Creditworthiness using Social Capital: A Theoretical Framework

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Abstract

"Can social capital generated from social networks be applied as an alternative or complement to the traditional bank score methods?" From a computational point of view, this question can be rephrased as "What types of data structures and mathematical models in the literature take social capital as input and predict the creditworthiness of an individual?" In practical terms, what if reputable members of someone's social network could endorse him/her about his/her trustworthiness and after a series of computations it arrives with a probability of how much this person could be trusted in a financial transaction? How can "wisdom of the crowds" concept be added to achieve a reasonable level of confidence in the probability of creditworthiness of a person? In the absence of a minimum number of endorsements for a given person, what are other information such as the topology of one's social network that could help to infer about his or her creditworthiness?

Trust and Reputation systems is an area of computer science which have attracted attention in various networking environments, including online social networks, wireless communication networks, multi-agent systems, and peer-to-peer networks. Trust and Reputation systems can use explicit or implicit information for decision making. A form of explicit information derives from let parties generate feedback about each other after completion of a transaction and aggregating the feedback to derive a reputation score. Another implicit form of trust information is the use of topological analysis in online social networks to determine reputation. In the Google search engine for example, reputation is determined by the number of links that point to a page, and from where the links originate.

This dissertation aims to shed some light in the credit problem above by analyzing computational models from the areas of Trust and Reputation systems. Then applying those models using two public social network datasets, that although not credit specific, can offer some playground for analysis: i) Yelp, an opinion review social network of products and services and ii) Indian villages database (microcredit research).

The goal of the dissertation is to propose a theoretical framework of how and which of these models could be used in a scenario of lending, highlighting advantages, limitations and areas for further research.

The potential benefits of such framework are to support the development of more inclusive credit scoring methods aimed to less-privileged segments of the population.

1 Introduction

"Can social capital generated from social networks be applied as an alternative or complement to the traditional bank score methods?" From a computational point of view, this question can be rephrased as "What types of data structures and mathematical models in the literature take social capital as input and predict the creditworthiness of an individual?" For example, what if reputable members of someone's social network endorsed him or her about his or her creditworthiness based on feedback of past interactions, and after a series of computations we arrive with a probability of how much this person could be trusted in another financial transaction? Can we use "wisdom of the crowds" [50] to yield in a reasonable level of confidence a probability of creditworthiness of a person? In the absence of a minimum number of endorsements for a given person, what are other information about the topology of one's social network that could help to infer about his or her creditworthiness?

The theoretical motivation comes from a growing body of research in economics and computer science on whether Social Capital affects economics outcomes. This is particularly beneficial in micro-finance, where the targeted customers are mostly economically under-privileged people and are not well screened in traditional bank scoring methods, which basically assess payment history and size of asset collaterals. In Brazil, it is estimated that 48% of population are unbanked, however, that does not mean that this segment does not use any finance solution in their daily lives. On the contrary, because of their vulnerable situation, they find numerous informal arrangements [38], most of them through their networks of family and friends. These networks have unique characteristics such as solidarity values and proximity of members that reduce information asymmetry and monitoring costs. In addition, the importance of trust and social reputation, works as social mechanism to reduce incentives to moral hazard between borrowers and lenders.

In some sociotechnical systems [2] such as e-commerce platform or product review websites, users can explicitly declare trust, normally as the result of positive interactions with the trustee. There are already a vast academic literature about reputation management methods and models to measure trust. However, when it comes to personal credit and finance, obtaining social information and transforming them into a usable format is difficult. Another issue with such information is its reliability, which can be mitigated if there is credible verification and if the mechanisms designs in gathering the information assure rational behavior.

The ambition of this work is to come up with a theoretical background and a practical framework of computational methods to be applied in social networks to alleviate information asymmetry in traditional credit markets.

In order to try to develop light in the question posed, the research plan will be composed into four parts:

1. Brief historical introduction of informal group lending arrangements and micro-finance, verifying what role social connections play [38] in providing efficiencies. We will be based on previous studies of the Graamen Bank case and other informal arrangements such as Rotating Savings and Credit Associations [25, 21, 6], to verify how information asymmetry and incentives to moral hazard are lowered. In addition, we will research the definitions and methods of measurement of Social Capital [45, 11, 30, 29], from a multidisciplinar point of view: social sciences, economics and computer science.

2. Big emphasis on the computer science methods in the literature for measuring Social Capital and Trust. Two areas in particular:

   – Reputation and Trust Management in on-line systems [22, 46]. This area has been receiving increasing attention recently as on-line interactions between people and services that have no prior real-world relationships are becoming common. Examples of interactive online sites include Social Networks, and modern paradigms such as file-to-file sharing and the social cloud. All these interactions can be considered to include an element of reputation, such as post-comments in forums, competencies in crowdsourcing and social linkages and endorsements in social networks and the social cloud. The aim of reputation systems is therefore to support the trust between unfamiliar parties. For that, a series of models and algorithms have been proposed [16] for example EigenTrust [28], PeerTrust [1], ROCQ [17], SocialTrust [7], among others.

   – Social Network Analysis using graph theory algorithms [33, 10, 35, 40, 14, 2] which provides insights such as social influence, strong and weak ties, on the basis on the topology of the network. These concepts and techniques are instrumental for the development of graph-based Trust models [27, 36] such as Regret [39]

3. Survey some papers that place Social Capital into Credit Scoring context and what have been achieved so far[13, 8, 48, 43, 23, 15, 31]. Relate and contrast with the usage of some methods discussed in item 2.

4. On the basis of the elements extracted from items 2 and 3, suggest a theoretical background and practical framework with data collection, methods and tools to analyze empirically one's social network and predict his or her creditworthiness. We will try to illustrate such usability by using available social network dataset from Yelp.com[49] and microfinance research[4] to evaluate, critique and suggest further improvements.

