TRUSTRANK — A TRUST MANAGEMENT SYSTEM FOR NON-CENTRALIZED ONLINE COMMUNITIES

ICS 691 FINAL PROJECT

MAY 2011

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1 Introduction

Electronic commerce and collaborative information repositories are becoming more and more popular. These online services provide their users great convenience in their daily lives. One advantage of these systems is the level of freedom they support regarding user actions. Participants can easily express their opinions, change their profiles, and etc. This advantage, however, makes it difficult for people to trust others when it comes to monetary exchanges since information can easily be forged. Therefore, trust management becomes an important issue because without some form of trust management, these online services would face the difficulty of defending their level of legitimacy and honesty. [1, 2, 3]

1.1 System-Imposed Trust Mechanism

We have many examples of well-established trust mechanisms. In some sense this problem is already solved. A couple of such examples are, Apple's itune store, Amazon.com, as well as online services provided by other large merchandise vendors. Users in general trust these services because of the reputation of their hosts.

Once in a while, these companies experience prestige crisis as well. For example, Sony PlayStation Network (PSN) made the headline news last week. 70 million Sony PSN users' profile together with their credit card information were illegally accessed. This posted Sony a great threat in the consumer trust. [4]

1.2 User-Imposed Trust Mechanism

On the other hand, there are many popular OCs that are not backed up by any well-established hosts. How could their users benefit from the OC while avoiding having to judge others when involved in monetary exchanges? The current situation is to let the OC users enforce rules and regulations. It would, however, not be practical to completely push to the users the responsibility of ranking their potential business partners with respect to how trustworthy they are. The only outcome of this approach is to reduce the popularity of handling monetary transactions on these OCs.

1.3 Proposed Trust Management System

In this paper, we propose a trust mechanism, TrustRank, to OCs that are not centrally managed. TrustRank takes into account of the entire interaction network among OC users, and it assigns a TrustRank score to each user based all direct and indirect interactions he has had with others. TrustRank computes and maintains TrustRank scores for all users. A TrustRank score is then used as a judgment measure of how trustworthy this user is.

TrustRank features in a minimal change in user experience comparing to what is already in place. Currently, users have multiple approaches to judge "strangers", e.g., based on their activity history, comments from others, and etc. All these mechanisms still apply. TrustRank provides the OC user another reference, which is systematic, objective, and extremely difficult to forge.

2 Related Work

In this section, we will work with an example OC that is heavily user-driven. This OC is not backed up by any well-established host, and its current trust management takes place entirely on the user end. We will first demonstrate the already-existing trust mechanisms, which are imposed by the OC users and developed over years. After pointing out the problems with such a trust management system, we will introduce TrustRank. We will go first through a brief system overview and then explain the the algorithm with its mathematical model. As the discussion of the algorithm proceeds, we will demonstrate the TrustRank system with a working example on an small OC network.

2.1 Choice of OC

For this study, I chose the mitbbs.com/exchange forum. Mitbbs.com, is a Chinese bulletin board system site. The majority of its users are overseas Chinese. The focus of this particular forum, mitbbs.com/exchange, is to provide a platform where its users buy, sell, and exchange a broad variety of goods. Since money is involved, trust is an important factor that affect people's activities on this OC.

2.2 Current Trust Mechanisms

The host, mitbbs.com, is not assumed to be a trusted third party. Anybody can participate in the discussion and hence can participate in the exchange activities. Mitbbs.com is not involved in the trust model. This is a fundamental difference from sites like Amazon.com. For instance, assume a person, U, purchased something from a seller at Amazon.com, and the product did not match with the its description. This transaction, hence, involves cheating or even commercial fraud. U can not only rate negatively of this seller, U can also report this seller to Amazon.com, which has the responsibility to maintain its business environment. U could demand his money back and Amazon.com will assist U to do so. Mitbbs.com, however, is not involved in any user activities, and it is not responsible for any fraud transactions. It does not provide a uniform rating mechanism as Amazon.com.

As a thriving forum, however, mitbbs.com/exchange has been serving its purpose for a long time, and hence it should have some kind of trust management in place. In our empirical study, it is not difficult to discover that the trust management lays implicitly in the contents of user participation. We will discuss these mechanisms in three categories, user reports, aggregated reports, and activity history research.

