Fuzzy Temporal Data Mining

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***Abstract*—the study of temporal databases is necessary in real time applications. Temporal databases contain temporal constraints. Sometimes temporal constraints are uncertain. For instance, late, early, shortly, intime etc. In this paper Fuzzy Temporal Data Mining is studied with temporal databases. Fuzzy temporal reasoning is studied. Blackboard Database System is studied for store and retrieval for independent data sources for minimal search and reuse. Some examples are given as an application.**

***Keywords*— fuzzy logic, temporal logic, data mining, fuzzy data mining, fuzzy temporal data mining. Blackboard syatems**

I. INTRODUCTION

The database problems may contain temporal information [1]. Sometimes the problem may contain with time constraints "before time", "after time", "in time". .Sometimes time constraints are uncertain. The fuzzy logic deals uncertain information with belief rather than other likelihood [12.] The fuzzy databases may contain time constrains .For instance"The flight will come late, shortly etc. This situation is falls under fuzzy temporal. In the following, temporal databases and fuzzy temporal MapReduce algorithms are discussed.

II. FUZZY TEMORAL LOGIC

The temporal logic is logic with time constraints and Time variables "t1-t0 "like "before", "meet", "after", where starting time t0 and ending time t1.The time constraints are necessary to deal with data [1, 4].

Sometimes temporal logic may con FL2n incomplete information of time constraints. Fuzzy will deal with incomplete information.

Fuzzy temporal proposition is of the form " x" is Ã", where Ã is temporal fuzzy set.

Definition:A temporal set Ã is characterized by its membership function $\mu_{\tilde{A}}(t)$, where $t=t_e-t_s$, $t_s$is starting time and $t_e$ending time and $t1>t_0$

For instance

$past=ts>t_e$

$Present=t_e=t_s$

$feature=ts<t_e$

$latte=ts>t_e$

$intime=t_e=t_s$

$early=ts<t_e$

For instance,

$$late= \mu_{late}(t)/t= \mu_{late}(t1)/t1 +\ldots+ \mu_{late}(tn)/tn$$

For instance,

The fuzzy proposition may con FL2n time variables like.

"x is early"

"x is late"

Late=0/1+0.1/10+0.3/20+0.6/30+0.8/40+1.0/50+1/60

early=0.1/5+0.3/20+0.6/30+0.8/40+0.9/50+1/60

The relation temporal relational algebraic operations on fuzzy temporal are similar to fuzzy sets are given as

Let P and Q be the fuzzy temporal relational data sets, and the operations on fuzzy sets are given below

$PVQ=\max(\mu_P(x) , \mu_Q(x)\}$ Disjunction

$P\Lambda Q=\min(\mu_P(x) , \mu_Q(x)\}$ Conjunction

$P'=1- \mu_P(x)$ Negation $PxQ=\min \{ \mu_P(x) , \mu_Q(x)\}$ Relation

$P \text{ o } Q==\min\{\mu_P(x), \mu_Q(x, x)\}$ Composition

$P\leftrightarrow Q=\max\{ \mu_P(x) , \mu_Q(x)\}$ Association

The fuzzy propositions may con FL2n quantifiers like "very", "more or less" . These fuzzy quantifiers may be eliminated as

$\mu_{very\ P}(x) =\mu_P(x)^2$ Concentration

$\mu_{more\ or\ less\ P}(x) = \mu_P(x)^{0.5}$ Diffusion

III. DATA MINING IN TEMPORAL DATABASES

Definition: Temporal relational database is defined as Cartesian product of Domains A_1, A_2, $A_m$with some temporal Attributes and is represented as