The potential benefits of such framework are to support the development of more inclusive credit scoring methods aimed to less-privileged segments of the population.

2 Document Structure

The structure of this document is presented as following:

Part 3: Problem Description, why the use of Social Capital to alleviate the credit problem of the poor population in many developing countries is relevant.

Part 4: Preliminary Concepts, where it is presented the concepts of social capital from different perspectives, and some evidences of its correlation in peer-to-peer (P2P) lending platforms. Moreover it is presented approaches to Social Capital from a computer science perspective:Trust/Reputation systems and social network analysis using graph-based algorithms. Lastly, it is presented some references of the latter approaches more specifically to the creditworthiness problem and the current stage of research.

Part 5: Methodology of the research.

Part 6: Expected results.

Part 7: Working plan/chronogram.

Part 8: Bibliographic references

3 Problem Description: financial exclusion of poor population

The banking system have several mechanisms to reduce information asymmetry embedded in all and every financing operation. The most conventional ones consist in obtain information about asset collateral, a detailed exam to the motives for the credit that will be used for and the individual history of the credit taker. The banking manager then rely on statistical techniques to determine a score -at which scale of credibility the individual credit proponent is placed-, to decide whether he concedes the credit [38].

In addition to the cost that this operation involves, it is evident that it tends to exclude population that lives in poverty, because they are unable to offer significant physical or financial collateral, which is a big problem to a population segment that just need liquidity the most.

This problem has been in part overcome by several organization capable to lend small amounts of money to the poor people, in a way that would be incompatible with the high transaction costs of the traditional banks. These types of organization can offer to these borrowers' valid substitutes for individual collateral, and to the lenders low-cost alternatives to imperfect creditworthiness information. In fact, they provide credit to the poor based on "social collateral", through which borrowers' reputation, or the social networks to which they belong, take the place of the traditional physical or financial collateral. Since these arrangements build, to various degrees, on the extent and strength of personal relationships, they provide a fertile ground for the analysis of the role of social capital in the provision of credit. Examples of such organization are the rotating credit and savings associations (ROSCAs)[21], the local moneylenders (usurers), trade credit and the group-based microfinance programs (Grameen Bank) [5].

Rotating Savings and Credit Associations (ROSCAs) [5] are a "response by a socially connected group to credit market exclusion, and a widespread way to crystallize social relations in an informal – yet often formally run – system of internal credit delivery [6]. The concept of ROSCA is known as chit funds in India, kye in Korea, partners in Jamaica, susu in Ghana, njangeh in Cameroon, tontine in Senegal, pasanaku in Bolivia, panderos in Peru, Tanda in Mexico, caixinhas e consorcios in Brazil, and in many other countries. Izumida [25] describes the Tanomoshi-Kou system, introduced in Japan in the 12th or the 13th century as the oldest form of ROSCA.

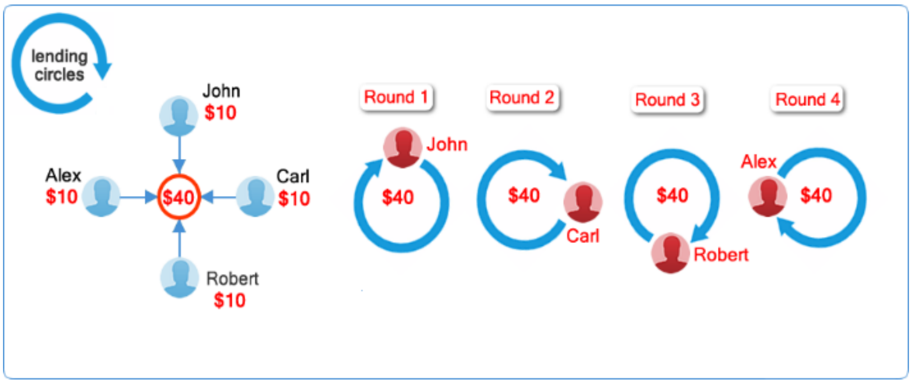


Figure 1: Dynamics of a Rotating Savings and Credit Association (ROSCA)

A ROSCA [21], depicted in figure 1, is a group of men and/or women who contribute to a collective fund which is at regular intervals distributed – randomly, by auction, or by collective decision – to one of the group's members. In effect, all the members of the group (except the last person in the rotation) receive an advance that they repay through their contribution to the fund for the duration of the cycle: the earlier and individual's position in the rotation, the larger the credit he/she receives, and the lower the risk he/she faces (if a person fails to contribute after he/she receives the fund, only those members after him/her will be adversely affected). At the end of a cycle, i. e., when each member has received the fund once, the ROSCA is dismantled or, more often, reconstituted with the same or similar membership. This creates the possibility that well-performing member can move up in the rotation, providing an incentive for good payment record that spans several rotations, and – if new entrants are chosen carefully – potentially reinforces the efficiency of the association.

ROSCAs function as long as individuals value the benefits of membership in the association more than the benefits of defaulting, as a result, all members contribute to the fund even after they have received the total group collection. Therefore, the main defining characteristic of a performing association lies in the reduction of the risk of opportunistic behavior. The costs of default include social mechanisms that extend beyond the domain of the ROSCA into community wide sanctions such as peer pressure and social ostracism, which affect every aspect of that individual's social and economic life.

The peer monitoring, group lending, or "solidarity group" approach to credit delivery is based on the assumption that the poor represent a much lower credit risk than the formal financial sector generally assumes and that, under specific circumstances, they can be trusted to repay small uncollateralized loans, using a lending methodology that relies on traditional and personal interactions among borrowers[38]. These principles of solidarity constitute a branch of microfinance.

