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Helping a Microfinance Institution Select its Clients: A Risk Analysis using Social Networks

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Introduction and Motivation

Determining credit worthiness in a developed society can be accomplished without great effort using an individual's credit history based on their previous financial transactions with formal banking institutions. However, in less developed societies where there is an absence of formal financial institutions, this becomes difficult. This is because of a variety of factors. Firstly, the absence of formal banking institutions leads to a lack of financial records and data regarding an individual's financial transactions. Secondly, poverty, which is common in these societies, implies the absence of assets that can be valued as collateral for formal loans. Therefore, informal financial institutions that serve these societies depend on alternative measures of determining credit worthiness of a borrower.

In traditional individual based microfinance, an eligible borrower is selected by a microfinance institution (MFI) on the recommendation of a local agent. The MFI agent judges the "credit worthiness" of an individual based on the opinions of the local community about the person and a subjective evaluation of the individual's ability to repay a loan. Thus, the eligibility of a potential borrower to receive a loan depends entirely on the judgement of the agent. However, this may be problematic as the agent's judgement might be heavily influenced by his/her personal biases, prejudices and background. This skews the MFI's valuation of the risk associated with lending to its clients. For example, this might lead the MFI to lend money to a person who, based on the agent's personal judgement, is considered "credit worthy" but actually has a high probability of defaulting. On the other hand, the MFI may also lose out on an opportunity to invest in a person who is considered to be "risky" but actually has a very low probability of defaulting. In this paper, we address this problem through the use of social networks. A social network is a network or pattern of social interactions or personal relationships which connect people. It consists of nodes, representing entities, and edges, representing the relationship or ties between those entities. Microfinance is the ideal example of a program that uses social capital in such a way that it mobilizes the social network to alleviate poverty [6]. The importance of the social network in modeling the diffusion of microfinance in a community has been documented in Banerjee, et al (2013) [2]. Therefore, it is natural to use social network analysis to aid us in formulating a mechanism for the MFI to determine the risk associated with a potential borrower. The contribution of this paper would be to use social networks to analyze the different characteristics of the loan portfolio. In this paper we deal only with credit risk, but it opens up a path to analyze other key characteristics of microfinance.

Therefore, there is a need for an objective model based on social network theory that can be used by MFIs globally to accurately assess the credit worthiness of a potential borrower in a community. This would provide the MFI with an objective method of screening potential borrowers that would depend minimally on judgment of the agent. The goal of this paper is to formulate an effective simplistic mathematical model that generates the credit worthiness of a potential MFI client based on his/her position in the social network in their community and their individual financial characteristics. Some of the financial characteristics we will be dealing with in this model include ownership of tangible assets, monthly per capita income and the risk associated with the proposed investment.

The Model

As stated in Section 1, our goal is to measure credit risk in an environment where conventional means fail. In order to create our model, we first describe the setting where this model is being implemented and the assumptions of the model before proceeding to set up the model. A community in this model is defined as a collection of n households which are situated in geographical proximity to each other which constitutes an administrative unit such as a village. This community is part of a less developed society with no formal financial institutions. The members of the community are poor and hence, do not own any tangible assets that can be sufficiently valued as a collateral for getting a loan. There is only one informal financial institution in the form of an MFI operating in the community. There is no information about the credit history of the individuals of the community. The MFI provides loans to only one individual per household. The MFI provides subsequent loans to households only after repayment of the previous loan. Thus, there is an incentive for the household to repay the loan.

Assumptions

- (A1) The MFI's decision to lend to an individual depends on the following factors:
- (A1.1) The level of trust of other community members regarding the potential borrower.
 - (A1.2) The monthly income per capita of the potential borrower's household.
 - (A1.3) The nature of the investment that the potential borrower wishes to use the loan for.
 - (A1.4) Ownership of transferable assets such as precious metals, which is not sufficient to be used as collateral in a formal financial institution.

- (A2) A relationship of trust between two households is mutual. For example, if household X trusts household Y, then it is assumed that household Y trusts household X.
- (A3) The more trusted a household is in the community, the higher the household's credit worthiness.

Role of Social Networks

A *network* is a collection of nodes, some of which are connected by edges. In a social network, a node represents an entity and an edge represents the ties between those entities. In this model, we construct a *social network* based on the trust that community members have for other households in the community. Let n denote the number of households in the community. Each household is represented by a node, N_i , for $1 \leq i \leq n$. An edge, $E_{i,j}$, connecting nodes N_i and N_j , with $i \neq j$, represents trust between households i and j . An edge is present between two households if the two households reveal that they trust each other. In light of (A2), the trust relation is symmetric and thus the network constructed here is *undirected*, i.e. household i trusts household j if and only if household j trusts household i .