$R=A_1XA_2X\ldots XA_m$

$t_i=a_{i1}xa_{i2}x,\ldots, x_{aim}$, i=1,…,n are tuples

Consider the flight databases

TABLE I. Departure

FLname	DEP	D
FL1	C1	21.30
FL1	C2	8.40
FL2	C3	11.20
FL2	C4	4.50
FL3	C3	20.45
FL3	C5	6.30
FL1	C3	20.45
FL1	C2	6.30

TABLE II. Arrival

FLname	To	A
FL1	C2	4.30
FL1	C5	1.40
FL2	C4	2.20
FL2	C6	6.50

FL3	C5	4.45
FL3	C7	8.30
FL4	C2	4.45
FL4	C5	8.30

The lossless decomposition is given by

TABLE III .Lossless Join

FLname	DEP	D	ARR	A
FL1	C1	21.30	C2	4.30
FL1	C2	8.40	C5	1.40
FL2	C3	11.20	C4	2.20
FL2	C4	4.50	C6	6.50
FL3	C3	20.45	C5	4.45
FL3	C5	6.30	C7	8.30
FL4	C3	20.45	C2	4.45
FL4	C2	6.30	C5	8.30

Data mining is knowledge discovery process dealing with methods like frequent items, association rules, clustering records, representation of tree, classification of trees and uncertainty in data [2,4]

In the following some of the methods are discussed. Consider Flight database of Fig.3.

Frequency items

The frequency of given by

TABLE IV .frequency

Fname	Frequency
FL1	4
FL2	2
FL3	2
FL4	2

Association rule

Customers who Flight Together is given by sorting

TABLE V .Association

FLname	DEP	ARR
FL1	C1	C2
FL1	C2	C5
FL2	C3	C4
FL2	C4	C6
FL3	C3	C5
FL3	C5	C7
FL4	C3	C2

Clustering

TABLE VI. Clustering

FLname	DEP	ARR
FL1	C1	C2
	C2	C5
	C3	C2
FL2	C3	C4
	C4	C6
FL3	C3	C5
	C5	C7

IV. FUZZY TEMPORAL DATA BASES

Definition: Given some universe of discourse X. fuzzy temporal relational data sets are defined as pair {t. $\mu_d(t)$}. where d is domains and membership function $\mu_d(x)$ taking values on the unit interval[0. 1] i.e. $\mu_d(t) \rightarrow [0.\ 1]$. where t_i€X is tuples .

TABLE VII. Fuzzy data set

	d_1	2_2	.	d_m	μ
t_1	a_{11}	a_{12}	.	a_{1m}	$\mu_d(t_1)$
t_2	a_{21}	a_{22}		A_{2m}	$\mu_d(t_2)$
.	.	.	.	.	.
t_n	a_{1n}	a_{1n}	.	A_{nm}	$\mu_d(t_n)$

$\mu_D(r) = \mu_d(t_1) + \mu_d(t_2) + \ldots + \mu_d(t_n)$, Where "+" is union, D is domain and t_i are tupls..

late =0.2/10 +0.4/20 +0.5/30 +0.6/40 +0.8/50+0.9/60

TABLE VIII.. .Departure

FLname	DEP	D	D.late
FL1	C1	21.30	0.1
FL1	C2	8.40	0.3
FL2	C3	11.20	0.5
FL2	C4	4.50	0.7
FL3	C3	20.45	0.7
FL3	C5	6.30	0.5
FL4	C3	20.45	0.3
FL4	C2	6.30	0.1

TABLE IX. .Arrival

FLname	ARR	A	A.late
FL1	C2	4.30	0.2
FL1	C5	1.40	0.4

FL2	C4	2.20	0.7
FL2	C6	6.50	0.9
FL3	C5	4.45	0.7
FL3	C7	8.30	0.5
FL4	C2	4.45	0.3
FL4	C5	8.30	0.1

TABLE X. Lossless join

FLname	DEP	ARR	D.late	A.late
FL1	C1	C2	0.1	0.2
FL1	C2	C5	0.3	0.4
FL2	C3	C4	0.5	0.7
FL2	C4	C6	0.7	0.9
FL3	C3	C5	0.7	0.7
FL3	C5	C7	0.5	0.5
FL1	C3	C2	0.3	0.3
FL4	C2	C5	0.1	0.1

