

PREDICTING THE ARRIVAL OF EMERGENT PATIENT BY AFFINITY SET

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Abstract: Predicting the time series of emergent patient arrival is valuable in monitoring/tracking the daily patient flow because these efforts keep doctors alarmed in advance. A prediction problem of the time series generated by actual arrival of emergent patient is considered here. Traditionally, such a problem is analyzed by moving average method, regression method, exponential smoothing method or some existed evolutionary methods. However, we propose a new affinity model to accomplish this goal. Our data of time series is actually recorded from hour to hour (hourly data) for three days: the data of the first two days are used to generate/train prediction model; after that, the data of the final/third day is used to test our prediction results. Two types of model: affinity model and neural network model are used for comparing their performances. Interestingly, the affinity model performs better prediction results. This hints there could be a special pattern within the time series generated by actual arrival of emergent patient.

1 INTRODUCTION

In many medical domains the doctors need to learn why a decision was made, otherwise they are unlikely to trust the advice generated by automated data analysis methods. Data mining/knowledge discovery can solve such problems (Abdel-Aal and Al-Garni, 1997). Important requirements for knowledge discovery are interpretability, novelty, and usefulness of the results. Many data mining problems involve temporal aspects. The most common form of temporal data is time series where some properties are repeatedly observed generating a series of data items similar in structure: we define this similarity as a special pattern sometime. However, the pattern could be very dynamic and complicated in reality (Agrawal and Srikant, 1995).

Correctly tracking, monitoring and predicting the arrival of emergent patient in hospital are important

and crucial to the clinical operation of hospital (TeleTracking, 2006). Because such efforts will help doctors realize what the level of service (LOS) for patients is, then they can appropriately response in advance by these data. In addition, these efforts are able to avoid system breakdown of hospital because of too many patients. There could be many ways of predicting time series, for example, moving average method, regression method, exponential smoothing method, or other evolutionary techniques. In this study, we show the innovative thinking to predict time series, this goal is achieved by affinity set (Larbani and Chen, 2006). Affinity is defined by two types (Larbani and Chen, 2006): the first type is natural liking for or attraction to a person, thing, idea, etc. For example, friendship is a kind of *direct affinity*. In order to take place, such affinity requires the subjects between whom the affinity takes place and the affinity itself. The second type is defined as

a close relationship between people or things that have similar qualities, structures, properties, appearances or features. In this paper we call it *indirect affinity*. Simply speaking, affinity represents the closeness/distances between any two objects. We only use the *direct affinity* modelling to predict the time series generated by actual arrival of emergent patient, and the performance of affinity model is compared with that of neural network (NN) model (Kim and Han, 2000). Interestingly, the errors of affinity model are smaller than those of the NN model. Thus, exploring and developing affinity models are valuable in the very near future.

This paper is organized as follows: in Section 2, we show the technical background for this study, including the necessary affinity definitions. In Section 3, an actual example of emergent patient arrival is presented. Two types of models: NN model and affinity model are both used to predict the time series; furthermore, their performances are compared. Finally, conclusions and recommendations are in Section 4.

2 TECHNICAL BACKGROUND

In this section, we will simply review two prediction models: affinity model and NN model.

2.1 Basic Concepts of Affinity

Here, the basic definitions are shortly reviewed (Larbani and Chen, 2006).

Definition 2.1. Affinity Function.

Let e be an object and A be an affinity set, respectively. The affinity between e and A is represented by a function that we call affinity function.

$$M_A^e(\cdot): [0, +\infty] \rightarrow [0, 1]$$

$$t \rightarrow M_A^e(t)$$

The value $M_A^e(t)$ expresses the degree or strength of the affinity between object e the affinity set A at time t . When $M_A^e(t) = 1$ this means that the object e satisfies completely the affinity that characterizes A . When $M_A^e(t) = 0$ this means that e doesn't satisfy the affinity characterizing A at all at times t . When $0 < M_A^e(t) < 1$, this means that e satisfies partially the affinity characterizing A at time t .