2.2.1 User Reports

In this trust mechanism, people post threads to report particular sellers. Usually, only extremal good and bad transactions would be mentioned since the buyers have to go out of his way to create these threads. Other users refer to these threads and adjust the implicit trust credits of particular sellers.

2.2.2 Aggregated Reports

This trust mechanism is built on top of the first one. Once in a while, some OC participants would summarize reported sellers and post a overall list of sellers to avoid. These threads are usually promoted to the first page of the forum and stay there for a reasonably long time.

2.2.3 Activity History Research

In this mechanism, the forum provides a searching tool. When it comes time to purchase goods, the buyer could conveniently search for this seller and evaluate his implicit trust credit from his previous activities. If a user is an experienced “exchanger” and has “happy” conversations with others, then this user is tend to be trusted

2.2.4 Problems With The Current Trust Mechanism

Apparently, the aforementioned trust mechanisms work, at least to some extent. They have brought the OC where it currently is. There, however, many obvious problems. Firstly, these mechanisms are not systematic and they would oversight good or bad individuals easily. Secondly, the accuracy of user contributed information is not guaranteed since the host does not work as trusted certification source as we discussed. One or two inaccurate comments would easily pose false impression of a particular individual.

2.3 TrustRank System

In this paper, we propose a trust management system, TrustRank, to OCs that are not centrally maintained. TrustRank takes into account of the entire interaction network among OC users, and it assigns a TrustRank score to each user based all direct and indirect interactions he has had with others. TrustRank features in a minimal change in user experience comparing to what is already in place. TrustRank computes and maintains TrustRank scores for all users. A TrustRank score is then used as a judgment measure of how trustworthy a user is.

2.3.1 System Overview

TrustRank imposes the system to keep a record for each user, U_i, of his outgoing transactions. Each entry of this record contains a score and another user, U_j, which is the seller involved in transactions with U_i . This score starts at zero. It increases by one when the seller is considered trustworthy in this transaction, and decrease by one otherwise.

Shown below is an example of the transaction records for a small OC network with six OC users. Every user keeps a record of transactions with other users. For example, U_1 has positive records for U_2, U_4, a negative a record for U_6, and a neutral record for U_3, U_5.

$$
\text{Record for } U_1 : \boxed{\begin{array}{ll} U_2 & 2 \\ U_3 & 0 \\ U_4 & 3 \\ U_5 & 0 \\ U_6 & -1 \end{array}}
\quad
\text{Record for } U_2 : \boxed{\begin{array}{ll} U_1 & -1 \\ U_3 & -4 \\ U_4 & 3 \\ U_5 & 1 \\ U_6 & 2 \end{array}}
\quad
\text{Record for } U_3 : \boxed{\begin{array}{ll} U_1 & 0 \\ U_2 & -1 \\ U_4 & 3 \\ U_5 & 4 \\ U_6 & 0 \end{array}}
$$

$$
\text{Record for } U_4 : \boxed{\begin{array}{ll} U_1 & 0 \\ U_2 & 3 \\ U_3 & 0 \\ U_5 & -2 \\ U_6 & 0 \end{array}}
\quad
\text{Record for } U_5 : \boxed{\begin{array}{ll} U_1 & 0 \\ U_2 & 2 \\ U_3 & -3 \\ U_4 & 0 \\ U_6 & 6 \end{array}}
\quad
\text{Record for } U_6 : \boxed{\begin{array}{ll} U_1 & 4 \\ U_2 & -3 \\ U_3 & 3 \\ U_4 & 0 \\ U_5 & 2 \end{array}}.
$$

Figure 1: Transaction Records Example

The system then aggregates this data from all of the users and compute a TrustRank score, a numeric value, for each user. The transaction record for each user changes continuously as more transactions are conducted, hence, the system constantly executes the TrustRank algorithm and updates the scores for all users. The TrustRank score can be published as part of the personal profile of a particular user. It could also be considered private and made available only to the individuals that need to have monetary transactions with this user.

