Fuzzy Temporal Data Mining Algorithms

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***Abstract*— Sometimes data mining has to deal with time constraints like "Train will come late". The time constraints may be incomplete. Fuzzy logic will deal with incomplete information. The fuzzy temporal logic will deal with incomplete time constraints. In this paper, Fuzzy temporal mining algorithms are discussed for data mining methods. The fuzzy temporal data mining algorithms will reduce the computations and time. Fuzzy temporal reasoning is discussed as classification. Some examples are given as an application.**

Key words: fuzzy logic, fuzzy databases, fuzzy temporal databases, fuzzy temporal data mining

I. Introduction

The database problems may contain incomplete information. Sometimes the problem may contain with time constraints "before time", "after time", "in time". There are many methods represent incomplete information. The fuzzy logic deals incomplete information with belief rather than other logics [11]. The fuzzy databases may contain time constrains. For instance "The flight "x" will come shortly". This situation is falls under fuzzy temporal,

The data mining has different models like frequent item sets, associations, clustering and classification. Data mining is necessary to study for statistical analysis for incomplete information with time component.

The MapReducing has two functions Mapping and Reducing. The Map function will read the database and Reduce function with perform the computation and write to database. In the following, temporal databases and fuzzy temporal databases 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.

Fuzzy temporal logic should deal with incomplete information of time constraints.[4]

A temporal variable is "t_1-t_0", where t0 is starting time and t1 ending time.

For instance "past"=t_1-t_0, t1<t_0

"Present"= t_1 approximately t_0

"feature"=t_1-t_0, t_1>t_0

A fuzzy temporal set is set of temporal variables with interval" t1-t0". [1]

.The fuzzy temporal logic is interpreted in simple method.

Let (I, t) and (J.t) are temporal sets.

For instance, "x was rich"

Was rich=rich X past.

(Rich, past)

not(I), t)=not (I,t)

(not(rich), past)=not (rich,past)

(I,t) and (J,t) = (I,t) Λ(J,t) conjunction

"x was rich and poor"

(rich,past) and (poor,past) = (rich, past) Λ(poor, past)

(I,t) or (J,t) =(I,t) V (J,t) disjunction

"x was rich or poor"

(rich,past) or (poor,past) = (rich, past) V (poor, past)

If (I,t) then (J,t)= (I,t)→ (J,t) implication

"if x was rich then x was poor"

If (rich,past) then (poor,past) = (rich, past)→ (poor, past)

Definition: Let p be the fuzzy temporal proposition of the form like 'x was A". The fuzzy temporal set Ã may be defined in terms of possibility Π as

p→$\Pi_{R(x)}$=A, where "R" is relation and xЄX is universe of discourse.

For instance,

The fuzzy proposition may contain time variables like.

" x was rich"

was rich=Π_{wealth}(x)= rich X past

Definition: The fuzzy temporal set Ã is characterized by membership function $\mu_{\tilde{A}}$: XxT→ [0,1], xЄX and TЄA

Suppose X is a finite set. The fuzzy temporal set Ã of X may be represented by

$\tilde{A}= (\mu_{\tilde{A}}(x_1,t_1)/x_1 + \mu_{\tilde{A}}(x_2,t_1)/x_{2\,+\ldots+}\ \mu_{\tilde{A}}(x_n,t_1)/x_n)/t_1$

$+ (\mu_{\tilde{A}}(x_1,t_2)/x_1 + \mu_{\tilde{A}}(x_2,t_2)/x_{2\,+\ldots+}\ \mu_{\tilde{A}}(x_n,t_2)/x_n)/t_2 +\ldots+$

$(\mu_{\tilde{A}}(x_1,t_m)/x_1 + \mu_{\tilde{A}}(x_2,t_m)/x_{2\,+\ldots+}\ \mu_{\tilde{A}}(x_n,t_1)/x_n)/t_m$