Definition 2.2. The Universal Affinity Set.

The universal affinity set, denoted by U , is the affinity set defined by the fundamental principle of *existence*, that is, $M_U^e(t) = 1$, for all existing objects at time t , and for all times t , that is, past present and future.

Often in real problems the complete affinity satisfaction $M_A^e(t) = 1$ may not be reached in real-world situations for a given affinity set A and an object e .

Definition 2.3. k - t -Core of a Affinity Set.

Let A be an affinity set and $k \in [0, 1]$. We say that an object/element e is in the k - t -core of the affinity set A at time t , denoted by k - t -core(A), if $M_A^e(t) \geq k$, that is, the k - t -core of A at time t is the traditional set k - t -core(A) = $\{e \mid M_A^e(t) \geq k\}$. When $k = 1$, the 1- t -core(A) is simply called the core of A at time t , denoted by t -core(A). The content of an affinity set can be defined at any time by its membership function. Let us give a formal definition of this function. The k could be pre-decided or be viewed as a decision value according to various problems.

Definition 2.4. Function Defining an Affinity Set.

Let A be a affinity set then the affinity defining A can be characterized by the following function

$$R_A(\cdot, \cdot): U \times [0, +\infty] \rightarrow [0, 1] \tag{1}$$

$$(e, t) \rightarrow R_A(e, t) = M_A^e(t)$$

called affinity function.

In general, in real world situations, some traditional referential set V , such that when an object e is not in V , $M_A^e(t) = 0$ for all t , can be determined, then the affinity defining A can be defined by the following function

$$R_A(\cdot, \cdot): V \times [0, +\infty] \rightarrow [0, 1]$$

$$(e, t) \rightarrow R_A(e, t) = M_A^e(t)$$

We had learned earlier in Section 1 there are two types of affinity : indirect affinity and direct affinity. In this study, we only use the direct affinity for modelling, which are briefly introduced as follows.

Definition 2.5. Let V and I be a referential set and a subset of the time axis $[0, +\infty[$ respectively. A time dependent fuzzy relation R such that

$$R_{(\cdot, \cdot)}(\cdot) : I \times (V \times V) \rightarrow [0, 1] \tag{2}$$

$$(t, (e, s)) \rightarrow R_{(e, s)}(t)$$

is called direct affinity on the referential V .

Interpretation 2.1. i) For any fixed time t the relation (2) reduces to an ordinary fuzzy relation

$$R_{(.,.)}(t) : V \times V \rightarrow [0,1]$$

$$(e, s) \rightarrow R_{(e,s)}(t)$$

that expresses the intensity or the degree of affinity between any couple of elements in V . Hence the fuzziness of affinity between elements is taken into account in Definition 2.5.

ii) For any fixed couple of elements $(e, s) \in V$, the relation (2) reduces to a fuzzy set defined on the time-set I

$$R_{(e,s)}(.) : I \rightarrow [0,1]$$

$$t \rightarrow R_{(e,s)}(t)$$

that expresses the evolution over time of affinity between the elements e and s .

Definition 2.6. Let R be a time-dependent fuzzy relation defined on a subset of time axis I and a referential V . Let A and B be two subsets of V . Then the affinity between A and B can be described by the following function

$$R_{(A,B)}(.) : I \rightarrow [0,1] \quad (3)$$

$$t \rightarrow R_{(A,B)}(t)$$

where $R_{(A,B)}(.)$ can be defined by many ways, depending on the decision maker. For example, $R_{(A,B)}(t) = \max_{(e,s) \in A \times B, e \neq s} R_{(e,s)}(t)$, for all $t \in I$, or $R_{(A,B)}(t) = \min_{(e,s) \in A \times B, e \neq s} R_{(e,s)}(t)$, for all $t \in I$ (Larbani and Chen, 2006).

Here also for practical purpose we define the t - k -affinity.