2.3.2 The Mathematical Model

TrustRank system uses the TrustRank algorithm to aggregate the transaction records and compute the TrustRank scores. This algorithm is not the first of its kind. Similar algorithms and applications have successfully been applied in different areas. Let's take a look at two example. In academics, academic literature counts citations or back links to a given paper. This gives some approximation of a paper's importance or quality. In industry, Google's PageRank extends this idea to the web. Google bases the importance of a page A on the number of links from other pages T_i that point to A. Furthermore, this importance is normalized by the total number of links on each page T_i. [5] In fact, Google's PageRank inspired me to give my system the name TrustRank.

2.3.2.1 Graph Representation

Through out the rest of the paper, we will use simple direct graphs to model the OC networks. Vertices represent OC users. Edges represent transaction record entries. The outgoing edges from one vertex indicate this OC user's full set of transaction records. An example is shown below. We will first show the transaction records for this exmaple network scenario.

OC User	***Transaction Record Description (Incoming only)***
Tom	from Bob two times, all bad, $w_{TB} = -2$; from Jim three times, all good, $w_{TJ} = 3$
Jim	from Ema six times, five times good, once bad, $w_{JE} = 5 + (-1) = 4$
Ema	N/A
Bob	from Ema two times, all good, $w_{BE} = 2$, from Lyn once, bad $w_{BL} = -1$
Lyn	from Jim two times, all good, $w_{LJ} = 2$; from Bob once, bad, $w_{LB} = -1$

$$\text{Record for } Tom : \boxed{\begin{array}{cc} Jim & 3 \\ Ema & 0 \\ Bob & -2 \\ Lyn & 0 \end{array}} \quad \text{Record for } Jim : \boxed{\begin{array}{cc} Tom & 0 \\ Ema & 4 \\ Bob & 0 \\ Lyn & 0 \end{array}} \quad \text{Record for } Ema : \boxed{\begin{array}{cc} Tom & 0 \\ Jim & 0 \\ Bob & 0 \\ Lyn & 0 \end{array}}$$

$$\text{Record for } Bob : \boxed{\begin{array}{cc} Tom & 0 \\ Jim & 0 \\ Ema & 2 \\ Lyn & -1 \end{array}} \quad \text{Record for } Lyn : \boxed{\begin{array}{cc} Tom & 0 \\ Jim & 2 \\ Ema & 1 \\ Bob & -1 \end{array}}.$$

Figure 2: Transaction Scenario Example

The graph representation is demonstrated below. Note that in this example, we didn't draw the edges that have zero weight since they do not affect the computation. In other words, alternatively, we can think of this graph as a fully connected graph but it has some zero weighted edges.

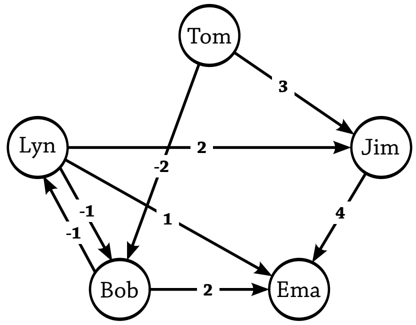

Figure 3: OC Network Example

We would not consider multigraph. This is determined by the nature of our application. It does not make sense for one user to have multiple different transaction records for another user, so multigraph is not our concern.

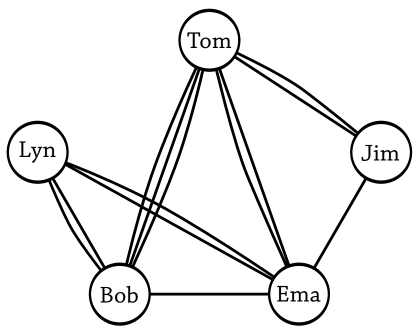

Figure 4: Multigraph Example (not applicable for this application)

We would not consider reflexivity on the OC network graphs. A user does not have to keep a record for himself. Even if he does, to others, this information does not hold any weight. So reflexivity is not our concern either.