The level of trust that a household enjoys in the community is increased by having trust relationships with other households that are themselves highly trusted in the network. This gives each household i a "trust score" T_i , proportional to the sum of the trust scores of the households to which it has a trust connection. This measure is more reliable than just measuring the number of people who have trust connections with a household (known as degree centrality). Here, we use the concept of eigenvector centrality. This is a measure of how central a node is in a network. This concept is used in network theory to measure influence and impact [5]. This measure was proposed by Bonacich [3] in 1987 as a measure of power [3].

In order to determine the trust score of the households using the above mentioned mechanism, we make some initial guess about the trust score T_i of each node (household) i . For instance, we could start off by setting $T_i = 1$ for all i . Obviously this is not a useful measure, but we can use it to calculate a better one T'_i , which we define to be the sum of the trust scores of i 's neighbors. Thus

$$T'_i = \sum_j a_{i,j} T_j,$$

where a_{ij} is the i, j th element of the adjacency matrix A of the trust network. The adjacency matrix is a matrix with rows and columns labeled by graph vertices, with a 1 or 0 in position (v_i, v_j) according to whether v_i and v_j are adjacent or not.

For a simple unidirected graph with no self-loops such as this trust network, the adjacency matrix has 0's on the diagonal and is symmetric. We can also write this expression in matrix notation as

$$\vec{T}' = A\vec{T},$$

where \vec{T} is the column vector with elements T_i . Repeating this process t times to make better estimates, we have a vector of trust scores $\vec{T}(t)$ given by

$$\vec{T}(t) = A^t \vec{T}'.$$

Now we write \vec{T}' as a linear combination of the eigenvectors \vec{v}_i of the adjacency matrix, thus:

$$\vec{T}' = \sum_i c_i \vec{v}_i,$$

for some appropriate choice of constants c_i . Then

$$\vec{T}(t) = A^t \sum_i c_i \vec{v}_i = \sum_i c_i \lambda_i^t \vec{v}_i.$$

In order to normalize the relation with respect to the largest eigenvalue λ_1 (also called the *spectral radius* of A),

$$\vec{T}(t) = \lambda_1^t \sum_i c_i \left(\frac{\lambda_i}{\lambda_1} \right)^t \vec{v}_i,$$

where λ_i are the eigenvalues of A , which are all smaller than λ_1 . By Perron's Theorem, a real square matrix with non-negative entries has a unique largest real eigenvalue and that the corresponding eigenvector has strictly non-negative components [4]. This holds true in this case as the adjacency matrix is a real square matrix with non-negative entries. Since $\lambda_i/\lambda_1 < 1$ for all $i \neq 1$, all terms in the sum, other than the first, decay exponentially as t becomes large. Therefore, the limit $t \rightarrow \infty$ we get $\vec{T}(t) \rightarrow c_1 \lambda_1^t \vec{v}_1$. In other words, the limiting vector of trust scores is simply proportional to the leading eigenvector of the adjacency matrix. Equivalently we could say that the trust score vector \vec{T} satisfies

$$A\vec{T} = \lambda_1 \vec{T}.$$

This can be re-written as

$$\vec{T} = \frac{1}{\lambda_1} A\vec{T}.$$

Rearranging, we get

$$(A - \lambda_1 I)\vec{T} = 0, \quad (1)$$

where I is the $n \times n$ identity matrix. Thus we see that \vec{T} is an eigenvector for the eigenvalue λ_1 . By the properties of eigenvectors and eigenvalues, we know

$$\det(A - \lambda_1 I) = 0.$$

Therefore, equation (1) has infinitely many solutions. We can find a particular solution in this case by setting the free variable equal to 1 (we know that there is only one free variable because the algebraic multiplicity is 1).

In order to illustrate this, let us consider a small hypothetical network with the given trust relationships.

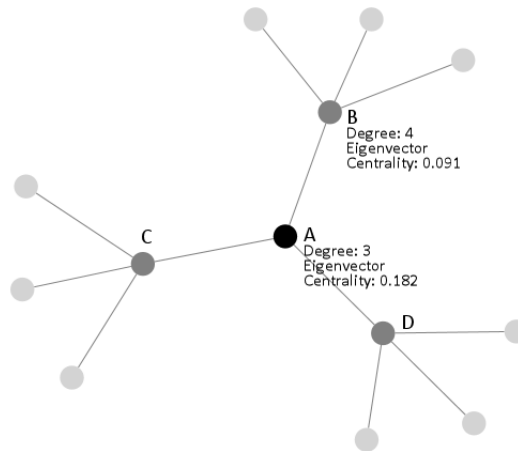


Figure 1: A simple network with eigenvector centrality, taken from <http://www.umasocialmedia.com/socialnetworks/glossary/eigenvector-centrality/>.