The most visible and studied example of group-based lending is the Grameen Bank in Bangladesh[5]. The bank was started in 1976 by Mohammad Yunus, a professor at the University of Chittagong, as a research project. By 1994, the Bank had served half of all villages in Bangladesh, with a total membership of more than 2 million, of which 94% are women. Using the group lending methodology and transparent lending decisions, the Bank has consistently reported repayment rates in excess of 95%. The main innovation of this microfinance program stems from the observation that potential customers of these programs have a comparative information over the lender, which could be mobilized to develop mutually advantageous financial services. In fact, the constitution of groups is a necessary condition to the concession of credit, as these groups are responsible for selecting the members (thereby smoothing the hidden information problem), creating mechanisms that subordinates the concession of one credit to the payment of another - "Joint-Liability", and reduce delinquency rates through an effective invisible monitoring. These adapted forms of social pressure cause the solidarity groups to necessarily assume transaction costs and responsibilities, i. e., those which were now in great part performed by the group's members. Therefore, the cost of lending on average is significantly lower, allowing it to disburse larger amounts and to reach poorer people (through riskier loans) than those of traditional banks.

Self-selection of group members is a major element of this process. The Bolivian BancoSol program[5], which relies on groups of five to seven borrowers, includes groups which previously existed as ROSCAs, contributing to their high success rates as microfinance institutions.

The Banco do Nordeste (BNB) created the CrediAmigo[47] program in 1997 to provide microcredit services to informal entrepreneurs in Northeast Brazil. It is the best consolidated program of its kind in Latin America and it uses extensively the above group-based lending principles (self-selection and "joint-liability") introduced by Grameen Bank. By the end of 2016, CrediAmigo had 2 million active clients who had received around R$ 2.8 billion (US$ 1.7 billion6) in loans, with an average value per loan of R$ 1,900.00 (US$ 1,144.58) at interest rates of between 1.7% and 2% per month, depending on the type of product. The program has run for 20 years and now operates in around 2000 of Brazil's 5570 municipalities with some 500 service outlets ("units"). From the risk management point of view, it is important to note that the CrediAmigo default rate is relatively low (around 1.9% in 2016). In 2014 the default risk rate was better: a mere 0.6%, following several years when even lower average rates were recorded.

4 Preliminary Concepts

4.1 Social Capital and Economic Outcomes

The example of the group-based lending associations and organizations in the preceding section, illustrates the intuition behind the role of social capital in economic transactions, however the term Social Capital has yet no consensus. To do this successfully, it requires an interdisciplinary approach which attempts at bridging some of the current different perspectives on social capital. Political scientists, sociologists, and anthropologists tend to approach the concept of social capital through the analysis of norms, networks, and organizations. Economists, on the other hand, tend to approach the concept through the analysis of contracts and institutions, and their impacts on the incentives for rational actors to engage in investments and transactions.

A concept of Social Capital is associated with Putnam [45, 37] who views it as a set of "horizontal associations" between people: social capital consists of social networks ('networks of civic engagement") and associated norms that have an effect on the productivity of the community. The key feature of social capital in this definition is that it facilitates coordination and cooperation for the mutual benefit of the members of the association1.

Social capital can be constructed either as an individual attribute that captures the embedded resources within the individual's social relations to generate a personal economic benefit[20], or as a group attribute that enhances group member's transactional efficacy for economic gain[9].

The social capital definition from Granovetter[19] says economic actions of individuals are determined by how the social relations between involved agents are. These social and economic relations are very much immersed in social networks, grounded by reciprocal trust either for the purpose of enabling economic transactions or more broad social relations. Ferrary[12] built on this definition, highlighting the roles of social networks and trust. Social networks, due to obligations that bond some of its members and the nature of information that they exchange, alter the economic regulation. In this context, one can define social network as a group of individuals in which the frequency of economic interactions and the density of social relations enable to reduce the uncertainty related to moral hazard, enabling discriminate precisely honest members from dishonest ones.

A first caveat of this network is that relevant information that is important to its members circulates very fast, and so well the effects on reputation, leading to information asymmetry between members (those part of the social network) and non-members.

The second is the by interacting with one member of the network, in fact, one interacts with the whole network itself. This is particularly important for the growth of the social network, the pre-existence of a trust relation with a member of the network is determinant in his/her admittance to the group.

According to Ferrary[12], there are 3 conditions of existence and strengthening of trust in an economic relation within a social network: proximity, temporality and personal nature of the relations:

- proximity primarily geographic, moreover recently communication advances are enabling virtual proximity. The key is that proximity favors a frequency and quality of the interaction between agents.

- temporality means interaction in a logic of repeated games with same players, which reduce the cost of information and enable a mutual learning between the agents. Therefore, any member who has a longstanding relation in a social network tends to be seen more trustworthy than new ones.

- personal nature of relation, this is a subtle concept, members of a social network are not necessarily only motivated to do economic relations with another member due to the economic reasons, but also due to social and psychological reasons. And sometimes these decisions have a more symbolic meaning that justifies it and strengthens the relationship rather than anything else.

Glaeser et al.[11] made a couple of experiments using "Trust Games" with Harvard undergraduates to try to measure Social Capital as an individual attribute. In these experiments they examined trust and trustworthiness relating the outcomes of the trust games with attitudinal questions (General Social Survey

– GSS) and background characteristics. They found that i) measures of past trusting behavior are better than the abstract attitudinal questions in predicting subjects' experimental choices in the trust games; ii) although questions about trusting attitudes do not predict trusting behavior, such questions do appear to predict trustworthiness; iii) the degree of social connection between the sender and recipient (the number of friends they have in common and the duration of their acquaintanceship) generally predicts the levels of trust and trustworthiness in the two-person trust game; iv) subjects who are paired with a partner of difference race or nationality send back less money to their partner; v) background characteristics capturing the level of status and organization membership (variables meant to serve as proxy for an individual's own social capital) strongly predict the amount of money that sender's receive back from recipients.

Social capital, given its informational and solidarity benefits, can ameliorate potential inefficiencies caused by information imperfection and to enhance market efficiency. A core proposition of social capital theory is that valuable resources are embedded within networks of relationship, providing collectively owned capital for their members to use as a credit[50].