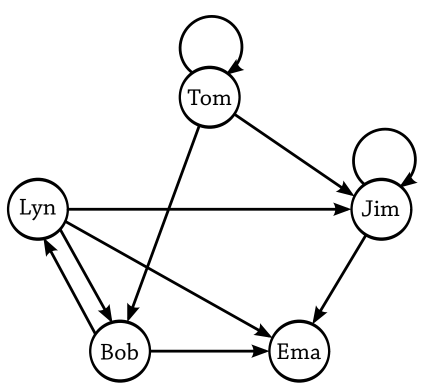

Figure 5: Graph with Reflexivity Example (not applicable for this application)

2.3.2.2 Adjacency Matrix Representation

We will use adjacency matrices to represent these simple direct graphs. An adjacency matrix is a means of representing which vertices of a graph are adjacent to which other vertices. [7] In the paper, the adjacency matrix of a graph on n actors is the $n \times n$ matrix where entry A_{ij} is the edge weight between OC user i and j. For the example shown in Figure 3, we have the following adjacency matrix.

$$A' = \sum_{i,j}^{n,n} x'_{ij} = \begin{array}{c} \\ T \\ J \\ E \\ B \\ L \end{array} \begin{array}{c} \begin{array}{ccccc} T & J & E & B & L \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 3 & 0 & 0 & 0 & 2 \\ 0 & 4 & 0 & 2 & 1 \\ -2 & 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & -1 & 0 \end{bmatrix} \end{array}$$

Figure 6: Adjacency Matrix Example

Note that this matrix is not symmetric. This reflects the nature of the underlying social network. A frequent buyer can credit a number of sellers, while not obtaining much credits from others since he's not involved much in selling goods on the OC. An example of this situation is the user with id Tom. Tom keeps non-neutral records for others. This is observed by looking at the column T. But Tom has all neutral records from others. This is observed by looking at the row T.

For this application, in order to avoid dealing with negative values, we will calibrate the adjacency matrix to one with only positive entries. We can think of this procedure as a increase in transaction record values for everybody. In other words, every user in the OC network increases their transaction records for others by a fixed amount. Shown below is the calibrated the adjacency matrix for the above example.

$$A_1 = \sum_{i,j}^{n,n} x_{ij} = \begin{array}{c} \\ T \\ J \\ E \\ B \\ L \end{array} \begin{array}{c} \begin{array}{ccccc} T & J & E & B & L \end{array} \\ \begin{bmatrix} 0 & 2 & 2 & 2 & 2 \\ 5 & 0 & 2 & 2 & 4 \\ 2 & 6 & 0 & 4 & 3 \\ 0 & 2 & 2 & 0 & 1 \\ 2 & 2 & 2 & 1 & 0 \end{bmatrix} \end{array}$$

Figure 7: Calibrated Adjacency Matrix Form I

We can also express this matrix with 2's on the diagonal. This operation would not affect the TrustRank scores. Just like we've discussed previously. Whether or not user U keeps a record of himself does not affect other users' decisions of how trustworthy U is.

$$
A_2 = \sum_{i,j}^{n,n} x_{ij} = \begin{array}{c c} & \begin{array}{ccccc} T & J & E & B & L \end{array} \\ \begin{array}{c} T \\ J \\ E \\ B \\ L \end{array} & \begin{bmatrix} 2 & 2 & 2 & 2 & 2 \\ 5 & 2 & 2 & 2 & 4 \\ 2 & 6 & 2 & 4 & 3 \\ 0 & 2 & 2 & 2 & 1 \\ 2 & 2 & 2 & 1 & 2 \end{bmatrix} \end{array}
$$

Figure 8: Calibrated Adjacency Matrix Form II

Basically the reflexivity edge weights are ignored, and the algorithm takes care of this automatically. In other words, both of these two forms of calibrated adjacency matrices can be used as the input of the TrustRank algorithm. The mathematics explanation of this exchange is no shown here since it is beyond the scope this study.

2.3.2.3 TrustRank Algorithm

TrustRank algorithm compute the TrustRank score of each user in the network. It assigns relative scores to all users in the OC network based on the principle that connections to high-scoring users contribute more to the score of the user than equal connections to low-scoring users. This is similar to the principle of eigenvector centrality in Social Network Analysis (SNA). [8] The TrustRank scores are computed so that they depends both on the number and the quality of its connections: having a large number of connections still counts for something, but a user with a smaller number of high-quality incoming contacts may outrank one with a larger number of mediocre contacts.

