure of the relationship between vendor trust and its antecedents as this structure pertains to the relative and complementary effectiveness of trust-building strategies. By understanding how the relationship between vendor trust and its antecedents is structured and why this relationship is structured the way it is, Tams (2012) hope to gain more holistic insights into trust in electronic market transactions and to provide online businesses with a clear recommendation of how to establish trust in an effective and efficient manner. Thus, while past research has made important contributions by uncovering a great number of antecedents to vendor trust, Tams (2012) examines two strategies more in depth: vendor reputation and Web site trust. Drawing

from the literature on trust, the authors propose vendor reputation to be more effective than Web site trust. Tams (2012) propose a small complementary effect between vendor reputation and Web site trust that may help online businesses to generate superior vendor trust.

Cassar and Rigdon (2011) focus on the interaction between network structure, the role of information, and the level of trust and trustworthiness in 3-node networks. They extend the investment game with one Sender and one Receiver to networked versions—one characterized by one Sender and two Receivers ([1S - 2R]) and one characterized by two Senders and one Receiver ([2S - 1R])—under two information conditions, full and partial. Cassar and Rigdon (2011) develop a comparative model of trust for the networked exchange environments and generate two hypotheses:

1. What counts as a signal of trust depends on investment behavior along the other link in the network, and

2. This type of trust can be leveraged under full information, increasing the rate of cooperation on the side of the exchange with multiple traders.

The results generally support our hypotheses: trust is comparative and under full information, the [1S - 2R] network shows higher trustworthiness and the [2S - 1R] network displays higher trust. Cassar and Rigdon (2011) Here is a very simple case of a three person network; however, these concepts may be extended to larger networks which we will discuss later on. Which kind of network fosters the diffusion of development-oriented trust? Sabatini (2009) carries out an empirical investigation into the causal relationships connecting four types of social networks (i.e. bonding, bridging, linking, and corporate), and different forms of trust (knowledge-based trust, social trust, trust towards public services and political institutions), in a community of

entrepreneurs. Their results suggest that the main factors fostering the diffusion of social trust among entrepreneurs is the establishment of corporate ties through professional associations. Trust in people is positively and significantly correlated also to higher levels of satisfaction and confidence in public services. Participation in voluntary organizations does not appear to increase trust towards strangers. Rather, Sabatini (2009) find evidence of the other way round: interpersonal trust seems to encourage civic engagement. Thus, it is important to create high levels of trust amongst individuals in a network so that there is confidence in the services being provided. Trust is essential to supply chain teams as it has a positive impact on team performance. Long-term relationships in supply chains have also emphasized trust as their key element. Yet traditional models of trust have a limited application in hastily formed networks that are formed on the spot without a long-term component. An example of such hastily formed networks is the humanitarian aid supply network, which consists of a number of individual logisticians from a variety of organizations, coming together to bring relief to a disaster-stricken area. The aim of this paper is, thus, to further the understanding of swift trust in hastily formed networks as a means of improving relief operations in rapid onset disasters. Tatham and Kovacs (2010) present a model of swift trust and conditions are discussed to unearth potential facilitators of swift trust. In the interest a startup Internet firm in the modern age, it is important to create lasting trust quickly. Research into two important control mechanisms for managing the supply chain relationship—contracts and trust—is on the rise. However, our understanding of how they influence innovation in a firm remains rather unclear. Thus, the primary objective of Wang et al. (2011) was to examine the individual and interactive effects of contracts and trust on firms' innovation performance

and the contingent effects of environmental uncertainty on those relationships in China. The empirical results from a survey of Chinese manufacturing firms indicate that there is a positive relationship between trust and firms' innovation performance, an inverted U-shaped relationship between the use of contracts and firms' innovation performance, and that contracts and trust are substitutes. Moreover, Wang et al. (2011) found that environmental uncertainty enhances the effects of trust, but does not influence the impact of contracts on innovation performance. Our network should help to decrease the uncertainty of the users; thus, creating a helpful environment to foster trust between users.

Pan (2010) propose a social learning framework where agents repeatedly take the weighted average of all agents' current opinions in forming their own for the next period. They also update the influence weights that they place on each other. It is proven that both opinions and the influence weights are convergent. In the steady state, opinions reach consensus and influence weights are distributed evenly. Convergence occurs with an extended model as well, which indicates the tremendous influential power possessed by a minority group. Computer simulations of the updating processes provide supportive evidence (Pan, 2010). Here we see validation for our scoring mechanism; given that the way people weigh individuals as well as how social learning for a network of agents tend to converge over time.

Trust is important: several transactions are based on it; unfortunately it is difficult to measure. The recent literature on social capital shows a positive association between this concept and trust. As given that social capital is easier to measure than trust, it is best to analyze the possibility of assessing trust using a measure of social capital. A basic trust game is played in three Western European countries with

undergraduate students; a questionnaire measures their level of social capital as time spent within social networks. This measure is stronger and more precise than the ones generally used. Migheli (2012) conducted an experiment that results support the fact that trust can be assessed through social capital, although the presence of a strong geographical effect has to be accounted for. The program used to calculate our score uses all of these factors plus several extras that make the score more robust.

5.0 Conclusions

Network formation on trust and trustworthiness needs to be sustainable for any online trust based economy. It is important to have a matching game within our program in order to match up the most compatible individuals. Similar individuals can have higher levels of trust at the start of the relationship and thus have lasting partnerships. However, we must also create a network structure that allows us to single out more trustworthy individuals in the network; so that people have more access to these individuals in the network. (i.e. broadcast these individuals as users of the week that show who has the highest ranking or who is the most trustworthy) Theory suggests that a three-stage process model in which a network facilitator, i.e. get2know may enhance inter-organizational trust by constituting in turn a substitute of alliance members' perceptions of ability, integrity and benevolence. Thus giving need to a third party to vouch for the trustworthiness of network members. In a network-based trust model we should be able to create a dense network thus generating social capital that allows transacting valuable assets; however, it must also be loose enough network to allow for bridging social capital to occur that improves access to cheap favors such as information. Drawing from the literature on trust, we can propose that reputation is more effective than Web site trust. There is a small complementary

effect between vendor reputation and Web site trust that may help online businesses to generate superior trust. Thus, the kind of network that we develop will foster the diffusion of trust. It is important to create high levels of trust amongst individuals in a network so that there is confidence in the services being provided. By modeling a network to build trust swiftly, we will create conditions that will be later discussed to unearth potential facilitators of swift trust. In the interest a start-up internet companies in the modern age, it is important to create lasting trust quickly. Our network will help to decrease the uncertainty of the users; thus, creating a helpful environment to foster trust between users. Trust is important: several transactions are based on it; unfortunately it is difficult to measure. However, trust can be determined via social capital, although the presence of a strong geographical effect will also be accounted for. Our program calculates the score based on verified factors that measure social capital and thus measures a person's trustworthiness.

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