Frequency items

The Flights frequently late are given by

TABLE XI. Frequency

Fname	Frequency
FL1	0.3
FL2	0.1
FL3	0.1
FL4	0.1

Association rule

Customers who Flight Together is given by sorting

TABLE X.II Association

FLname	Association	D.late↔A.late
FL1	C1 ↔C2	0.2
FL1	C2 ↔ C5	0.4
FL2	C3 ↔C4	0.7
FL2	C4↔ C6	0.9
FL3	C3↔ C5	0.7
FL3	C5↔ C7	0.5
FL1	C3↔C2	0.3
FL4	C2↔ C5	0.1

Clustering

TABLE XII. Clustering

FLname	Association	D.late↔A.late
FL1	C1 ↔C2↔ C5	0.4
FL2	C3 ↔C4↔ C6	0.9
FL3	C3↔ C5↔ C7	0.5
FL1	C3↔C2↔ C5	0.1

V. FUZZY TEMPORAL MAPREDUCE ALGORITHMS

The Map function will read the database and Reduce function with perform the computation and write to database .The fuzzy algorithms are used to solve the fuzzy problems . The fuzzy mapReducing algorithms read fuzzy rough set as input and write output. The operations on fuzzy rough sets .are given bellow

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The fuzzy temporal MapReduce algorithms are discussed based on fuzzy operations.

The fuzzy temporal MapReduce algorithm has two functions Mapping and Reducing. The Mapping read databases and Reducing will compute and write the database.

Negation

The fuzzy temporal MapReduce algorithm reads fuzzy temporal rough sets and writes negation of output.

The negation of late Flight Departure is given by

TABLE XIII. Negation

FLname	ARR	A	Not A.late
FL1	C2	4.30	0.8
FL1	C5	1.40	0.6
FL2	C4	2.20	0.3
FL2	C6	6.50	0.1
FL3	C5	4.45	0.3
FL3	C7	8.30	0.5
FL4	C2	4.45	0.7
FL4	C5	8.30	0.9

Disjunction

The fuzzy temporal MapReduce algorithm reads fuzzy temporal rough sets and writes disjunction of output.

TABLE XIV. Disjunction

FLname	DEP	D-late	ARR	A-late	DVA

FL1	C1	0.1	C2	0.2	0.1
FL1	C2	0.3	C5	0.4	0.4
FL2	C3	0.5	C4	0.7	0.5
FL2	C4	0.7	C6	0.9	0.9
FL3	C3	0.7	C5	0.7	0.7
FL3	C5	0.5	C7	0.5	0.5
FL4	C3	0.3	C2	0.3	0.3
FL4	C2	0.1	C5	0.1	0.1

Conjunction

The fuzzy temporal MapReduce algorithm reads fuzzy temporal rough sets and writes conjunction of output.

TABLE XV. Conjunction

FLname	DEP	D-late	ARR	A-late	D ΛA
FL1	C1	0.1	C2	0.2	0.1
FL1	C2	0.3	C5	0.4	0.3
FL2	C3	0.5	C4	0.7	0.5
FL2	C4	0.7	C6	0.9	0.7
FL3	C3	0.7	C5	0.7	0.7
FL3	C5	0.5	C7	0.5	0.5
FL4	C3	0.3	C2	0.3	0.3
FL4	C2	0.1	C5	0.1	0.1

Implication

if arrival Flight is late then Departure Flight is late is given by implication.