Karlan[29] experimented with FINCA-Peru, a group lending organization in Peru that provides loans with joint-liability). It has found evidence that individuals with a stronger social connection to their fellow group members (i.e., either living closer or being of a similar culture) have higher repayment rates and higher savings.

More recently sites such as Facebook and LinkedIn have changed the landscape by greatly facilitating the creation and maintenance of many social relations and making them highly visible, more and more online platforms are seeking to leverage these social relations for economic activities such as lending, car sharing and rentals[32]. As individuals connected by powerful social networking tools transact with each other, it is inevitable that economic decisions are embedded in social relations. Such is the case with online peer-to-peer (P2P) lending where individual lenders collectively bid on loan request by individual borrowers in an online platform supported by social networking tools.

There are several peer-to-peer lending platforms worldwide, such as Prosper, Lending Club, Zopa, Funding Circle, Kiva, Lenddo and PPiDai. As with crowd funding platforms, P2P leverages the "wisdom of the crowd"[13, 50] by allowing multiple lenders to collectively fund a loan. P2P lending also provides online social networking functions so that lenders and borrowers can declare friendship with one another[50]. These friendships include both existing offline social relations and newly formed online groups. P2P lending platforms provide tools for members to formally recognize these social relations, together with benefits such as the ability to broadcast loan request to friends, and to receive notifications of friends' borrowing and lending activities. The ability to leverage friendship networks in borrowing/lending activities is a key difference between online P2P lending and traditional lenders such as banks.

Fredman and Jim[13] found that borrowers' friendship networks were consistently significant predictors of lending outcomes. Lin et al.[34] found that the number of friends that a borrower has and the number of friends that actually bid on a loan increase the probability of successful funding of a loan and reduce interest rates and ex post default rates.

On the other hand, Chen et al.[8] showed that social connections from group networks (groups formed online, with no previous connection offline) improves funding performance but has no impact on repayment performance.

The table 1 shows some academic papers that analyze funding and lending outcomes of P2P lending platforms using data-driven classifiers such as logistic regression. All the results are consistent with the fact that social ties in the context of P2P lending improve funding and repayment outcomes.

Sukamaningsih[42] made a throughout assessment of the academic papers in the topic of trust in peer-to-peer lending and observed that P2P lending still lack risk assessment methodologies. His paper proposed a model of trust between lender and borrower based on Elaboration likelihood Model (ELM) and literature review. This model, depicted in figure 2, categorizes trust factor for borrowers into three categories: hard information as part of central route and soft information and social capital as parts of peripheral route. Moreno et al.[3] also performed a literature review and identified 10 success factors in peer-to-peer lending, dividing them into three groups: borrower factors, platform information and lender factors. Among them, trust is one of the key factors, which is not considered in tradition banking.

Although some progress has been made in proposing a more comprehensive P2P lending model, it still very incipient the number of papers assessing specifically the trust or social capital parts and incorporating them into a credit scoring model.

Wei et al.[48], to the best of knowledge is the first paper that develop a series of models to study the impact of social tie formation and compare the accuracy of credit scores with and without network data. They did not however evaluate the performance on real data.

Tan et al.[43] claimed to be among the first paper to empirically predict repayment in P2P loans based on social networks. In their research, they used microfinance loans data together with Facebook profiles

Table 1: Seminal papers that analyze P2P lending outcomes with social networks

Year	Authors	Paper	P2P platform	Findings	Methods
2012	Haewon Yum, Byungtae Lee, Myungsin Chae	From the wisdom of crowds to my own judgment in microfinance through online peer-to-peer lending platforms	Popfunding.com (Korea)	- Lenders seek the wisdom of the crowds when information on creditworthiness of new borrowers are very limited.	Logistic Regression
2008	Seth Freedman, Ginger Zhe Jim	Do Social Networks Solve Information Problems for Peer-to-Peer Lending? Evidence from Prosper.com	Prosper.com (USA)	- Loans with friend endorsements and friend bids have fewer missed payments and yield significantly higher rates of return than other loans. - Group leader rewards motivated leaders to fund lower quality loans in order to earn their rewards.	Logistic Regression
2009	Mingfeng Lin, N.R. Prabhala, Siva Viswanathan	Social Networks as Signaling Mechanisms: Evidence from Online Peer-to-Peer Lending	Prosper.com (USA)	- The stronger the social tie, and the more verifiable and visible to lenders, the greater the probability to attract funds. - Social networking variables reduce the interest rates on funded loans; - Borrowers with strong and verifiable relationships are less likely to default.	Logistic Regression
2015	De Liu, Daniel Brass, Yong Lu, Dongyu Chen	Friendships in Online Peer-to-PeerLending: Pipes, Prisms, and Relational Herding	PPDai.com (China)	- distrust of "friend bid" by third parties, supported by view that friends of borrowers feel a social obligation to endorse or support their friends; - people are more likely to follow the "wisdom of the crowds" when those crowds include friends rather than strangers.	Logistic Regression
2015	Xiangru Chen, Lina Zhou, Difang Wan	Group social capital and lending outcomes in the financial credit market: An empirical study of online peer-to-peer lending	Prosper.com (USA)	- Group social capital generated from group networks improves funding performance but has no impact on repayment performance. - Group networks are formed in a virtual online environment where group members are anonymous and have little opportunity for a face-to-face interaction. - As opposed to friendship networks, where relationships are formed outside the online context with a real life connection.	Logistic Regression
2015	Seth Freedman, Ginger Zhe Jim	The information value of online social networks: Lessons from peer-to-peer lending	Prosper.com (USA)	- Borrowers with social ties are consistently more likely to have their loans funded and receive lower interest rates - However, most borrowers with social ties are more likely to pay late or default. - Only endorsements from friends who also contribute money to the loan themselves produce consistently better *ex post* repayment.	Logistic Regression

