PREDICTIVE DATA MINING BASED ON SIMILARITY AND CLUSTERING METHODS

Sarjon Defit, Mohd Noor Md Sap
Faculty of Computer Science and Information System
University Technology of Malaysia , KB. 791
80990 Johor Bahru, Malaysia
Telp: (607)-5576160, Fax: (607) 5566155
{sarjon@fsksm.utm.my},{mohdnoor@fsksm.utm.my}

Abstract

Predictive data mining is an attractive goal in data mining. It has wide application, including credit evaluation, sales promotion, financial forecasting and market trend analysis. In this paper we propose a predictive data mining model based on the combination of similarity, clustering and predictive modeling. This model is implemented and tested using real estate data. Our study concludes that our predictive data mining model can improve the prediction ability by using all attributes in the different clusters with the nearest distance as input fields. In this paper we explain the importance of data mining, similarity, the proposed predictive data mining model, the testing of the model, discussion and conclusion.

Keywords: Data Mining, Predictive Data Mining, Similarity, Clustering, Predictive Modeling

1. Introduction

With the development of high capacity storage technology, a large amount of data can be stored. The data stored in databases consists of simple information, text document, or complex information such as multimedia, spatial databases, and hypertext documents (Tung, L., Kyung, K., 1997; Olaru, C., Wehenkel, L., 1999; Zaiane, R., 1999; Sarjon, D., Mohd, N., 2000). The stored data carry numerous valuable knowledge that can be extracted using many available tools such as SQL (Structure Query Language) and QBE (Query By Example). Generally these techniques can only extract the meaning of data. We need a technique that can be used to extract not only the meaning but also the knowledge from the large amount of data. One of the tools is data mining. The result of the extracted knowledge can be applied to information management, query processing, decision process, process control and many other applications (Yongjian, 1996; Sarjon, D., Mohd, N., 2000)

There are many definitions of data mining taken from different views. Jiawei, H. et.al (Jiawei, H., Chiang, Y. et.al., 1997) give the definition data mining as the discovery of knowledge and useful information from the large amounts of data stored in databases and Olaru, C. et.al (Olaru, C., Wehenkel, L., 1999) define data mining as the non trivial process of extracting valid, previously unknown, comprehensible and useful information from large databases. McLauren (McLauren, I., 1997) defines data mining as the automatic extraction of non trivial potentially useful, patterns from large databases, while Sheng-Chai, C. et.al (Sheng-Chai, C., Hung-Pin, C. et.al. 1999) defines data mining as the process of extracting valid, previously unknown information from large databases and using it to make crucial business decision. Last, Goebel, M et.al (Goebel, M., Le, G., 1999) define data mining as the extraction of patterns or models from observed value. From the above definitions, we concludes that data mining is the automatic extraction of patterns, previously unknown and potentially useful information from large amount of data in databases and using it to make crucial business decision.

Data Mining is divided into two main categories, namely, descriptive and predictive data mining (Jiawei, H., 1999; Olaru, C., Wehenkel, L., 1999; Zaiane, R., 1999, Sarjon, D., Mohd, N., 2000). The function of descriptive data mining is to describe the general properties of existing data, and to create meaningful subgroups such as demographic cluster. Compared to descriptive data mining, predictive data mining is used to forecast explicit value based on inference on available data.

Predictive data mining is a major task in data mining and has a wide application, including credit evaluation, sales promotion, financial forecasting and market trend analysis (Shan, C., 1998; Wei, W., 1999). Many predictive data mining algorithms have been developed in the past research. For example, (Shan, C., 1998) proposed predictive data mining method which consists of three steps, namely data generalization, relevance analysis and statistical regression model. In the middle of 1999, (Wei, W., 1999) proposed two predictive data mining methods. The first method is a classification-based method which integrates Attribute Oriented Induction (AOI) with the ID3 decision tree method. The second method is a pattern matching-based method which integrates statistical analysis with Attribute Oriented Induction to predict data values of the attribute of interest based on similar groups of data in databases. These predictive data mining methods provide high prediction quality and it leads to efficient and interactive prediction in large databases. However, these methods still encounter several weaknesses and need further improvement. Some of the weaknesses are as follow:

a. These methods did not pursue a best subset of similarity attributes for prediction (Shan, C., 1998)

b. These methods did not apply special data preprocessing techniques to identify which of data in databases are inaccurate, irrelevant or missing value (Shan, C., 1998; Wei, W., 1999).