Using the graph notations, with the ith user, the TrustRank score, x_i is proportional to the sum of the scores of all users which are connected to it. We can express this relation with the following formula, where A_{ij} is the adjacency matrix of the network graph, n is the number of actors in this network, and λ is a constant that relates to the share each user takes from the sum of its neighbors' TrustRank scores.

$$
x_i = \frac{1}{\lambda} \sum_{j=1}^{n} A_{ij} x_j. \tag{1}
$$

We shall look at an example. In the OC network shown in Figure 3, we can use the expression above, Formula (1), to demonstrate an individual's TrustRank score, x_i's.

$$
A = \begin{array}{c} \\ T \\ J \\ E \\ B \\ L \end{array}
\begin{array}{c} \begin{array}{ccccc} T & J & E & B & L \end{array} \\
\begin{bmatrix} 0 & 2 & 2 & 2 & 2 \\ 5 & 0 & 2 & 2 & 4 \\ 2 & 6 & 0 & 4 & 3 \\ 0 & 2 & 2 & 0 & 1 \\ 2 & 2 & 2 & 1 & 0 \end{bmatrix} \end{array}
$$

$$
\begin{aligned}
\Rightarrow x_T &= \frac{1}{\lambda}\left(A_{JT} \cdot x_J + A_{ET} \cdot x_E + A_{BT} \cdot x_B + A_{LT} \cdot x_L\right) \\
&= \frac{1}{\lambda}\left(2A_{JT} + 2A_{ET} + 2A_{BT} + 2A_{LT}\right) \\
x_J &= \frac{1}{\lambda}\left(A_{TJ} \cdot x_T + A_{EJ} \cdot x_E + A_{BJ} \cdot x_B + A_{LJ} \cdot x_L\right) \\
&= \frac{1}{\lambda}\left(5x_T + 2x_E + 2x_B + 4x_L\right) \\
x_E &= \frac{1}{\lambda}\left(A_{TE} \cdot x_T + A_{JE} \cdot x_J + A_{BE} \cdot x_B + A_{LE} \cdot x_L\right) \\
&= \frac{1}{\lambda}\left(2x_T + 6x_J + 4x_B + 3x_L\right) \\
x_B &= \frac{1}{\lambda}\left(A_{TB} \cdot x_T + A_{JB} \cdot x_J + A_{EB} \cdot x_E + A_{LB} \cdot x_L\right) \\
&= \frac{1}{\lambda}\left(2x_J + 2x_E + x_L\right) \\
x_L &= \frac{1}{\lambda}\left(A_{TL} \cdot x_T + A_{JL} \cdot x_J + A_{EL} \cdot x_E + A_{BL} \cdot x_B\right) \\
&= \frac{1}{\lambda}\left(2x_T + 2x_J + 2x_E + x_B\right).
\end{aligned}
$$

In Formula (1), λ is a constant and A is the adjacency matrix, we can express it in a matrix-vector notation. In other words, we rewrite the formula in the following form.

$$
x = \frac{1}{\lambda} \cdot A \cdot x. \tag{2}
$$

Following the OC network shown in Figure 3, we have the system of equations below to describe the TrustRank scores for all users.

$$
\begin{bmatrix} x_T \\ x_J \\ x_E \\ x_B \\ x_L \end{bmatrix} = \frac{1}{\lambda} \cdot \begin{bmatrix} 0 & 2 & 2 & 2 & 2 \\ 5 & 0 & 2 & 2 & 4 \\ 2 & 6 & 0 & 4 & 3 \\ 0 & 2 & 2 & 0 & 1 \\ 2 & 2 & 2 & 1 & 0 \end{bmatrix} \cdot \begin{bmatrix} x_T \\ x_J \\ x_E \\ x_B \\ x_L \end{bmatrix}
$$

$$
\begin{aligned}
\Rightarrow \quad x_T &= \frac{1}{\lambda}\left(2A_{JT} + 2A_{ET} + 2A_{BT} + 2A_{LT}\right) \\
x_J &= \frac{1}{\lambda}\left(5x_T + 2x_E + 2x_B + 4x_L\right) \\
x_E &= \frac{1}{\lambda}\left(2x_T + 6x_J + 4x_B + 3x_L\right) \\
x_B &= \frac{1}{\lambda}\left(2x_J + 2x_E + x_L\right) \\
x_L &= \frac{1}{\lambda}\left(2x_T + 2x_J + 2x_E + x_B\right).
\end{aligned}
$$