In Figure 1, degree refers to the number of nodes a particular node is connected to, which is also referred to as the “degree centrality”. The eigenvector centrality in this example represents the “trust score” of each household. As demonstrated above, being trusted by a large number of households (degree centrality) is not the same as being trusted by households that are themselves trusted (eigenvector centrality). In the above example, household B is connected

to more households than household A, but household A has a higher trust score as it is connected to other trusted households C and D.

Role of individual financial characteristics

Besides the role of the trust that other community members have in a particular household, the household's financial characteristics play a significant role in determining its credit worthiness. Specifically, the monthly income of the household, the value of transferable assets owned by the household and the nature of the proposed investment of the loan are considered as vital determinants of credit worthiness in our model.

The monthly income per capita of the household is said to affect the credit worthiness of the household in this model. A high monthly income per capita can be correlated with the availability of funds to overcome financial shocks, which would ensure a lesser probability of default on the loan. We use the per capita income and not the total household income in order to account for the number of dependents per household.

The value of the transferable assets that the household owns is also a key determinant of the credit worthiness of the household. The ownership of these assets (which are not sufficient to be used as collateral) can be a source of emergency funds in times of financial shocks. Therefore, the household can use these assets to repay a loan, thus reducing the chances of default.

Finally, the nature of the proposed investment that the loan would be used for plays a pivotal role in deterring credit worthiness. Specifically, the risk factor involved with such an investment is key to our calculation. The risk of the potential business/investment varies from one geographical region to another and is determined by the resources available at hand and the demand in the market for the particular service or product proposed. For example, investment in an agricultural business would be considered a risky venture in an area that is characterized by infertile soil, but may be the safest investment in an area which is highly irrigated.

The individual financial characteristics can be aggregated with the variable β_i which is represented as

$$\beta_i = f(M_i, A_i, R_i),$$

where M_i is the monthly per capita income of household i , A_i is the value of the transferable assets of the household i , and R_i is the measure of how risky the proposed investment of the household i is.

The exact functional form of β cannot be determined presently; the range of

β_i is $[0, 1]$ in order to ensure a balanced measure of credit risk. It would require an MFI to collect data regarding these characteristics and find a relation between these characteristics and repayment rates.

The model for credit-worthiness

Our model incorporates the trust level of a household in a social network with the financial characteristics of an individual household to predict the credit worthiness of a potential borrower. Incorporating the financial characteristics into the trust score provides each household (node) in the network with a specific credit-worthiness score. It provides a small amount of centrality for free to each node, regardless of its position in the network or the centrality of its neighbors. This can be formulated in the form of a Katz centrality approach, where the β_i is added to the trust score T_i for each node [5]. Therefore, the credit worthiness can be represented as

$$C_i = T_i + \beta_i,$$

where T_i stands for the trust level of the household in the social network and β_i stands for the individual financial characteristics of the household.

Limitations

We derive this model based on our understanding of the current Grameen Bank model of individual-based microfinance [7]. This might not be an accurate approach that can be reciprocated in all parts of the globe.

This model requires households to reveal their trust networks, which may not be very easy to obtain. In certain cases, it might not be feasible and against the rights of clients to reveal their trust networks to MFIs. However, this is an empirical question which can be dealt with in innovative ways of questioning.

Moreover, this model assumes a very idealistic model of microfinance where there is only one MFI in the community and it lends only to the extremely poor in the community. Relaxing these assumptions might have effects that may not follow from this model and these can be the basis for further research.

Conclusion

This model can be utilized by MFI's in less developed countries around the world to check the eligibility of a potential borrower without relying on the judgement of an agent. This eliminates the source of human error in evaluating the risk associated with lending. This model would also help an MFI cut administrative costs that it would have to incur to employ an agent to evaluate the

eligibility of potential borrowers.

This model also seeks to address the problem of high interest rates, which is one of the key issues that plague microfinance globally. Using this model, it will be possible for MFIs to accurately judge the risk potential associated with the borrowers. This will allow them to charge an interest rate that is proportionate to an individual's risk potential, thus eliminating high interest rates which impoverish poor families and leave out safe borrower households from the MFI's client pool [1].

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