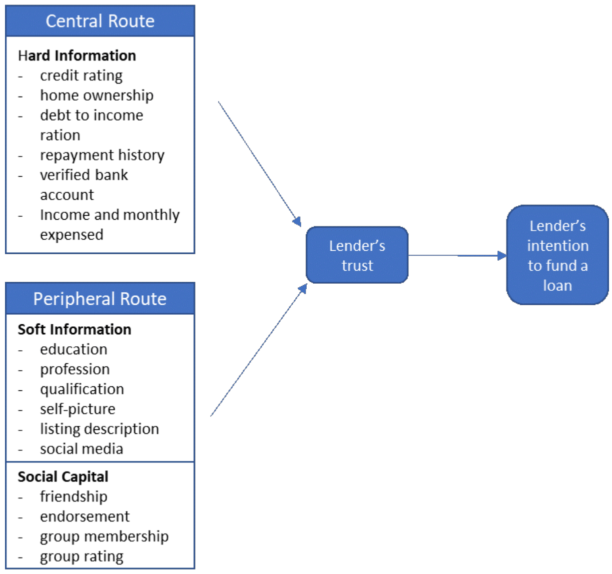


Figure 2: Proposed Trust Model for peer-to-peer lending

and full history of interactions with friends, and applied both attribute-based models and graph-based models. Overall they showed that social network based prediction alone improve the repayment by more than 18% as compared with traditional models.

Hwang et al.[23] simulated a loan funding in existing P2P platforms adding user's Facebook social information and by collecting user's response to a questionnaire. By integrating graph-based social metrics, they achieved a higher funding rate than the existing P2P lending platforms.

Gao et al.[15] obtained a dataset from a P2P lending platform that has its own embedded social network environment. In this platform, users can invite his/her friends to register whereby they interact with each other by posting comments and discussing in forums. They found evidences, by using signaling theory, that friendship network does provide significant insights in determining is/her loan success in terms of the number and also the percentage of friends with successful loan applications.

In the next section will look at other areas in computer science that have more advances in modeling economic outcomes from social networks to see what can be applied to the creditworthiness problem.

4.2 Social Capital in Computer Science

Online social networks[27] are popular tools for users, as to find new friends who share similar interests, maintain social relationships, and locate various user-generated content. The high popularity of online social networks even leads to a new computer paradigm, that is social computing. Nowadays, more and more people join online social networks for daily communications or even business activities. Many of those activities involve the process of forming opinions on a particular user or product, about whether to trust or not. Interactions among people in online social networks are rather complex, as they involve interactions with others, who may even be strangers.

The notions of trust are the central issues in online social networks. Thus, quantifying trust is a notoriously difficult problem, because of the complexity of the online social network and the trust itself. Studies in trust span multiple disciplines including economics, sociology, political science, psychology, and computer science. Meanwhile, researchers in online social networks have been conducted from multiple aspects, including network structure, user behaviors, community detection, and so on[27].

One of the most commonly accepted definitions of trust is from the sociologist Diego Gambetta[44] "... trust (or symetrically, distrust) is a particular level of subjective probability with which an agent will perform a particular action..." A trust relationship exists between two agents when one agent has an opinion about the other agent's trustworthiness and a recommendation is an opinion about the trustworthiness from a third-party agent. Reputation is defined as an "expectation about an agent's behavior based on information about or observations of his past actions". Therefore, reputation can be considered as a collective measure of trustworthiness (in the same sense of reliability) based on the referrals or ratings from members in a community.

The trust mechanisms (or trust evaluation) is a tool used to facilitate decision making in diverse applications. Trust and trust-related issues have attracted attention in various networking environments, including online social networks, wireless communication networks, multi-agent systems, and P2P networks.

Trust and reputation systems can use explicit or implicit information for decision making[44]. Example of explicit information derives from let parties generate feedback about each other after completion of a transaction and aggregating the feedback to derive a reputation score. Example of implicit information can be found in social networks such as Facebook or LinkedIn. Entities within a social network can extract some degree of trust from information gathered through friends of friends (FOF). Another implicit form of trust information is the use of topological analysis in online social networks to determine reputation[2]. In the Google search engine, reputation is determined by the number of links that point to a page, and from where the links originate.

The reputation score is then disseminated to assist others in deciding whether to trust that party in the future. Figure 3 shows a schematic flow of a trust system.

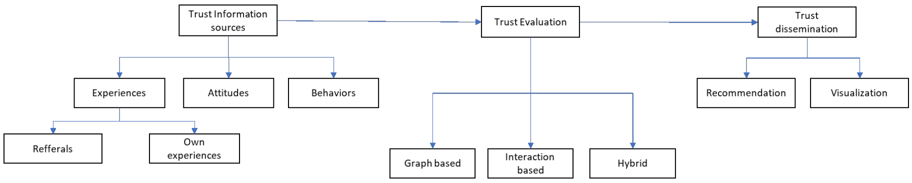


Figure 3: Trust evaluation framework

Resnick et al.[**resnick**] Further define three requirements for a reputation system:(1) to help people decide whom to trust, (2) to encourage trustworthy behavior and appropriate effort, and (3) to deter participation by those who are unskilled or dishonest. To this, we [the author of the paper] can add the requirements that a reputation system (4) must preserve anonymity associating a peer's reputation with an opaque identifier, and (5) have minimal overhead in terms of computation, storage and infrastructure.

The participation of an individual in a virtual community strongly depends on whether and how much benefit they expect to derive from their participation. If an individual feel that they will not gain anything from joining the community, they are unlikely to participate. Hence, a good reputation system must be designed such that it incentivizes cooperation by making it profitable for users to participate and withhold services that are perceived as benefits[27].

