Dynamic Trustee Behaviour Pattern for User Support and Its Forecast Prediction

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Abstract: The Major focuses on the various trustee behavior patterns namely random, stable, trend, jumping and two phases with data analysis. The Forecast was based on the predictions between the previous predictions of mean square error and its ratings were discussed. At that point figure was made for the reasonable model with the moving normal, weighted moving normal, single exponential smoothing, twofold exponential smoothing triple exponential smoothing and holt's direct changes. The value of double exponential smoothing with the five behavior patterns yields larger mean square errors which had been further quantified with data analysis. The performance metrics of each had been made with forecast and its moving average error.

Keywords: Forecast, Smoothing, Mean square error, prediction

I. INTRODUCTION

The word trusted computing denotes consistency in computer behaves in an anticipated way with regard to its software or hardware. The categorization of trust can be either by conceptual trust or by an operational trust. Conceptual trust defines the description of its construct i.e. it may refer to a disposition of trust, institution-based trust, and trust belief and trusting intentions and further divided into its own hierarchical order [1][12] the other category is based on the operational trust is based on the functionality of the trust model. Online social network (OSN) analysis studies the relationship between the social entities of a group with respect to its classification such as corporations; nation etc [2]. The important concept in (OSN) has been calibrated in a unique manner by graph theoretic, algebraic and socio-metric methods. Graph-theoretic method wherein viewing of networks is a graph connected by lines. An algebraic method which represents a combination of relations with the distinct relationship between them and finally socio-metric wherein two-way matrices called socio-matrix is used which is in binary or crisp form notation [11][3]. The paper is organized as follows chapter II focuses on a literature survey, chapter III on Algorithm development, chapter IV Results, and Discussion and chapter V Conclusions.

II. LITERATURE SURVEY

The requester seeks permission with a proxy to look up the data on behalf of itself. Once the supplier is found, the proxy will get the data and deliver it to the requester this is the primary conventional trust based reservation scheme discussed in [4] the authors further enhanced the work with two levels wherein a trustworthiness is being provided by a proxy requester between the requester and server and the second level wherein two proxy's where found both at the requester and the supplier levels [4]. Policy-based distributed data dissemination discussed in [5] focus on data sharing by opaque means, privacy violations in undetected areas, and the absence of policy infrastructure.

Mathematical structure with algebraic semi groups for providing an interpersonal relationship with the periodic survey with social network was discussed specific to every member [6].

The type of trust was defined and was presented both automatically and manually as in [7]. However, the approach discussed in [7] was confined to software services neglecting their interactions. In order to quantify this analysis, insight has been developed with data analysis of forecast as in table I.

Taxonomy of Trust is [8] may be classified as Initial trust and ongoing trust [8]. The navigation from the explanatory stage to the commitment stage which has been clearly explained in [8] but to manage the uncertainty a forecast had been developed.

The relationship between thrusters' (registered buyers of the auction site) and trustees (registered sellers of the auction site) was associated with mutual trust was developed with dynamic trust model considering social networks with automated trust management as in [9]. The computational dynamic trust model [9] was discussed in with single exponential smoothing (SES), bound double exponential smoothing (B DES-S), based on Mean square Error and also by using the Average and Regret all the above integrity models were compared with instance of random, stable, trend, jumping and two-phase for Absolute error and Relative error.

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Table1. Analysis of Mean Square Error for Each Behaviour pattern as stated by authors in [9]

	Random	Stable	Trend	Jumping	Two phase
Average	0.086069	0.037669	0.026811	0.072545	0.63554
Single exponential smoothing	0.93301	0.007613	0.014744	0.021522	0.014272
Regert	0.08932	0.0075901	0.016907	0.055423	0.046255
Bound double exponential smoothing	0.12558	0.0056795	0.0062433	0.012282	0.0074293

III. ALGORITHM DEVELOPMENT FOR DATA ANALYSIS

Time series is a sequence of observations which are ordered in time. In this collection of data taken in Table 1 over time some form of random variation exists even though, reducing of canceling the effect due to random variation techniques called "smoothing" are available in the Single exponential smoothing and Bound double exponential smoothing. In order to make a forecast on the model and predict which model would suit the data pairs for comparing and analyzing our work data analysis is done here.

Single and double exponential smoothing

"Single exponential smoothing weights past observations with exponentially decreasing weights to forecast future values" [10]

$S_t = \alpha y_{(t-1)} + (1-\alpha)S_{(t-1)}$ $0 < \alpha \leq 1$: (Equation 1)

The problem with single exponential smoothing is it cannot handle trends. So as to make the model more flexible here in double exponential smoothing is introduced.

$S_t = \alpha y_t + (1-\alpha)(S_{t-1} + b_{t-1})$ $0 \leq \alpha \leq 1$: (Equation 2)

$b_t = \gamma[S_t - S_{t-1}] + (1-\gamma)b_{(t-1)}$ $0 \leq \gamma \leq 1$: (Equation 3)

γ is the second constant

Double exponential smoothing provides the methods of handling trends whereas

Proposed methodology for data analysis

Triple exponential smoothing handles parabolic trends.

Triple exponential smoothing handles parabolic trends.