Looking at the above mentioned weaknesses, we are interested to overcome the first weakness.

The rest of the paper is organized as follow. Section 2 explains the importance of similarity. The proposed predictive data mining model is given in section 3 and testing of the model in section 4. The results of the experiment and conclusion are given in section 5 and 6.

2. Similarity

Similarity is a measure of similar or dissimilar between two or more attributes in the databases (Everitt, S., 1993; Ronkainen, P., 1998). This is one of the central concepts in data mining and knowledge discovery (Ronkainen, P., 1998; Shan, C., 1998; Wei, W., 1999). In searching patterns and regularities, it is not enough to consider only the equality or inequality of data. Instead, we have to consider how the similarity between two or more attributes (Ronkainen, P., 1998; Balasubramanian, S., Hermann, J. W., 1999).

Ronkainen, P. (Ronkainen, P.,1998) proposed two similarity methods, internal and external measure of similarity. The internal measure of similarity is used to measure the similarity between two attributes, while external measure of similarity is used to measure the similarity between more than two attributes. In this paper, we will use the internal measure of similarity.

The similarity between attributes is needed in some databases and knowledge discovery applications. Some examples of such applications are given in the following:

i) Real estate data contains valuable information about the indicators that affects the movement of the house price. Information about indicator with similar effect pattern can be useful in predicting the house prices.
ii) In financial market data, finding stocks that had last week price fluctuation from financial time series data, or identifying companies whose stock price have similar pattern growth.

These examples describe how important and essential the notion of similarity for data mining. Searching for similarity attributes can help the prediction, hypothesis testing and discovery rules. It is not feasible to use all the attributes in databases to do prediction. In most cases, a few of these attributes are highly similar and valuable for prediction. Thus, the effective similarity is necessary to filter out those attributes which are similar or dissimilar.

The meaning of similarity depends on what kind of similarity we are looking for. Using the different similarity measure can determine two attributes to be very similar by one measure and very different by another. This means that we have to carefully choose one particular measure, or we have to try several measure on the data and then choose the one that suits best our purposes (Ronkainen, P., 1998; Shan, C., 1998).

There is no single definition for similarity. In this paper, we define the similarity between attributes is a complementary notion of distance. A measure d for distance between two attributes should be a metric. There are four standard criteria that can be used to determine whether a similarity measure is a true metric or not (Aldenderfer, S., Blashfield, K., 1984, Everitt, S., 1993; Ronkainen, P., 1998) . These are:

i) Symmetry. Given two entities, x and y, the distance, d,. Between them satisfies the expression:

$$(x,y)\ d = d(y,x) \geq 0 \tag{1}$$

ii) Triangle inequality. Given three entities, x,y,z, the distances between them satisifies the expression

$$d(x,y) \leq d(x,z) + d(y,z) \tag{2}$$

iii) Distinguishability of nonidenticals. Given two entities x and y,

$$\text{If } d(x,y) \neq 0, \text{ then } x \neq y \tag{3}$$

iv) Indistinguishability of identicals. For two identical elements, x and x',

$$d(x,x') = 0 \tag{4}$$

3. The Predictive Data Mining Model

At the present stage we propose a predictive data mining based on the combination of similarity, clustering and predictive modeling (PDMSCP). The general architecture is shown in figure 3.1.

This model consists of three sub modules; similarity; clustering and prediction. In the first module, we identify which of the attributes within the databases that have strong or weak similarity. The reason for identifying the similarity attributes is because not all attributes are feasible and suitable for making a prediction.