An equally serious challenge to distributed systems and virtual communities comes from users who act in a malicious fashion with the intention of disrupting the system [cheating and other examples]. Therefore, a central objective of all digital reputation schemes is to identify such users and punish them or exclude them from the community. This exclusion is usually achieved by allowing members to distinguish between trustworthy and untrustworthy members. An untrustworthy member will not be chosen for future interactions[16].

Currently, researches on trust evaluation are conducted using the tools in mathematics, statistics, or artificial intelligence. To be specific, many trust models have been proposed using fuzzy theory, subjective logic, machine learning, information entropy, game theory, graph theory, and so on. Table 2 shows some of the various trust and reputation systems that have been proposed in the literature by Sherchan et al.[41]. While this list is not exhaustive, it shows the diversity of approaches and perspectives.

Just to illustrate a few, Eigentrust[28] proposed by Kamvar et al. presented a distributed algorithm for the computation of the trust values of all peers in a network. Its algorithm is inspired by the PageRank algorithm used by Google and assumes that trust is transitive. A user weights the trust ratings it receives from other users by the trust it places in the reporting users themselves. Global trust is then computed in a distributed fashion by updating the trust vector at each peer using the trust vectors of neighboring peers. They show that trust values asymptotically approach the eigenvalue of the trust matrix, conditional on the presence of pretrusted users that are always trusted.

In PeerTrust[1], Xiong and Liu define five factors used to compute the trustworthiness of a peer: i) feedback obtained from other peers, ii) scope of feedback such as number of transactions, iii) credibility of the feedback source, iv) transaction context factor to differentiate between mission-critical and non-critical transactions and v) community context factor for addressing community-related characteristics and vulnerabilities.

TidalTrust[18], given two peers in the network, the model generates a calculation about the trust degree that one peer can put on the other, based on the trust paths. The trusted paths are explored by taking breadth-first search from the trustor to the trustee. Therefore, only the shortest strongest trusted paths are used in TidalTrust.

These approaches and many others in table 2 evaluate trust based on a graph representation model in which the peers normally value trust based on own or through other's experience of a transaction, whose

Table 2: Comparison of Existing Trust and Reputation Systems in the Literature[41]

Method	Origin Discipline	Trust Properties	Trust Computation Model	Trust Information Collection	Trust Evaluation	Trust Dissemination	Malicious Attack Resistance	Application Domains
EigenTrust Kamvar et al. (2003)	C	Pr, Sj	LN	E	G	TR	Y	P2P
PeerTrust Xiong et al. (2004)	C	Dy, Cs, Sj	LN	E	G	TR	Y	P2P
Yu et al. (2004)	C	Pr, Sj	LN	E	G	TR	Y	P2P
TidalTrust Goldbeck at al. (2005)	C	Pr, Sj	Prob.	E	G	TR	N	SN
Josang et al. (2006)	C	Dy, Pr, Sj	Prob.	BI	G	TR	N	P2P
Zhang et al. (2006)	S	Pr, Sj	LN	E	G	TR	N	SN
SUNNY Kuter et al. (2007)	C	Sj	BN	B	G	-	N	SN
Maheswaran et al. (2007)	C	Pr, Cs, Sj	LN	E	G	TR	N	SN
PowerTrust Zhou et al. (2007)	C	Pr, Sj	BN	E	N	-	Y	P2P, SN
Caverlee et al. (2008)	S	Dy	LN	B, E	G	TR	Y	P2P, SN
Liu et al. (2008)	C	Dy	Binary Classification	B	I	-	N	SN, e-commerce
Paradesi et al. (2009/2009)	C	Cp	BN	E	-	-	N	WS
Yan et al. (2009)	C	Sj	LN	B	-	-	N	MA
Zuo et al. (2009)	C	Pr, Cp	LN	TC	G	-	N	SN
Adali et al. (2010)	S	-	Log	B	G	-	N	SN
Nepal et al. (2010)	S	Es	Prob.	B	-	-	N	WS, SN
Trifunovic et al. (2010)	S	Pr, Sj	LN	B, E	H	-	Y	SN
Nepal et al. (2011)	S	Sj, Dy, Cs	LN	B	I	-	N	SN

Origin Discipline	Trust Properties	Trust Computation Model	Trust Information Collection
P: Psychology S: Sociology C: Computer Science	Cs: Context-specific, Dy: Dynamic, Pr: Propagative, Cp: Composable, Sj: Subjective, Es: Event Sensitive	Log: Logarithmic, Prob: Probabilistic, BN: Bayesian Networks, LN: Linear Model (sum or product)	B: Behavior E: Experience, BI: Belief, TC: Trust Certificate

Trust Evaluation	Trust Dissemination	Attack Resistance	Application Domains
G: Graph-based, I: Interaction-based, H: Hybrid, -: Not specified	TR: Trust-based Recommendation, VZ: Visualisation, -: Not specified	Y: Malicious attack considered, N: Malicious attacks not considered	P2P: Peer-to-peer networks, SN: Social Networks, WS: Web Services, MA: Mobile Applications

values can be propagated to other peers according to some decay mathematical model. In the context of e-commerce (opinions review) in sites such as Yelp (figure 4), the transaction could be a real experience of a product or service from one peer to the other, in where the buyer evaluates the final outcome using a review score and also can write recommendations or endorsements, raising or lowering the reputation of the vendor. This reputation is in turn propagated to other peers who may never made a transaction with that vendor before, but through this mechanism they may feel confident to trust the vendor in a possible future transaction.