TABLE XVI Implication

FLname	DEP	D-late	ARR	A-late	D →A
FL1	C1	0.1	C2	0.2	0.1
FL1	C2	0.3	C5	0.4	0.3
FL2	C3	0.5	C4	0.7	0.5
FL2	C4	0.7	C6	0.9	0.7
FL3	C3	0.7	C5	0.7	0.7
FL3	C5	0.5	C7	0.5	0.5
FL4	C3	0.3	C2	0.3	0.3
FL4	C2	0.1	C5	0.1	0.1

TABLE XVII. Very late

FLname	DEP	D	D-very late
FL1	C1	21.30	0.1
FL1	C2	8.40	0.3
FL2	C3	11.20	0.5
FL2	C4	4.50	0.7
FL3	C3	20.45	0.7
FL3	C5	6.30	0.5
FL4	C3	20.45	0.3
FL4	C2	6.30	0.1

VI. TEMPORAL REASONING

Reinforcement learning is Machine Learning. Fuzzy Reinforcement learning will deal incomplete information. Fuzzy temporal reinforcement learning takes actions with temporal constraints.

Time series is the present time is present depending on previous time,

if Departure Flight is late then Arrival Flight is late

Departure Flight is very late

____

Departure Flight is very Decatur late o (Departure late → Arrival late)

Madman [8] fuzzy conditional inference is given by

Departure Flight is very Decatur late o (Departure late x Arrival late)

TABLE XVIII. Fuzzy Reasoning

FLname	DEP	D	D-very late
FL1	C1	21.30	0.1
FL1	C2	8.40	0.3
FL2	C3	11.20	0.5
FL2	C4	4.50	0.7
FL3	C3	20.45	0.7
FL3	C5	6.30	0.5
FL4	C3	20.45	0.3
FL4	C2	6.30	0.1

The blackboard systems may construct with the creation of data item sources..Blackboard databases may , store and retrieve for data item sources. Independently.

VII. BLACK BOARD TEMPORAL FUZZY DATABAE

These data items are stored in blackboard structure.

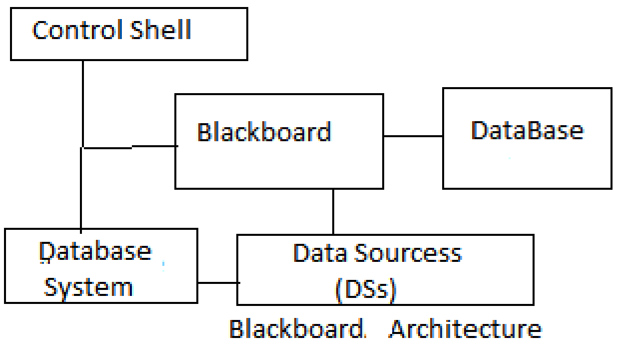

Fig.1.Blackboard System

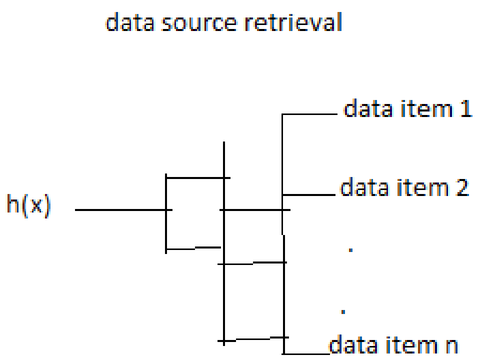

Fig.2.Indexed database

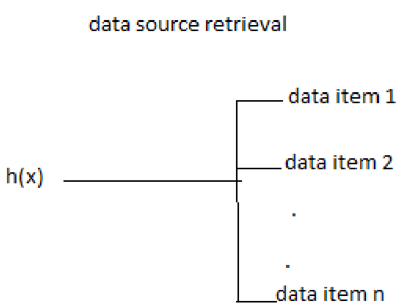

Fig.3. Blackboard database

h(x) is create, store and retrieval of data sources. When transaction being possessing, there is no need to take entire database into main memory. Just it is sufficient to retrieval of particular data item of particular transaction from the blackboard system.

The advantage of blackboard architecture is directly operated on data sources.

VIII. CONCLUSION

Blackboard Systems will be useful to store, retrieve and control the database. Blackboard System is studied for temporal data mining. Blackboard Systems will be useful for minimal search and reuse the database with control shell.

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