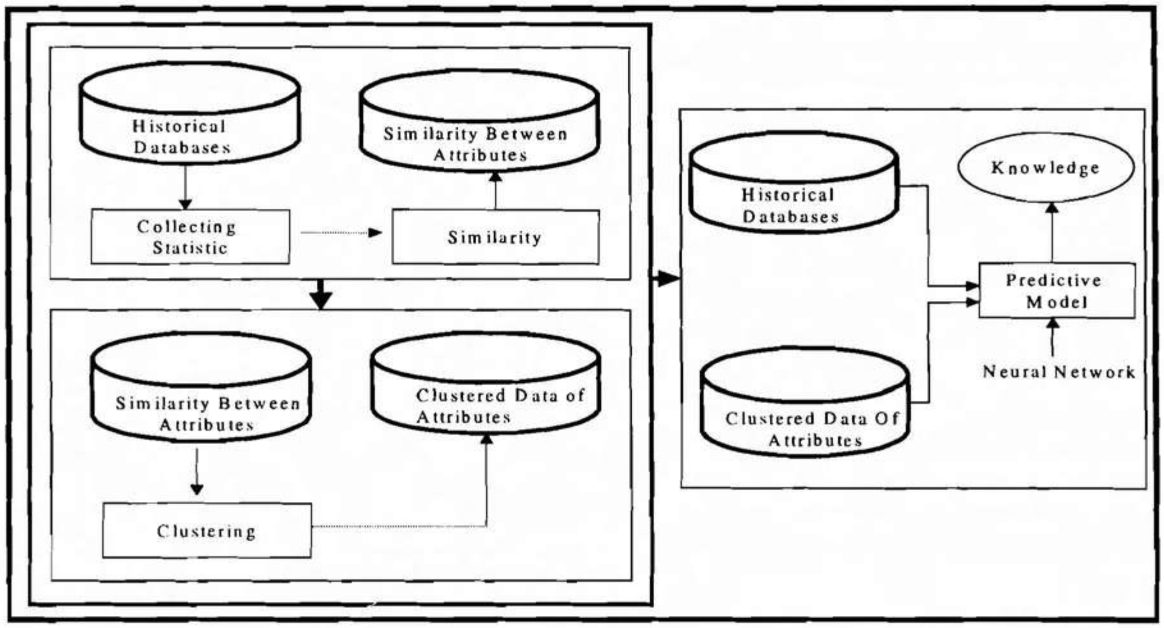


Figure 3.1: The General Architecture of Predictive Data Mining Model

The following module focuss on clustering those similarity attributes into one cluster and dissimilarity attributes into another different clusters. The idea of this step is to separate similarity and dissimilarity attributes into different clusters. The final step is made to construct the predictive modeling.

4. Testing The PDMSCP Model

This model is tested using real estate data as is shown in table 4.1. The definition of table for real estate data is:

Real Estate (House Price, Tax Rate, House Size, Lot Size, River Side, Crime Rate, Industrial, Air Quality, Distance, Highway, Pupils/Teacher, Blocks, Poverty).

These attributes are categorized into two classifications;

a) The House Price which is used as predicted value.
b) The indicators that affect the movement of the house price. It consists of Tax Rate, House Size, Lot Size, River Side, Crime Rate, Industrial, Air Quality, Distance, Highway, Pupils/Teacher, Blocks, Poverty. These attributes are used as predictors.

Table 4.1 : The Real Estate Samples Data

House Price	Tax Rate	House Size	House Age	Lot Size	......	Poverty
24.4	277	6.064	59.1	0		14.66
21.2	432	6.176	72.5	0		12.04
22.2	300	6.358	52.9	30		11.22
13.4	666	6.103	85.1	0		23.29
23.8	403	5.877	79.2	12.5		12.14
17.4	345	5.594	36.8	0		13.09
22.2	224	6.316	38.1	22		5.68
26.2	330	6.718	17.5	0		6.56
14	437	6.174	93.6	0		24.16
19	224	5.995	45.4	0		9.74
17	666	7.393	99.3	0		16.74
8	384	6.781	71.3	90		7.67
26.5	187	6.728	36.1	0		4.5
30.1	437	6.454	98.4	0		14.59
17.1	307	6.618	80.8	25		7.6
30.1	281	6.619	70.4	0		7.22
23.9	188	5.87	69.7	0		14.37
22	307	6.072	100	0		13.04
14.5	666	6.833	94.3	0		19.69
14.1	279	5.966	30.2	0		10.13
24.7	666	6.98	67.6	0		11.66
29.8	304	5.972	76.7	0		9.97
20.3	233	6.03	85.5	0		18.8
16.6	403	5.012	88	0		12.12
15.3	305	6.065	7.8	0		5.52
22.8	222	6.43	58.7	0		5.21
28.7	224	5.968	58.5	0		9.29
18.7	348	6.162	38.4	0		7.43
24.1	223	5.856	42.1	82.5		13
...	...	...	...	...	...	...
...	...	...	...	...	...	...
31.5	307	6.552	21.4	0		6.2

The prediction is done as follows:

a. Calculate the average and standard deviation of the predictors from table 4.1. Table 4.2 shows the average and standard deviation of predictors.