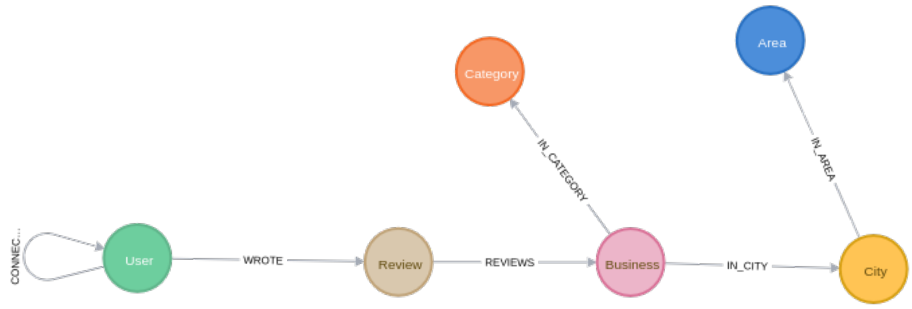


Figure 4: Schema of a typical review social network of Yelp.com

Regret[39] expands the sources coming from i) direct interactions and ii) propagation of experiences from other peers (witnesses) to a third component: information obtained from the analysis of their social network and its topology. The Regret takes a subset of the selected sociogram over the peers that had had interactions with the target peer as the initial graph and apply the following heuristic: identify strongly connected components, find the set of cut-points for each component. The cut-point indicates some kind of local centrality, because if they are eliminated the graph is subdivided in other components. For each component that does not have cut-points, the model chooses the node with the larger degree. The aggregation of these selected peers composes the witness reputation, which took the social relations into account.

In fact, social network analysis can be used to infer about the target peer by some properties that it exhibits in the network. Peers who are well-known and highly regarded by other members of the community tend to be easily identified as highly connected node in the social network graph. As eluded in the previous paragraph, centralities metrics can be used to address trust and reputation models, as these measures provide an indication of a node's position relative to the other nodes in an ego network graph[26, 33, 10, 35, 40, 14, 36]. Isherwood et al[24] mention three centrality measures as examples:

- Degree centrality identifies popular and well-connected nodes in the social graph. A node with the higher degree may be trusted more, based on the number of connections and the strength of relationship;
- Density centrality is used to ensure that group leaders are chosen more accurately. Dense groups have members that constantly collaborate and work together to enhance their businesses and those of their groups and therefore the ecosystem;
- Betweenness centrality identifies nodes in the network that are in central positions that control information flow and are therefore influential.

This kind of information can be used as a basis for reputation mechanisms instead or complementarily of having to resort to explicit rating issued by every peer[36].

5 Methodology of the Research

In the preceding sections, it was introduced the problem of financial exclusion of poor people in the traditional scoring systems. Moreover, it was introduced the idea of using social capital to overcome this problem, and in fact, it was shown that the idea is not new, many communities around the World have been using informal ways of microfinance during long time. ROSCAs have its origins in Tanomoshi-Kou in Japan, much before the existence of formal banks. Grameen Bank is another example of how social mechanisms such as "joint-liability" use the social monitoring to reduce incentives to moral hazard, and thus contribute to the higher repayment rates of loans.

Social Capital is a multidisciplinary concept and have been studied in the beginning mainly from a sociological and economical perspective. In both areas, the concept of Trust and Trustworthiness have emerged as a proxy to measure Social Capital through trust games and attitudinal questions.

More recently, with the emergence of online social networks, Social Capital started to be studied from a computer science perspective. Social networks can be well represented by a graph data structure, in which people are nodes and relationships are vertexes, therefore opening a wide array of metrics, algorithms and machine learning models.

A new subset of specialization in computer science was then created known as Trust or Reputation Systems to tackle the problem of identify trustworthy nodes in several areas: P2P networks, e-commerce, opinion reviews and social networks. Many models have been proposed so far, but there is no unique approach. Trust systems in general lack robustness to deal with malicious nodes and other problems such sparsity of the network and cold start. Some papers proposed successfully the use of social network analysis using graph theory as both alternative or complement to a reputation system and they showed evidences of improvements of the robustness of the models.

With the emergence of online P2P lending platforms, many researchers managed to positively correlate how friendships affect overall funding outcomes and subsequent loan performance. However, there are very few papers proposing models used for credit scoring, and most of them present a theoretical framework. A plausible hypothesis is the difficulty to find a suitable database that contains social network data and loan data (funding and repayment).

In this context, a proposed methodology to this dissertation is:

1. Brief historical introduction of informal group lending arrangements and micro-finance, verifying what role social connections play[38] in providing efficiencies. We will be based on previous studies of the Graamen Bank case and other informal arrangements such as Rotating Savings and Credit Associations[25, 21, 6], to verify how information asymmetry and incentives to moral hazard are lowered. In addition, we will research the definitions and methods of measurement of Social Capital[45, 11, 30, 29], from a multidisciplinar point of view: social sciences, economics and computer science.

2. Big emphasis on the computer science methods in the literature for measuring Social Capital and Trust. Two areas in particular:

    – Reputation and Trust Management in on-line systems[22, 46]. This area has been receiving increasing attention recently as on-line interactions between people and services that have no prior real-world relationships are becoming common. Examples of interactive online sites include Social Networks, and modern paradigms such as file-to-file sharing and the social cloud. All these interactions can be considered to include an element of reputation, such as post-comments in forums, competencies in crowdsourcing and social linkages and endorsements in social networks and the social cloud. The aim of reputation systems is therefore to support the trust between unfamiliar parties. For that, a series of models and algorithms have been proposed [16] for example EigenTrust[28], PeerTrust[1], ROCQ[17], SocialTrust[7], among others.

    – Social Network Analysis using graph theory algorithms [33, 10, 35, 40, 14, 2] which provides insights such as social influence, strong and weak ties, on the basis on the topology of the network. These concepts and techniques are instrumental for the development of graph-based Trust models[27, 36] such as Regret[39].

3. Survey some papers that place Social Capital into Credit Scoring context and what have been achieved so far[13, 8, 48, 43, 23, 15, 31]. Relate and contrast with the usage of some methods discussed in item 2.

4. On the basis of the elements extracted from items 2 and 3, suggest a theoretical background and practical framework with data collection, methods and tools to analyze empirically one's social network and predict his or her creditworthiness. We will try to illustrate such usability by using available social network dataset from Yelp.com[49] and microfinance research[4] to evaluate, critique and suggest further improvements.

