# OPTIMIZING TRUST PREDICTION IN DIGITAL BUSINESS ECOSYSTEM

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The process of predicting the future trust value of an entity, based on its past value is a challenging issue. The prediction process is even more imperative in the scenario where in the interaction would take place at a future point in time. Being able to determine the confidence value of the predicted trust value is of prime importance to enable optimized trust prediction. In this paper we propose a set of metrics for determining the confidence level in the predicted trust value.

## 1. Introduction

Modeling trust and reputation among business entities is one of extreme importance in Digital Business Ecosystems. Given the importance of this research area, it has received a huge amount of research attention and there is a huge plethora of corresponding literature. Beside modeling and managing trust, another important issue is the accurate predictions of these trust values [4]. The concept of prediction and forecasting in time series for future values is not new. Different models and theories on forecasting such as Markov Model, Kalman Filter Theory [15], Holt-winter forecasting etc are considered as most reliable for prediction purposes and hence have been used widely in the literature. Our work is based on the methodology called FC Direct trust value-based decision-making and prediction [4]. This methodology uses the previous trust and reputation values of an entity to predict its possible future value. However this method does not determine or associate the confidence level associated with the predicted value. In this paper, we propose a set of predicted value for optimized and reliable trust based decision-making. This paper is organized as follows:

In section 2 we will present few of the applied prediction and forecasting models used in different domain. Section 3 will provide a brief introduction of the FC methodology and its limitations. Our proposed optimization model is presented in section 4 followed by future research directions in section 5. The paper is concluded in section 6.

## 2. Taxonomy of Trust Modeling

The definition of Trust in our work is taken from [1], which states that Trust is "the belief the trusting agent has in the trusted agent's willingness and capability to deliver a mutually agreed service in a given context and in a given time slot". There has a lot of work been done on trust management and modeling. Comprehensive work on defining and managing trust and reputation can be found in [1] [2] [3]. One of the main challenges, which are faced in trust management, is predicting the trust value in the future point in time. This issue has not received much research attention in the literature. The existing literature does not provide a distinction between the terms of '*trust modeling*' and '*trust prediction*'. It is important to note that the concepts of trust modeling and trust prediction are different from each other. In the subsequent part of this section, we define the concepts of '*trust modeling*', '*trust prediction*' and '*trust determination*'.

We define trust modeling as "*the process of expressing the trust value of an entity either quantitatively or qualitatively*".

We define trust determination as "*the process of expressing the trust value of an entity, either quantitatively of qualitatively, either in the past or during the current point in time*".

We define trust prediction as "*the process of expressing the trust value of an entity, either quantitatively or qualitatively, at a future point in time*".

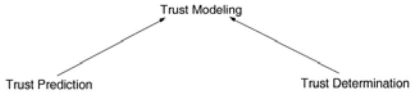


Figure 1. Relationship between Trust Modeling, Trust Prediction and Trust Determination.

It is important to note that the primary basis for distinction between the concepts is the time dimension. Additionally, it is important to note that almost all the existing literature on trust modeling is focused on trust determination. However recently there has been little effort in trust prediction.

However, the issue of prediction has received a large amount of research attention and various models have been proposed for prediction. Trust prediction can be found using different approaches and models such as Markov Model [4], [5]. Markov model is a well-known mathematical model used for prediction in several domains such as load prediction in power systems, weather prediction, stock market forecasting using Hidden Markov Model [6] etc. Kalman Filter Theory [7] [8] [15] has also been used as basis for prediction models [9]. Holt-winter forecasting [10] [11] [12] method is one of the famous prediction approaches, which is also based on exponential smoothing. Some prediction models such as [13], address the existence of trust relation between entities, which is based on link prediction problem [14].

## 3. FC Prediction Methodology

In this paper we propose and optimization method on top of the FC prediction methodology [4] which is one of the most comprehensive in predicting trust and reputation values. In their work [4], they consider trust and reputation as dynamic entities. This makes the decision-making process very challenging. The FC methodology [4] for prediction is a modified version of the Markov Model. As discussed in the previous section, Markov model is considered as one of the reliable models for prediction in different domain.

The FC prediction methodology has few limitations in terms of their assumption in defining seasonal, trend and noise reputation series. The assumption that is made in order to qualify as seasonal variations is that “the peak (and/or) the low reputation value(s) should occur at regular intervals of time within a given reputation series [4]” and the peak (and/or) low value(s) should be of the same value. Similar is the case with the assumption for a trend which is regular downward of upward movement of reputation values. The FC prediction methodology assumes a trend as “… the amount of decrease or the amount of increase from one time slot to the next time slot is the same over the whole reputation series...[4]”. The main issue/shortcoming of this prediction methodology is that it cannot work when the seasonal or trend time series is not smooth, regular and recurring. But the problem is faced when there is no smooth or regular variation for seasonal or trend series. Moreover the FC methodology does not provide any clear definition of the exact reputation series (history).