Table 4.2 : The Average and Standard Deviation of Predictors

Attribute	Average	Standard Deviation
Tax Rate	408	169
House Size	6.28	0.70
House Age	68.6	28.1
Lot Size	11	23
River Side	0.07	0.25
Crime Rate	3.6	8.6
Industrial	11.1	6.9
Air Quality	0.55	0.116
Distance	3.8	2.1
Highway	9.5	8.7
Pupils/Teacher	18.46	2.16
Blocks	357	91
Poverty	12.7	7.1

b. Calculate the similarity between attributes. In this step we identify which attributes in table 4.2 have strong or weak similarity. The Euclidean Distance was employed. It is defined as :

$$d_{ij} = \sqrt{(x_{ik} - x_{jk})^2} \qquad (5)$$

where :

d_{ij} = the distance between case i and j

x_{ik} = the value of the k_{th} variable for the i_{th} case

x_{jk} = the value of the k_{th} variable for the j_{th} case

Table 4.3 shows the result of similarity between predictors in table 4.2.

Table 4.3 : The Results of Similarity Between Predictors

	Tax Rate	HouseSize	HouseAge	Lot Size	Riverside	CrimeRate	Industrial	Air Quality	Distance	Highway	Pupil	Block	Poverty
Tax Rate	0.00												
HouseSize	168.3	0.00											
House Age	140.9	27.4	0.00										
Lot Size	146	22.3	5.1	0.00									
River Side	168.75	0.45	27.85	22.75	0.00								
Crime Rate	160.4	7.9	19.5	14.4	8.35	0.00							
Industrial	162.1	6.2	21.2	16.1	6.65	1.7	0.00						
Air Quality	168.88	0.584	27.98	22.88	0.13	8.48	6.78	0.00					
Distance	166.9	1.4	26	20.9	1.85	6.5	4.8	1.98	0.00				
Highway	160.3	8	19.4	14.3	8.45	0.1	1.8	8.58	6.6	0.00			
Pupils	166.84	1.46	25.94	20.84	1.91	6.44	4.74	2.04	0.06	6.54	0.00		
Blocks	78	90.3	62.9	68	90.75	82.4	84.1	90.88	88.9	82.3	88.84	0.00	
Poverty	161.9	6.4	21	15.9	6.85	1.5	0.2	6.98	5.00	1.6	4.94	83.9	0.00

c. Clustering the attributes in table 4.3 into clusters based on similarity. We employed the single linkage clustering as is given in algorithm 4.1. The inter cluster in this method is defined as the distance between the closest members of the two clusters.

$$d(c_i,c_j)=\min(\{d_f(\gamma_k,\gamma_l)\gamma_k \subseteq c_i and \gamma_l \subseteq c_i\}) \tag{6}$$

where :

d(ci, cj) = the inter cluster distance between two singleton cluster ci = (γk) and cj = (γl)

Algorithm 4.1 : The Single Linkage Clustering Algorithm

Start : Cluster C_1, C_2,..., C_n. Each containing a single individual.

1. *Find nearest pair of distinct cluster, say C_i and C_j.*
2. *Merge C_i and C_j*
3. *Delete C_j*
4. *Decrement number of cluster by one*
5. *If number of clusters equal one then stop*
6. *Else return to 1*

Table 4.4 shows the result of clustering the predictors in table 4.3.

Table 4.4: The Clustering of Predictors

Number of Cluster	Description
Cluster-1	{Distance, Pupils}
Cluster-2	{ Crime Rate, Highway}
Cluster-3	{ River Side, Air Quality}
Cluster-4	{ Industrial , Poverty}
Cluster-5	{House Size}
Cluster-6	{House Age, Lot Size}
Cluster-7	{Blocks}
Cluster-8	{Tax Rate}

d. Prediction modeling. In this step we employed Back Propagation Neural Network. Figure 4.1 shows the Neural Network Prediction Model.