As pointed out above, for testing the proposed model, the plan is to use the two following public databases:

– Yelp (yelp.com) is a platform that help people find great local businesses like dentists, hair stylists, mechanics, etc. Other users that have experienced some of these services, write reviews, that can be accessed by anyone. In addition, one can verify if a reviewer is part of his/her social

Table 3: Fact Sheet - Yelp database

Types of Nodes	Quantity
Persons	1.637.138
Businesses	192.609
Reviews	6.685.900
Category	1.300
City	1.203
Area	36
Total	**8.518.186**

Types of relationships	Quantity
Person connected to person	7.392.271
Person write reviews	6.685.900
Review of a business	6.685.900
Business in category	787.059
Business in City	191.405
City in Area	1.258
Total	**21.743.793**

network, so it may increase the effect of the recommendation based on the trust/reputation. Yelp make the database available to researchers and students and promote a yearly challenge (https://www.yelp.com/dataset/challenge)[49] to incentivize people to share their discoveries.

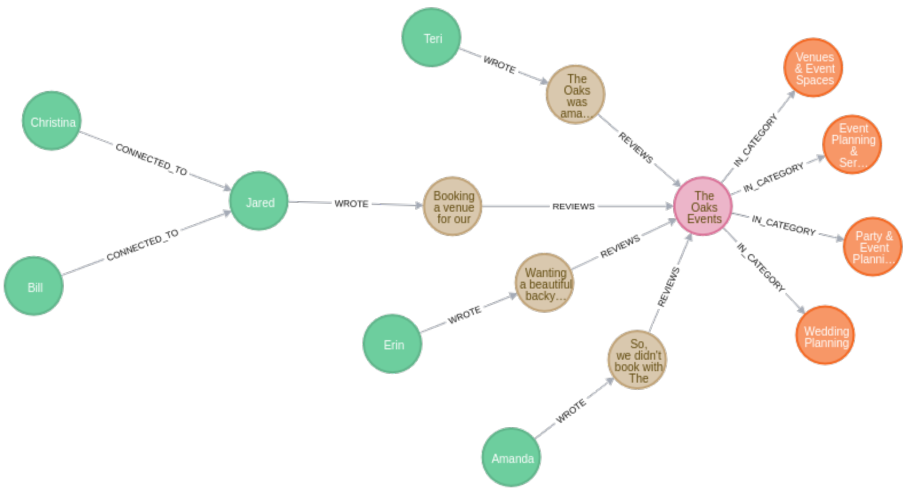


Figure 5: Example of Yelp.com

In figure 5, it is possible to visualize users writing reviews of a business as well as identify other users connected to reviewers.

This database, whose elements are listed in table 3, can provide opportunities to measure direct transactions rated by users who lived the experience of a service, and test models to observe how the aggregate result of several reviews can be propagated over the network. Typical questions can be investigated such as what elements (network topology, quantity of reviews, credibility of the reviewers) do contribute for the robustness of the measurements, i.e. is perceived by a third party as a trustworthy review; what is the effect on the credibility of a review when reviewers are part of one's network as compared when reviewer is a friend of a friend, etc.

– Social Networks and Microfinance Database, from the paper "The Diffusion of Microfinance" By Abhijit Banerjee, Arun G. Chandrasekhar, Esther Duflo and Matthew Jackson[4]. This project contains data from a survey of social networks in 75 villages in rural southern Karnataka, a state in India. A census of households was conducted, and a subset of individuals was asked detailed questions about the relationships they had with others in the village. This information was used to create network graphs for each village. About half of households received detailed surveys in which individuals were asked to list the names of people with whom they shared a certain relationship. Households were randomly sampled and stratified by religion and geographic sub-region. For each variable, an individual matrix and a household matrix were constructed. A relationship between households exists if any household members indicated a relationship with members from the other household. These questions were asked in the individual survey. Individuals were asked who they:

  – borrow money from
  – give advice to
  – borrow kerosene or rice from
  – lend or kerosene or rice to

- lend money to
- obtain medical advice from
- engage socially with
- are related to
- go to temple with
- invite to one's home
- visit in another's home

The above relationships seem to be good indicative of how much trust one person consider from others, therefore, it is expected to be a good place to test proxies for measuring Social Capital.

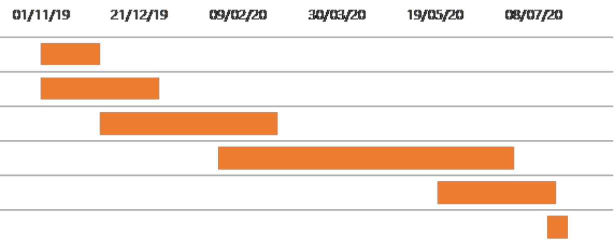
6 Expected Results

The expectation of the research is to narrow down to one or two models, starting from the literature presented previously and by testing them in the two public databases: Yelp and Indian Villages, and produce a ranking of nodes(individuals) that are to be considered trustworthy. In this manner it may be possible to evaluate the effectiveness and weaknesses of proposed models, indicating areas of improvement in the algorithm and in the data collection. Lastly but no least, produce a critical analysis of these methods based on the problem at hand which is to evaluate the creditworthiness on an individual, to decide whether one should lend money to him or her.

7 Working Plan - Chronogram

The below, show the milestones and deliverables in each of the phases:

Item	Initial Date	Duration	Conclusion Date
Phase I: Historical Introduction	01/11/19	30	01/12/19
Phase II: Review on Trust Systems and SNA	01/11/19	60	31/12/19
Phase III: Review on social capital and credit	01/12/19	90	29/02/20
Phase IV: Evaluation, conclusions	30/01/20	150	28/06/20
Phase V: Preparation for Dissertation	20/05/20	60	15/07/20
Dissertation	15/07/20	10	25/07/20



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