This computation serves as an verification of the formula conversion between Formula (1) and (2). We see that they are expressing the same system of equations in a slightly different way. Now, we can just move the constant λ to the left side of the formula and obtain the standard form for eigenvalues and eigenvector, where λ is a eigenvalue and x is a eigenvector.

$$\lambda \cdot x \quad = \quad A \cdot x. \tag{3}$$

At this point, given any OC network, we can derive its adjacency matrix and compute its eigenvalues and eigenvectors. In general, though, there will be many than one different eigenvalues for which an eigenvector solution exists. In this application as well as other SNA applications, however, we have an additional requirement. That is all the entries in the eigenvector need to be positive. [8] This implies that only the greatest eigenvalue results in the desired centrality measure.

The conclusion above directly follows the Perron-Frobenius Theorem, which asserts that a real square matrix with positive entries has a unique largest real eigenvalue and that the corresponding eigenvector has strictly positive components. [9] This largest eigenvalue is called the principal eigenvalue and the corresponding eigenvector is called the principal eigenvector.

At this point, following the standard procedure of computing eigenvalues and eigenvectors, we are ready to compute the TrustRank scores for each user with a given OC network. We will continue to use the OC network shown in Figure 3 as our example.

We first compute the greatest eigenvalue. Note that the steps of computing the determinate of of the adjacency matrix are omitted. So do the steps of solving the characteristic polynomial. They are beyond the scope of this study.

$$
\begin{aligned}
A &= \begin{bmatrix} 0 & 2 & 2 & 2 & 2 \\ 5 & 0 & 2 & 2 & 4 \\ 2 & 6 & 0 & 4 & 3 \\ 0 & 2 & 2 & 0 & 1 \\ 2 & 2 & 2 & 1 & 0 \end{bmatrix} \\
det\left(\lambda I_5 - A\right) &= det\left(\begin{bmatrix} \lambda & -2 & -2 & -2 & -2 \\ -5 & \lambda & -2 & -2 & -4 \\ -2 & -6 & \lambda & -4 & -3 \\ 0 & -2 & -2 & \lambda & -1 \\ -2 & -2 & -2 & -1 & \lambda \end{bmatrix}\right) \\
&= -\lambda^5 + 57\lambda^3 + 282\lambda^2 + 506\lambda + 316 \\
&\Rightarrow \lambda_1 \approx 9.60 \\
&\quad\ \lambda_2 \approx -3.15 + 1.28i \\
&\quad\ \lambda_3 \approx -3.15 - 1.28i \\
&\quad\ \lambda_4 \approx -1.66 + 0.34i \\
&\quad\ \lambda_5 \approx -1.66 - 0.34i.
\end{aligned}
$$

Plugging in the greatest eigenvalue in Real, $\lambda = 9.60$, we can compute its corresponding eigenvectors, which is the TrustRank score solution for this OC network. The details of this computation is again omitted. They are beyond the scope of this study.

$$
\begin{aligned}
&\lambda \cdot x = A \cdot x \\
\Rightarrow \quad & 9.60 \cdot \begin{bmatrix} x_T \\ x_J \\ x_E \\ x_B \\ x_L \end{bmatrix} = \begin{bmatrix} 0 & 2 & 2 & 2 & 2 \\ 5 & 0 & 2 & 2 & 4 \\ 2 & 6 & 0 & 4 & 3 \\ 0 & 2 & 2 & 0 & 1 \\ 2 & 2 & 2 & 1 & 0 \end{bmatrix} \cdot \begin{bmatrix} x_T \\ x_J \\ x_E \\ x_B \\ x_L \end{bmatrix} \\
\Rightarrow \quad & \begin{bmatrix} x_T \\ x_J \\ x_E \\ x_B \\ x_L \end{bmatrix} \approx \begin{bmatrix} 1.07 \\ 1.52 \\ 1.82 \\ 0.80 \\ 1.00 \end{bmatrix}
\end{aligned}
$$

$$\Rightarrow \quad TS_T = 1.07,\ TS_J = 1.52,\ TS_E = 1.82$$
$$TS_B = 0.80,\ TS_L = 1.00.$$