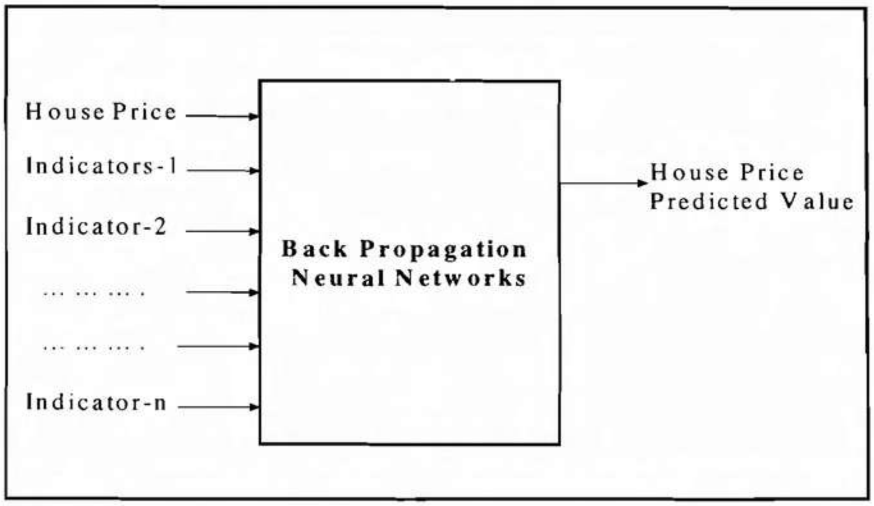


Figure 4.1 : The Neural Network Prediction Model

In this model, we suppose that the next house price is determined by the some indicators that always affect the movement of house price.

We have studied and tested our model using real estate data which contains 506 records. We tested five data samples with 506 train data, 506 test data, momentum equivalent to 50, learn rate equivalent to 50 and verify rate equivalent to 0.5.

The performance ability of our model is measured based on the following criteria:

a. Normalized RMS Error. Normalized RMS error indicates the Root Mean Square (RMS) error for the entire testing data. This error is also called Standard Error of Estimate which is defined as:

$$Normalized \quad RMS \quad Error = \sum \frac{(Actual \quad \Pr edicted \,)^2}{Number \quad of \Pr ediction} \tag{7}$$

The smaller the Normalized RMS Error value indicates that the prediction is better . For example, the Normalized RMS Error of experiment-1 is smaller than in experiment-2. It indicates that experiment-1 gives a better prediction than in experiment-2.

b. Unexplained Variance which indicates what portion of the target value is not explained by the prediction value. The Unexplained Variance is defined as follow:

$$Unexplained\,Variance = \frac{(Actual\,RMS\,Error)^2}{Variance\ of\ Target\,Column} \tag{8}$$

The smaller the Unexplained Variance value gives a better prediction. For example, the Unexplained Variance of experiment-3 is smaller than in experiment 4. It indicates that experiment 3 gives a better prediction than in experiment 4.

c. Correlation Coefficient. It is a number between zero and one which indicates how well the prediction is correlated to the actual. A value of one indicates perfect predictions, and a value of zero indicates no relationship between prediction and target. The Correlation Coefficient is defined as follow:

$$Corr.\,Coefficient = \sqrt{(1 - Unexplained\,Variance)} \tag{9}$$

5. The Experimental Results and Discussion

In the following, we demonstrate the results of the experiment on prediction based on table 4.4.

a. Using the attributes in the same cluster as input fields. For example, predict the next house price using attributes in cluster-1. Table 5.1 shows the result of experiment.

Table 5.1: The Result of Experiment

Normalized RMS Error	16.20
Unexplained Variance	0.63
Correlation Coefficient	0.61

The difference between actual and predicted values is given in Table 5.2

Table 5.2 : The Difference Between Actual and Predicted Values

House Price	Predicted	Difference	Distance	Pupils	......	Poverty
24.4	22.2	2.2	4.2392	18.6		14.66
21.2	29.1	7.9	2.7301	17.8		12.04
22.2	24.3	2.1	7.0355	16.6		11.22
13.4	15.4	2	2.0218	20.2		23.29
23.8	31.8	8	2.4259	14.7		12.14
17.4	22	4.6	6.498	18.9		13.09
22.2	20.2	2	6.4584	20.2		5.68
26.2	21.9	4.3	7.8265	19.1		6.56
14	14	0	1.6119	21.2		24.16
19	20	1	4.8122	20.2		9.74
17.8	15.5	2.3	2.4527	20.2		16.74
26.5	12.5	14	2.8561	20.9		7.67
30.1	24.3	5.8	12.1265	17		4.5
17.1	14	3.1	1.8498	21.2		14.59
30.1	29.9	0.2	3.2721	17.4		7.6
23.9	21.8	2.1	5.4007	19		7.22
22	16.8	5.2	2.2577	19.1		14.37
14.5	18.6	4.1	4.175	21		13.04
14.1	15.4	1.3	2.0882	20.2		19.69
24.7	21.5	3.2	3.8473	19.2		10.13
29.8	15.5	14.3	2.5329	20.2		11.66
20.3	28.8	8.5	3.1025	18.4		9.97
16.6	23.1	6.5	5.6894	17.9		18.8
15.3	20.3	5	1.6102	14.7		12.12
22.8	21.5	1.3	5.2873	19.2		5.52
28.7	22.2	6.5	6.0622	18.7		5.21
18.7	20	1.3	4.8122	20.2		9.29
...	...	...	...	...	...	...
...	...	...	...	...	...	...
31.5	29.9	1.6	3.375	17.4	...	3.76