$\tilde{A} =1-\mu_{\tilde{A}}(x,t)$

$\tilde{A}= \{(0.1/x_1+ 0.2/x_2+0.3/x_3+0.35/x_4+0.4/x_5)/t_1$

$+(0.4/x_1+0.45/x_2+0.5/x_3+0.55/x_4+0.6/x_5)/t_2$

$+(0.7/x_1+0.75/x_2+0.8/x_3+0.85/x_4+0.9/x_5)/t_{3\}}$

Flight arrival= $\{(0.2x_1+$

$0.3/x_2+0.5/x_3+0.7/x_4+0.9/x_5)$/before

$+(0.6/x_1+0.65/x_2+0.7/x_3+0.8/x_4+0.9/x_5)$/normal

$+(0.7/x_1+0.75/x_2+0.8/x_3+0.\ 85/x_4+0.9/x_5)$/after }

For instance "Flight came in normal time"

"Flight will come after 10 minutes"

"Flight left 10 munities before"

"usually the flight x is Departure"→ $\mu_{\tilde{A}}(x)^{2}$

"the flight x comes more or less in time"→ $\mu_{\tilde{A}}(x)^{0.5}$

"x was rich"

$\Pi_{\text{was rich}}$ (x)=rich X past

where rich X past = min {rich, past}

rich= $0.5/x_1 +0.5.5/x_2 + 0.7/x_3 +0.7.5/x_4 +0.8/x_5$

past= $0.4/t_1 +0.6/t_2 + 0.7/t_3 +0.8/t_4 +0.85/t_5$

was rich =rich X past =min $\{0.5/x_1 + 0.5.5/x_2 + 0.7/x_3 +0.7.5/x_4 +0.8/x_5, 0.4/t_1 +0.6/t_2 + 0.7/t_3 +0.8/t_4 +0.85/t_5\}$

$= 0.4/t_1 +0.55/t_2 + 0.7/t_3 +0.7.5/t_4 +0.8/t_5$

The fuzzy temporal propositions like "x was A" may contain quantifiers like "very", "More or Less" etc. These fuzzy quantifiers may be eliminated as

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$\mu_{very\ richXpast}(x) = \mu_{richXpast}(x)^{2}$ Concentration
$\mu_{more\ or\ less\ richXpast}(x) = \mu_{richXpast}(x)^{0.5}$ Diffusion

III. TEMPORAL DATABASES

The Map function will read the database and Reduce function with perform the computation and write To City database The Relational Database representation is simple representation of databases [7].

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

$R(A_1,A_2,\ldots, A_n)$, R is relation, A_1, A_2,… A_m are domains

R (ai1, ai2…, aim, i=1, n are tuples

Consider the flight databases

TABLE I. Arrival

Fno	From City	Arrival
F101	Hong Kong	22.30
F201	Dubai	0.40
F301	Colombo	8.20
F402	New York	10.50
F502	New York	20.45
F601	Kuala Lumpur	6.30

TABLE II. Departure

Fno	To City	Departur e
F101	Colombo	23.30
F201	Hong Kong	1.40
F301	New York	9.20
F402	Kuala Lumpur	11.50
F502	Kuala Lumpur	21.45
F601	Dubai	8.30

TABLE III. Lossless Join

Fno	From City	Arrival	To City	Departure
F101	Hong Kong	22.30	Colombo	23.30
F201	Dubai	0.40	Hong Kong	1.40
F301	Colombo	8.20	New York	9.20
F402	New York	10.50	Kuala Lumpur	11.50
F502	New York	20.45	Kuala Lumpur	21.45
F601	Kuala Lumpur	6.30	Dubai	8.30

Functional Dependency

Definition: Suppose Y is depending on X or X→Y iff t1(X)=t2(X) than t1(Y)=t2(Y)

2NF for TABLE III is given by

Fno → From City, Arival

Fno→To Coty, Departure

2NF or Decomposition is given by TABLE I and TABLE II.

IV. FUZZY TEMPORAL DATA MINING

The Map function will read the database and Reduce function with perform the computation and write to database .The fuzzy algorithms are use 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.