Note that the eigenvector solution is not unique. Basically, we've found a set of eigenvectors in the following form, where $\alpha \in \mathbb{R}$ is a constant. The ratios are the same, which is what we care about. Here we will switch the matrix notation to the TrustRank notation, where TS_U indicates a the TrustRank score for user with id U.

$$\begin{bmatrix} TS_T \\ TS_J \\ TS_E \\ TS_B \\ TS_L \end{bmatrix} = \alpha \cdot \begin{bmatrix} 1.07 \\ 1.52 \\ 1.82 \\ 0.80 \\ 1.00 \end{bmatrix}.$$

TrustRank makes a good network measure. Unlike many other measures that weight every contact equally, the TrustRank uses eigenvector measure, and it weights contacts according to their own TrustRank scores. The TrustRank score can also be seen as a weighted sum of not only direct connections but indirect connections of every length. Thus it takes into account the entire pattern in the network. [6]

2.3.3 Result Evaluation

In this section, we will evaluate the calculated TrustRank scores. We will see how they make sense and can thus serve as a guideline to judge OC user's trustworthy level. Recall the example OC network used in the example of this paper.

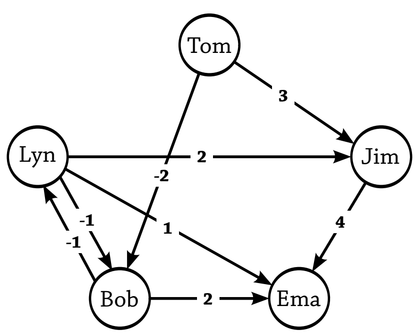

Figure 9: OC Network To Be Evaluated

We first aggregated the user transaction records and constructed the initial adjacency matrix. We then calibrated the adjacency matrix so that all entries are positive. We then followed the TrustRank algorithm to compute the eigenvector corresponding to the greatest eigenvalue. The eigenvector gives us a set of relative scores, TrustRank scores, for every OC user in this network. We obtained the following result of the example OC network.

$$
\begin{aligned}
& TS_T = 1.07,\ \ TS_J = 1.52,\ \ TS_E = 1.82 \\
& TS_B = 0.80,\ \ TS_L = 1.00 \\
\Rightarrow \quad & TS_B < TS_L < TS_T < TS_J < TS_E.
\end{aligned}
$$

This result tells us that Bob is the least one to be trusted. We observe from the OC network that Bob seems to be involved in many dishonesty transactions as a seller, so Bob might not be whom other OC users want to buy from. Lyn hasn't been participating as a seller as much, but she doesn't have a good record either. Tom has a neutral record, and TrustRank score rated him somewhere in the middle. Jim has a pretty good track record. Multiple OC user credited Jim positively, so he earned a good TrustRank score. Ema is a best. . In this small network, she's not only been credited positively by multiple users, she's also been credited by another well-trusted user, namely Jim. The connection, $Jim \rightarrow Ema$, contributed more to Ema's TrustRank score through the TrustRank algorithm.

3 Conclusions

In this project, we studied the trust mechanism for the electronic commerce. We investigated the system-imposed as well as user-imposed trust mechanisms. The former is usually for services backed up by trusted hosts. The latter is popular on may user-driven, non-centralized OC services. We focused our study on this second case. We observed and discovered many problems with such a trust management system. Firstly, it is not systematic and it oversights good or bad individuals easily. Secondly, the accuracy of user contributed information is not guaranteed. One or two inaccurate comments could easily pose false impression of a particular individual.

To improve this situation, we propose the TrustRank system to OCs that are not centrally managed. TrustRank takes into account of the entire interaction network among all OC users, and it assigns a TrustRank score to each user based the entire pattern of the OC network. TrustRank features in a minimal change in user experience comparing to what is already in place. TrustRank computes and maintains TrustRank scores for all users. A TrustRank score is then used as a judgment measure of how trustworthy a user is. The TrustRank score can be published as part of the personal profile of a particular user. It can also be considered private and made available only to the individuals that need to have monetary transactions with this user.

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