b. Using the attributes in different clusters with the nearest distances as input fields. For example, predict the next house price using one attribute in cluster-1 and another attribute in cluster-2. The house price predicted attribute is given in table 5.3.

Table 5.3: The House Price Predicted Attribute

Normalized RMS Error	16.11
Unexplained Variance	0.62
Correlation Coefficient	0.61

Table 5.4 shows the difference between actual and predicted values.

Table 5.4 : The Difference Between Actual and Predicted Values

House Price	Predicted	Difference	Crime Rate	Pupils	......	Poverty
24.4	22.7	1.7	0.13587	18.6		14.66
21.2	23.4	2.2	0.13158	17.8		12.04
22.2	24	1.8	0.1029	16.6		11.22
13.4	17.5	4.1	7.05042	20.2		23.29
23.8	21.7	2.1	1.80028	14.7		12.14
17.4	22.3	4.9	0.13554	18.9		13.09
22.2	19.7	2.5	0.05083	20.2		5.68
26.2	22	4.2	0.19073	19.1		6.56
14	16.3	2.3	0.2909	21.2		24.16
19	19.7	0.7	0.054497	20.2		9.74
17.8	14.8	3	8.24809	20.2		16.74
26.5	17.5	9	0.11432	20.9		7.67
30.1	23.9	6.2	0.01709	17		4.5
17.1	16.3	0.8	0.35233	21.2		14.59
30.1	23.7	6.4	0.6147	17.4		7.6
23.9	22.1	1.8	0.04462	19		7.22
22	22	0	0.06899	19.1		14.37
14.5	17	2.5	1.35472	21		13.04
14.1	12.5	1.6	10.0623	20.2		19.69
24.7	21.8	2.9	0.17505	19.2		10.13
29.8	19.3	10.5	4.64689	20.2		11.66
20.3	22.9	2.6	0.3494	18.4		9.97
16.6	23.3	6.7	0.22927	17.9		18.8
15.3	26.3	11	1.12658	14.7		12.12
22.8	21.8	1	0.09164	19.2		5.52
28.7	22.6	6.1	0.02985	18.7		5.21
18.7	19.7	1	0.06151	20.2		9.29
...	...	...	...	...	...	...
...	...	...	...	...	...	...
31.5	23.7	7.8	0.44178	17.4	...	3.76

c. Using the attributes in different clusters with the furthest distances as input fields. For example, predict the next house price using one attribute in cluster-1 and another attribute in cluster-8. Table 5.5 shows the house price predicted attribute.