Fuzzy Temporal Data Mining is knowledge discovery process with data associated with uncertainty or incompleteness. The fuzzy logic[12] is more suitable to deal with such data because fuzzy logic deals with commonsense rather than likelihood.

Fizzy Temporal Relational Databases are discussed with Rough set theory. Rough Set theory is another approach to incomplete information[2]. The incomplete Information may be deal with fuzzy logic.

Definition: Given some universe of discourse X, a fuzzy rough set is defined as pair {t, $\mu_d(t)$}, where d is domains and membership time function $\mu_d(x)$ taking values on the unit interval[0,1] i.e. $\mu_d(t)$→[0,1], where t_iЄX is tuples .

TABLE VII. . Fuzzy temporal rough 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}	$\mu_d(t_n)$

Consider the fuzzy proposition “x is late” and the fuzzy set ‘late is defined as

$\mu_{late}(x)$→[0, 1], x Є X, x is minutes.

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

$R(A_1,A_2,\ldots, A_n)$, R is relation, A_1, A_2,… A_m are domains
R(ai1,ai2…, aim, i=1,…,n are tuples.

TABLE VIII. . Arrival Fuzzy temporal rough set

Fno	From City	Arrival	late
F101	Hong Kong	22.30	0.5
F201	Dubai	0.40	0.2
F301	Colombo	8.20	0.9
F402	New York	10.50	0.4
F502	New York	20.45	0.6
F601	Kuala Lumpur	6.30	0.8

TABLE IX. . Departure Fuzzy temporal rough set

Fno	To City	Departure	late
F101	Colombo	23.30	0.4
F201	Hong Kong	1.40	0.5
F301	New York	9.20	0.8
F402	Kuala Lumpur	11.50	0.2
F502	Kuala Lumpur	21.45	0.9
F601	Dubai	8.30	0.6

TABLE XI. Lossless join

Fno	From City	Arrival	To City	Departure	late
F101	Hong Kong	22.30	Colombo	23.30	0.4
F201	Dubai	0.40	Hong Kong	1.40	0.2
F301	Colombo	8.20	New York	9.20	0.8
F402	New York	10.50	Kuala Lumpur	11.50	0.2
F502	New York	20.45	Kuala Lumpur	21.45	0.6
F601	Kuala Lumpur	6.30	Dubai	8.30	0.6

Fuzzy Decomposition is given by

TABLE X.

Fno	From City	Arrival	late
F101	Hong Kong	22.30	0.4
F201	Dubai	0.40	0.2
F301	Colombo	8.20	0.8
F402	New York	10.50	0.2
F502	New York	20.45	0.6
F601	Kuala Lumpur	6.30	0.6

TABLE XI.

Fno	To City	Departure	late
F101	Colombo	23.30	0.4
F201	Hong Kong	1.40	0.2
F301	New York	9.20	0.8
F402	Kuala Lumpur	11.50	0.2
F502	Kuala Lumpur	21.45	0.6
F601	Dubai	8.30	0.6

Let C and D be the fuzzy sets.
The operations on fuzzy sets are given as

$1\text{-}C = 1 - \mu_C(x)$ Negation
$C \cup D = \max\{\mu_C(x), \mu_D(x)\}$ Disjunction
$C \cap D = \max\{\mu_C(x), \mu_D(x)\}$ Conjunction

Zadeh [11] Implication is given by
$C \rightarrow D = \min\{1.\ 1 - \mu_C(x) + \mu_D(x)\}$

Mamdani [7] Implication is given by
$C \rightarrow D = \min\{\mu_C(x), \mu_D(x)\}$

Reddy [11] Implication when consequent pat not known is given by
$C \rightarrow D = \min\{-\mu_C(x)\}$

The fuzzy temporal MapReducing algorithms are discussed based on fuzzy operations.
The fuzzy temporal MapReducing algorithm has two functions Mapping and Reducing. The Mapping read databases and Reducing will compute and write the database.