Therefore the FC methodology for prediction needs to be optimized to overcome these problems. In the next section we will present our optimization model, which will help to achieve more accurate predicted trust values.

## 4. Proposed Approach

Our work is primarily based on [4] as we already discussed previously the limitations in the FC Direct Trust Value-based Decision making and prediction. We produce an extension to their work by optimizing and overcoming to the limitations in their work. Our Proposed Solution is in the form of a confidence level, which can be associated with the predicted trust value for any trusted entity in a point in time in the future. This will boost the trusting entity's confidence in the predicted value for any given entity. Our proposed optimization method is based on the assumption in [4] which states that "It is possible that a given entity has access to previous '*n*' reputation values for another entity corresponding to 'n' consecutive time slots [4]".

### 4.1. *The Confidence Level*

In this section, we propose three metrics to determine the confidence level *clevel* in the predicted trust value. These metrics are (a) Distance (b) Maturity and (c) Density. In section 4.1.1, we introduce and define the distance metric, in section 4.1.2, we introduce and define the maturity metric and finally in section 4.1.3, we introduce and define the density metric.

#### 4.1.1. *Distance*

We define distance (*ds*) as "a metric that expresses the distance between the current time spot ($t_c$) and the time spot in the future ($t_p$) for which the trust value is to be predicted".

The distance (*ds*) between $t_c$ and $t_p$ has a great impact on the overall predicted trust value. The uncertainty (*uncert*) in the predicted trust value will increase with the increase in the distance between $t_c$ and $t_p$. The value of *ds* is in accordance with the maturity (life span) of the trusted entity.

Mathematically, *ds* is expressed as

$$ds = (t_c - t_f)/( t_p\ t_c) \quad (1)$$

If the value of *ds* is greater than 0 the then the distance metric has a *Max* value. Similarly, if *ds* have a value equal to 0 then the value of the distance metric is considered as *Normal* and if *ds* have a value less than 0 then the distance metric has the *Min* value.

$$clevel \propto \frac{1}{ds} \qquad (2)$$

Figure 2 shows the distance *ds* between the current time spot $t_c$ and the time spot $t_p$ in the future.

### 4.1.2. *Maturity*

We define maturity (*m*) of an entity as "*the total life span of an entity which it has been in existence*". Mathematically, it can be computed as the difference between current time spot ($t_c$) and the time spot for the first interaction ($t_f$), represented as follows:

$$m = t_c - t_f \qquad (3)$$

This time span has a great impact on the predicted value for the trusted entity in any point in time in the future. Ignoring other factors, we believe that the longer the maturity of the entity the higher would be the confidence in the predicted value and vice versa.

$$m \propto clevel \qquad (4)$$

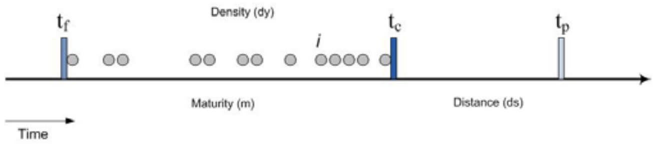


Figure 2. Time spots and previous interaction density.

We consider the maturity level as the same for the following two scenarios:

- The length of time span for which the trusted entity is known to the Digital Business Ecosystem and
- A scenario where two entities having same maturity but with different number of interactions.

In the second scenario we consider an entity *A* as more mature to entity *B* if entity *A* has more number of interactions as compare to the entity *B* although both of them have the same life span. Figure 2 show the maturity m which is the distance between the current time spot $t_c$ and the time spot $t_f$ which is the time spot of the first interaction by the trusted.

### 4.1.3. *Density*

We define density (*dy*) of the previous interactions as "*the frequency of the various interaction values recorded at different time spots over its life span*". During the interactions entities may come with different trust values at different time spots and these time spots are randomly distributed in the time space *m* which is the distance between $t_f$ and $t_c$. During the time space *m*, the frequency of the interactions may be denser either at the first half of *m*, the last half or could be equally distributed within time space *m*. The density of interactions at different parts of the time space *m* has a great impact on the predicted trust value for the future. We classify these three kinds of distribution in terms of interaction density and describe them as three scenarios as follows:

- LRI (Least Recent Interactions): This is the case where the density of the interactions is lesser towards the last half of the time space *m* then we can say that the entity has least recent interactions. This type of density distribution has a great impact on the overall predicted value of the trusted entity. The uncertainty uncert in the predicted future value of the trusted entity will increase as we do not have maximum interaction results (trust values) of the recent history.
- MRI (Most Recent Interactions): This is the case where the density of the interactions is greater towards the last half of the time space *m*. We can say that the entity has most recent interactions. This type of density distribution has different impact on the predicted value of the trusted entity as compared to LRI. In this case the uncertainty (*uncert*) in the predicted future value of the trusted entity will decrease as we have maximum interaction results (trust values) of recent history.
- Evenly Distributed: If the density of the interaction is evenly distributed within the time space *m* then the impact of this distribution is normal and does not affect the uncertainty (*uncert*) in predicting the future trust value of the trusted entity as compared to the other two scenarios i.e. LRI and MRI.

Figure 2 shows the direction of the time along with a number of interactions *i* at different time spots in the time space *m*.

## **4.2. *Metrics Weights***

All of the previously mentioned three metrics have their individual importance and impact on the predicted trust value. At this point in our work we are assuming that each of the three metrics has three distinct levels. We also have assigned the same weights to corresponding or same levels for each metrics.

Table 1 presents the weights *w* associated with each of the levels of the three metrics. We sum $S_w$ (equation 5) the weights *w1*, *w2* and *w3* of each metric that will decide the confidence level *clevel* for the predicted trust value. Equations 6,7 and 8 shows our criteria in qualifying for different confidence levels.

Table 1. Metrics scales and their associated weights.

| Density (*w1*) | Maturity (*w2*) | Distance (*w3*) | Weight (w) |
|---|---|---|---|
| MRI | Max | Max | 30 |
| Even | Normal | Normal | 20 |
| LRI | Min | Min | 10 |

The highest calculated value of *clevel* in this model will be the value of 90. This is also according to the fact that the confidence level also cannot be 100 percent (similar to the predicted trust value). Figure 3 shows graphically that at the coincidence of the different levels of the three metrics a different confidence level *clevel* will be produced.

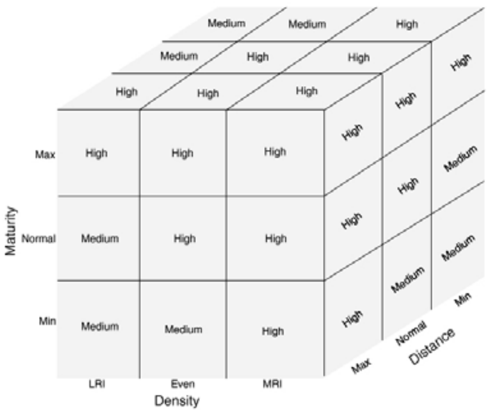


Figure 3. Three dimensional table presenting confidence levels at different metrics intersections.

$$Sw = w1 + w2 + w3 \tag{5}$$

$$\begin{aligned} &if\ 0 < Sw \leq 30, then \\ &clevel = low \end{aligned} \tag{6}$$

$$\begin{aligned} &if\ 30 < Sw \leq 60, then \\ &clevel = medium \end{aligned} \tag{7}$$

$$\begin{aligned} &if\ 60 < Sw \leq 90, then \\ &clevel = high \end{aligned} \tag{8}$$

Because of the weaknesses and limitations mentioned in the previous sections in FC direct trust value-based decision making method [4], our method for generating confidence value will optimize the predicted trust values generated through FC [4] method.

## 5. Discussion

The importance of associating a Confidence level with the predicted trust value can be justified by considering a scenario where a trusting entity A, will need a service from a trusted entity B in a point in time (*t1*) in the future. But the entity A should engage into an agreement in the current time spot (*t2*) because: (a) Entity B might not be available at *t1*, (b) No entity of the same trust level (including entity B), be available at *t1*. In this scenario we definitely need to obtain the trust value of entity B for a future time spot in order to negotiate and finalize the agreement according to the predicted trust value.

The problem here arises because of the facts that trust level for entities changes due to the dynamic environment. We can easily predict the trust value for entity B in the future time spot (*t1*) using any trust prediction model for instance, the FC model and so on. But this predicted trust value couldn't be always 100 percent accurate. That is why the predicted trust value should have some level of confidence associated with it.

## 6. Conclusion

The importance of forecasting and prediction can easily be seen in different domains. So far a lot of forecasting theories have been introduced which are applied in different research areas. Trust prediction is also one of the challenging issues in today's electronic marketplaces. In this paper we have presented an optimization model which is based on the FC methodology. Our model is capable of producing an optimized trust value if associated with the predicted trust value by FC methodology.

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