Table 5.5: The House Price Predicted Attribute

Normalized RMS Error	16.7
Unexplained Variance	0.68
Correlation Coefficient	0.57

The difference between actual and predicted values is given jn table 5.6

Table 5.6: The Difference Between Actual and Predicted Values

House Price	Predicted	Difference	Tax Rate	Pupils	......	Poverty
24.4	22.3	2.1	277	18.6		14.66
21.2	18.4	2.8	432	17.8		12.04
22.2	25.2	3	300	16.6		11.22
13.4	15.8	2.4	666	20.2		23.29
23.8	22.7	1.1	403	14.7		12.14
17.4	19.6	2.2	345	18.9		13.09
22.2	17.3	4.9	224	20.2		5.68
26.2	19.7	6.5	330	19.1		6.56
14	16.3	2.3	437	21.2		24.16
19	17.3	1.7	224	20.2		9.74
17.8	15.8	2	666	20.2		16.74
26.5	16.7	9.8	384	20.9		7.67
30.1	30.7	0.6	187	17		4.5
17.1	16.3	0.8	437	21.2		14.59
30.1	23.4	6.7	307	17.4		7.6
23.9	21.3	2.6	281	19		7.22
22	22.3	0.3	188	19.1		14.37
14.5	16.2	1.7	307	21		13.04
14.1	15.8	1.7	666	20.2		19.69
24.7	20.9	3.8	279	19.2		10.13
29.8	15.8	14	666	20.2		11.66
20.3	21.7	1.4	304	18.4		9.97
16.6	26	9.4	233	17.9		18.8
15.3	22.7	7.4	403	14.7		12.12
22.8	20.2	2.6	305	19.2		5.52
28.7	23.8	4.9	222	18.7		5.21
18.7	17.3	1.4	224	20.2		9.29
24.1	25.9	1.8	348	14.7		7.43
...	...	...	...	...	...	...
...	...	...	...	...	...	...
31.5	23.4	8.1	307	17.4	...	3.76

d. Using all of the attributes in different clusters with the nearest distance as input fields. For example, predict the next house price using all attributes in cluster-1 and in cluster-2. The house price predicted attributes is given in table 5.7.

Table 5.7: The House Price Predicted Attribute

Normalized RMS Error	14.71
Unexplained Variance	0.52
Correlation Coefficient	0.69

Table 5.8 shows the difference between actual and predicted values.

Table 5.8: The Difference Between Actual and Predicted Values

House Price	Predicted	Difference	Crime Rate	Distance	......	Poverty
24.4	20.9	3.5	0.13587	4.2392		14.66
21.2	27.1	5.9	0.13158	2.7301		12.04
22.2	24.4	2.2	0.1029	7.0355		11.22
13.4	15.1	1.7	7.05042	2.0218		23.29
23.8	32.3	8.5	1.80028	2.4259		12.14
17.4	24.4	7	0.13554	6.498		13.09
22.2	23.4	1.2	0.05083	6.4584		5.68
26.2	24.2	2	0.19073	7.8265		6.56
14	12.2	1.8	0.2909	1.6119		24.16
19	20.7	1.7	0.054497	4.8122		9.74
17.8	14.7	3.1	8.24809	2.4527		16.74
26.5	15.4	11.1	0.11432	2.8561		7.67
30.1	24.4	5.7	0.01709	12.1265		4.5
17.1	15	2.1	0.35233	1.8498		14.59
30.1	32.2	2.1	0.6147	3.2721		7.6
23.9	24.1	0.2	0.04462	5.4007		7.22
22	23.3	1.3	0.06899	2.2577		14.37
14.5	15.3	0.8	1.35472	4.175		13.04
14.1	13.1	1	10.0623	2.0882		19.69
24.7	17.6	7.1	0.17505	3.8473		10.13
29.8	17.3	12.5	4.64689	2.5329		11.66
20.3	26.8	6.5	0.3494	3.1025		9.97
16.6	24.4	7.8	0.22927	5.6894		18.8
15.3	19.2	3.9	1.12658	1.6102		12.12
22.8	23.9	1.1	0.09164	5.2873		5.52
28.7	24.4	4.3	0.02985	6.0622		5.21
18.7	20.7	2	0.06151	4.8122		9.29
24.1	24.5	0.4	0.03445	6.27		7.43
...	...	...	...	...	...	...
...	...	...	...	...	...	...
31.5	32.9	1.4	0.44178	3.375	...	3.76

e. Using all of the attributes in different clusters with the furthest distances as input fields. For example, predict the next house price using all attributes in cluster-1 and in cluster-8. Table 5.9 shows the house price predicted attribute.

Table 5.9: The House Price Predicted Attribute

Normalized RMS Error	15.38
Unexplained Variance	0.57
Correlation Coefficient	0.66

The difference between actual and predicted values is given in table 5.10.