Definition 2.7. Let R be a time-dependent fuzzy relation defined on a subset of time axis I and a referential V . Let $k \in [0,1]$, and $t \in I$.

i) We say that a couple (e, s) has k affinity degree at time t or it has t - k -affinity degree if $R_{(e,s)}(t) \geq k$.

ii) A subset D of V has t - k -affinity degree if $R_{(D,D)}(t) \geq k$. Thus the t - k -affinity degree of subsets depends on how is defined the affinity between groups or subsets as indicated in Definition 2.6. In this study, k is regarded as a decision variable, we want to find an affinity set that maximizing k .

2.2 Neural Network Model

Since NN models are very popular and have significant contributions in the data mining history, we won't duplicate the importance of NN so as to save the paper length. Neural network models are popularly used in many fields for prediction of time series (Kim and Han, 2000; Kimoto and Asakawa, 1990). In addition, the NN models had already achieved good prediction results. Therefore, in this study, we introduce a simple NN model of time series for prediction, this is shown in Fig. 1. This model is designed as using the previously four observations to reason the coming/fifth observation.

3 PREDICTING THE ARRIVAL OF EMERGENT PATIENT

In this section, we use two models: affinity model and NN model to predict the arrival of emergent

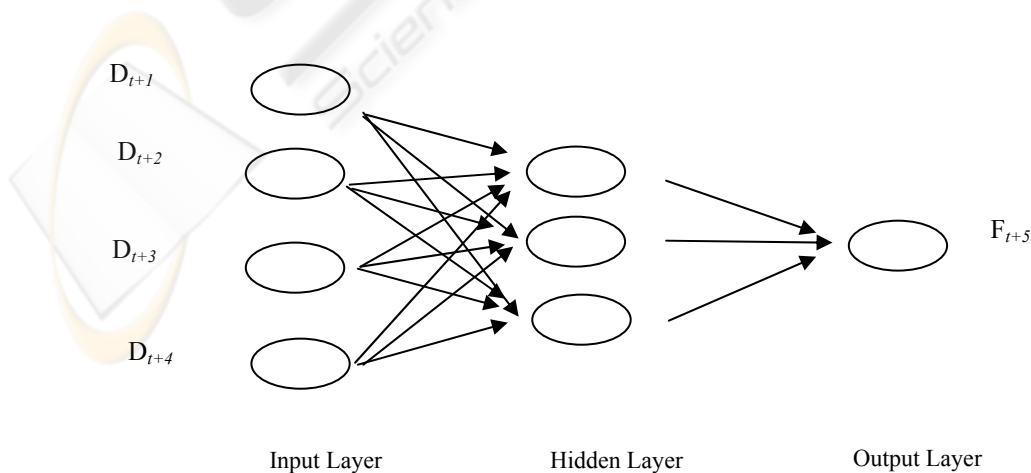


Figure 1: Structure of NN Model.

patient simultaneously. Data of emergent patient arrival for three days are actually collected: the data of the first two days are used to train/generate the affinity or NN prediction model. After that, we simulate the generated models: affinity and NN, for their outcomes in order to predict the actual arrival of the third day. The affinity model is designed as using Definition 2.6. Our idea is really simple, the hourly data of time series of day 1 is defined as the affinity set A; in addition, the hourly data of time series of day 2 is defined as the affinity set B. The affinity set C is our exploring/decision set, which should be close to the set A and the set B simultaneously. Let $a(t)$ represents the hourly element/data in A, $b(t)$ represents the hourly element/data in B and $c(t)$ represents the hourly element/data in C; $t=1,2,\dots,24$ (from 01:00 am to 24:00 pm). Then finding $c(t)$ could be viewed as an optimization problem, which should satisfy the following two objectives (by Definitions 2.5-2.6):

$$\text{Max } R_{(a,c)}(t), \quad \forall t \quad (4)$$

$$\text{Max } R_{(b,c)}(t), \quad \forall t$$

And constraints are two existed time series $a(t)$ and $b(t)$. Here the k value in Definitions 2.6-2.7 is undecided, which is viewed a decision variable and should be maximized. When defining/assuming the content of $R_{(a,c)}(t)$ and $R_{(b,c)}(t)$, respectively, we can resolve the aforementioned bi-objective optimization problem (4) using observed/training data in set A and set B. It is easy to find each $c(t)$, $t=1,2,\dots,24$ in set C by our arbitral perception of closeness/distance.