Pre-processing of time series requires a moving average and has been worked here by

$$Movingaverage = \frac{\sum Mostrecentndatavalues}{n}$$

(Equation 4)

$$WeigthedMovingaverage = \frac{\sum(Woeightforperiodn)(Valueinperiodn)}{\sum Weights}$$

(Equation 5)

Based upon these equations here comparisons is made for each and every integrity model i.e
random, stable, trend, jumping and two- phase.

IV. PERFORMANCE EVALUATION

Table 2. Performance Analysis Of Random Method

	Random
Average	0.086069
Single exponential smoothing	0.93301
Regert	0.08932
Bound double exponential smoothing	0.12558

Results for data analysis

Period is taken as 2

Moving average forecast is 0.511165 and Moving average error is 0.287815.

Weighted Moving average forecast is 0.340777and Moving average error is 0.299573.

The value of α is taken as 0.3

Single exponential smoothing

Forecast is 0.223105 and Moving average error is 0.216491.

Double exponential smoothing

Forecast is 0.36751 and Moving average error is0.237744.

Triple exponential smoothing

Forecast is 0.36139 and Moving average error is0.224476.

Holt's Linear smoothing

The value of α is taken as 0.3 and β is 0.03

Forecast is 2.32473 and Moving average error is1.834769.

Table (2),(3) shows the forecast method of Random and Stable analysis of average for the single, double bound exponential and regert techniques

Table 3 . Performance Analysis Of Stable Method

	Stable
Average	0.037669
Single exponential smoothing	0.007613
Regert	0.0075901
Bound double exponential smoothing	0.0056795

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Results for data analysis
Period is taken as 2
Moving average forecast is 0.007602 and Moving average error is 0.005332.
Weighted Moving average forecast is 0.005068 and Moving average error is 0.003753.
The value of α is taken as 0.3
Single exponential smoothing
Forecast is 0.017337 and Moving average error is 0.01186.
Double exponential smoothing
Forecast is 0.009703 and Moving average error is 0.01807.
Triple exponential smoothing
Forecast is 0.006123 and Moving average error is 0.02096.
Holt’s Linear smoothing
The value of α is taken as 0.3 and β is 0.03
Forecast is -0.057895 and Moving average error is 0.039466.
Table (4) shows the forecast method of Trend and analysis of average and single, double bound exponential and regert techniques.

Table 4. Performance Analysis Of Trend Method

Method	Trend
Average	0.026811
Single exponential smoothing	0.014744
Regert	0.016907
Bound double exponential smoothing	0.0062433

Results for data analysis
Period is taken as 2
Moving average forecast is 0.015826 and Moving average error is 0.004149.
Weighted Moving average forecast is 0.01055 and Moving average error is 0.002907.
The value of α is taken as 0.3
Single exponential smoothing
Forecast is 0.016787 and Moving average error is 0.005847.
Double exponential smoothing
Forecast is 0.016886 and Moving average error is 0.008586.
Triple exponential smoothing
Forecast is 0.015724 and Moving average error is 0.009797.
Holt’s Linear smoothing
The value of α is taken as 0.3 and β is 0.03
Forecast is -0.01346 and Moving average error is 0.012733.

Table(5) shows the forecast method of jumping analysis of average for the single, double bound exponential and regert techniques.

Table 5. Performance Analysis of Jumping Method

Method	Jumping
Average	0.072545
Single exponential smoothing	0.021522
Regert	0.055423
Bound double exponential smoothing	0.012282

Results for data analysis
Period is taken as 2
Moving average forecast is 0.038473 and Moving average error is 0.021344.
Weighted Moving average forecast is 0.025648 and Moving average error is 0.016632.
The value of α is taken as 0.3
Single exponential smoothing
Forecast is 0.04337 and Moving average error is 0.017019.
Double exponential smoothing
Forecast is 0.045434 and Moving average error is 0.025379.
Triple exponential smoothing
Forecast is 0.043658 and Moving average error is 0.029257.
Holt’s Linear smoothing
The value of α is taken as 0.3 and β is 0.03
Forecast is -0.083973 -and Moving average error is 0.075744.
Table(6) shows the Performance analysis of two phase method single, double bound exponential and regert techniques.

Table 6. Performance Analysis of Two phase Method

Method	Two phase
Average	0.63554
Single exponential smoothing	0.014272
Regert	0.046255
Bound double exponential smoothing	0.0074293

Results for data analysis
Period is taken as 2
Moving average forecast is 0.030264 and Moving average error is 0.115346.
Weighted Moving average forecast is 0.020176 and Moving average error is 0.079626.
The value of α is taken as 0.3
Single exponential smoothing
Forecast is 0.232031 and Moving average error is 0.235381.
Double exponential smoothing
Forecast is 0.076951 and Moving average error is 0.359615.
Triple exponential smoothing
Forecast is 0.007063 and Moving average error is 0.417766.
Holt’s Linear smoothing
The value of α is taken as 0.3 and β is 0.03
Forecast is -1.322342 and Moving average error is 0.843545.

V. CONCLUSIONS

Thus the aid of computational trust model using multidimensional concept had been worked with five social models and research finding had been made with data analysis for smoothing organized for each behaviour pattern. Thus the tradeoffs between privacy and trust can be computed and analysed for each and every pattern for mean square error and absolute error.

Future work will deal with the development of contextual transaction trust computations.

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