Table 5.10: The Difference Between Actual and Predicted Values

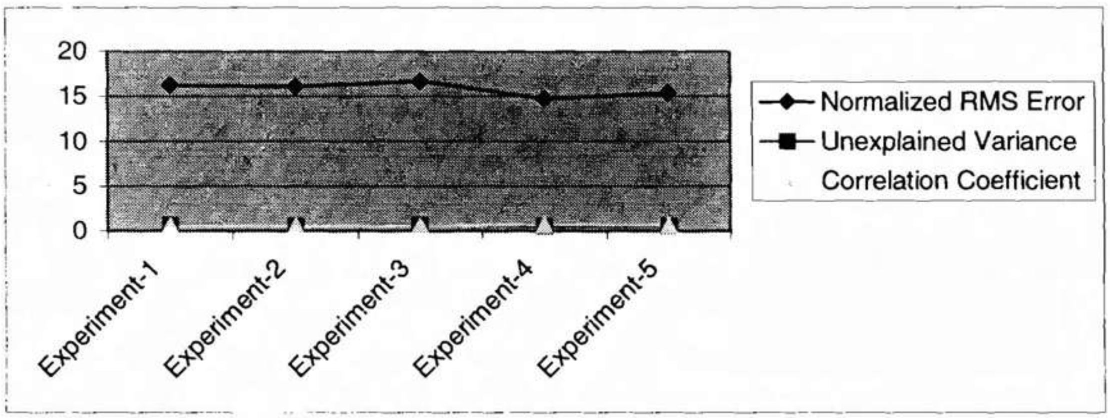
House Price	Predicted	Difference	Tax rate	Distance	......	Poverty
24.4	23.9	0.5	277	4.2392		14.66
21.2	17.5	3.7	432	2.7301		12.04
22.2	19.7	2.5	300	7.0355		11.22
13.4	12.9	0.5	666	2.0218		23.29
23.8	26	2.2	403	2.4259		12.14
17.4	18.4	1	345	6.498		13.09
22.2	21.4	0.8	224	6.4584		5.68
26.2	19.1	7.1	330	7.8265		6.56
14	17.6	3.6	437	1.6119		24.16
19	18.4	0.6	224	4.8122		9.74
17.8	13.9	3.9	666	2.4527		16.74
26.5	17.8	8.7	384	2.8561		7.67
30.1	41.1	11	187	12.1265		4.5
17.1	17.6	0.5	437	1.8498		14.59
30.1	28.2	1.9	307	3.2721		7.6
23.9	26.1	2.2	281	5.4007		7.22
22	20.6	1.4	188	2.2577		14.37
14.5	17.9	3.4	307	4.175		13.04
14.1	13.1	1	666	2.0882		19.69
24.7	20.1	4.6	279	3.8473		10.13
29.8	14.1	15.7	666	2.5329		11.66
20.3	22	1.7	304	3.1025		9.97
16.6	21.3	4.7	233	5.6894		18.8
15.3	21.1	5.8	403	1.6102		12.12
22.8	25.6	2.8	305	5.2873		5.52
28.7	28.9	0.2	222	6.0622		5.21
18.7	18.4	0.3	224	4.8122		9.29
24.1	27.8	3.7	348	6.27		7.43
...	...	...	...	...	...	...
...	...	...	...	...	...	...
31.5	28.4	3.1	307	3.375	...	3.76

In the following we illustrate the comparison among the results. Table 5.11 summarizes the results of Normalized RMS Error, Unexplained Variance and Correlation Coefficient. Graph 5.1 shows the comparison among the results.

Table 5.11 : The Results of Normalized RMS Error, Unexplained Variance and Correlation Coefficient

	Normalized RMS Error	Unexplained Variance	Correlation Coefficient
Experiment-1	16.20	0.63	0.61
Experiment-2	16.11	0.62	0.61
Experiment-3	16.7	0.68	0.57
Experiment-4	14.71	0.52	0.69
Experiment-5	15.38	0.57	0.66

Graph 5.1: The Comparison Among the Results



The previous results of the experiment shows that :

a) Using all attributes in different clusters with the furthest distances as input field gives a better prediction. The prediction has Normalized RMS Error equivalent to 14.71, Unexplained Variance equivalent to 0.52 and Correlation Coefficient equivalent to 0.69 Using the similarity technique we can pursue the best subset of similarity attributes to do prediction. This means that the combination of distance, pupils, crime rate and highway attributes as predictors in real estate data can improve the prediction ability.

6. Conclusion

Similarity is one of the important techniques in predictive data mining. Not all attributes within databases are feasible and suitable to do prediction. Therefore, we need to identify which of the attributes that have strong or weak similarity. At the present stage, we propose a predictive data mining model based on similarity method which consists of three main steps, similarity, clustering and predictive modeling. This model has been implemented and tested using real estate data. The result of the experiment shows that:

a) Using all attributes in different clusters with the nearest distances as input fields could give a better prediction.

b) Using similarity technique can improve the ability of making a prediction.

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