Here, the $R_{(a,c)}(t)$ and $R_{(b,c)}(t)$ are simply defined/assumed as:

$$R_{(a,c)}(t) = 1 - \frac{[c(t) - a(t)]^2}{d} \quad (5)$$

$$R_{(b,c)}(t) = 1 - \frac{[c(t) - b(t)]^2}{d}$$

Where d is a constant, which is large enough so that $0 \leq R_{(a,c)}(t), R_{(b,c)}(t) \leq 1$. If we assume these two objectives in (4) are equally important at each time t and use the weighting method (each objective is weighing by 0.5) to combine these two objectives (Yu, 1985). Thus it is easy to show we

have the optimal solution of $c(t) = \frac{a(t) + b(t)}{2}$,

which results in maximizing the affinity degree of $0.5 \times R_{(a,c)}(t) + 0.5 \times R_{(b,c)}(t)$. The predicted results from different models are all shown in Figure 2. Interestingly, the sum of square errors of affinity model is 566, which is smaller than those of NN models (780 and 932). NN1 model is trained for 100 runs, NN2 model is trained for 500 runs. This hints there could be a unknown pattern within the patient arrival curve (from 00:00 am to 23:00 pm). Our affinity model is able to catch such a special pattern in time series. Of course, the NN model could be restructured for better competence advantage later. For example, integrating affinity concept and NN altogether could perform better than affinity model or NN model.

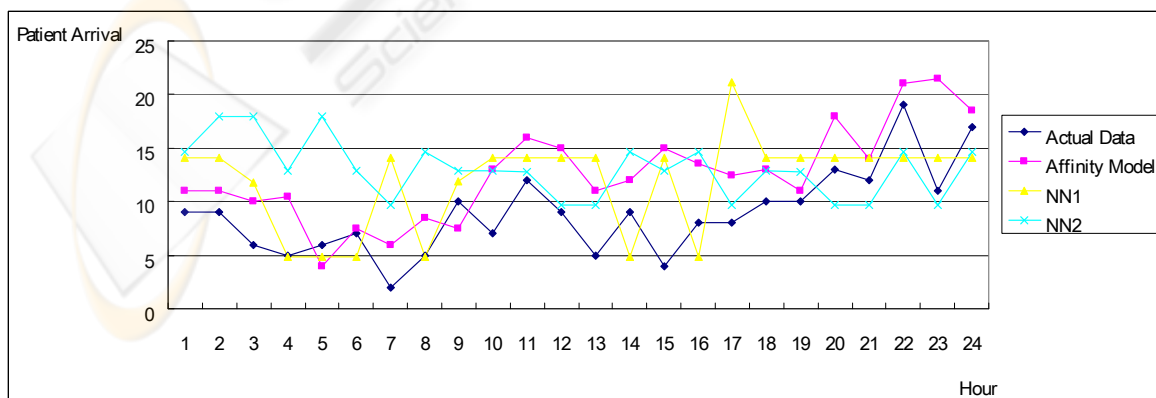


Figure 2: Performance Comparison of Different Models.

4 CONCLUSIONS AND RECOMMENDATIONS

We proposed a simple prediction method in this study, although the idea is really simple, it interestingly performs good. However, pattern could exist in a very dynamic and complicated form. In this study, we may be just lucky to find this simple pattern. A decision maker is encouraged to develop his/her own perception of closeness/distance in (4)-(5); thus, various affinity models of data mining are waiting for exploration.

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