A. Negation

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

The negation of late Flight Departure is given by

TABLE XII. Negation

Fno	To City	Departure	late
F101	Colombo	23.30	0.6
F201	Hong Kong	1.40	0.5
F301	New York	9.20	0.2
F402	Kuala Lumpur	11.50	0.8
F502	Kuala Lumpur	21.45	0.1
F601	Dubai	8.30	0.4

B. Disjunction

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

TABLE XII. Disjunction

Fno	From City	Arrival	To City	Departure	late
F101	Hong Kong	22.30	Colombo	23.30	0.5
F201	Dubai	0.40	Hong Kong	1.40	0.5
F301	Colombo	8.20	New York	9.20	0.9
F402	New York	10.50	Kuala Lumpur	11.50	0.4
F502	New York	20.45	Kuala Lumpur	21.45	0.9
F601	Kuala Lumpur	6.30	Dubai	8.30	0.8

C. Conjunction

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

TABLE XIII. Conjunction

Fno	From City	Arrival	To City	Departure	late
F101	Hong Kong	22.30	Colombo	23.30	0.4
F201	Dubai	0.40	Hong Kong	1.40	0.2
F301	Colombo	8.20	New York	9.20	0.8
F402	New York	10.50	Kuala Lumpur	11.50	0.2
F502	New York	20.45	Kuala Lumpur	21.45	0.6
F601	Kuala Lumpur	6.30	Dubai	8.30	0.6

D. Implication

The fuzzy temporal MapReducing algorithm reads fuzzy temporal rough sets and writes implication of output.

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

TABLE XIV. Implication (arrival→departure)

Fno	From City	To City	Zadeh	Mamdani	Reddy
F101	Hong Kong	Colombo	0.9	0.4	0.5
F201	Dubai	Hong Kong	1.0	0.2	0.2
F301	Colombo	New York	0.9	0.8	0.9
F402	New York	Kuala Lumpur	0.8	0.2	0.4
F502	New York	Kuala Lumpur	1.0	0.6	0.6
F601	Kuala Lumpur	Dubai	0.8	0.6	0.8

TABLE XV. Very late

Fno	From City	Arrival	Very less late
F101	Hong Kong	22.30	0.25
F201	Dubai	0.40	0.04
F301	Colombo	8.20	0.81
F402	New York	10.50	0.04
F502	New York	20.45	0.36
F601	Kuala Lumpur	6.30	0.8

E. Frequency items

TABLE XVI. Frequency

From City	To City	Frequency
Hong Kong	Colombo	0.1
Dub1ai	Hong Kong	0.1
Colombo	New York	0.1
New York	Kuala Lumpur	0.2
Kuala Lumpur	Dubai	0.1

F. Association rule

TABLE XVI. Association

Fno	µ
F402<==>F502	0.2

G. Clustering

The Flights which are late for New York.

TABLE XVII. Clustering

Fno	Coty
F402	New York
F502	

H. Reasoning

Zadeh [11]fuzzy reasoning is given by

if arrival is late then Departure is late
very less arrival late

Departure =
very less arrival o (arrival → departure)
very less arrival o (min{1, 1-arrival + departure})

Mamdani [7] fuzzy reasoning is given by

if arrival is late then Departure is late
very less arrival late

Departure =
very less arrival o (arrival → departure)
very less arrival o (min{arrival, departure})

Reddy [9] fuzzy reasoning is given by

if arrival is late then Departure is late
very less arrival late

Departure =
very less arrival o (arrival)
very less arrival o (arrival → departure)

TABLE XVII. Reasoning

Fno	From City	To City	Zadeh	Mamdani	Proposes
F101	Hong Kong	Colombo	0.25	0.25	0.25
F201	Dubai	Hong Kong	0.04	0.04	0.04
F301	Colombo	New York	0.81	0.81	0.81
F402	New York	Kuala Lumpur	0.04	0.04	0.04
F502	New York	Kuala Lumpur	0.36	0.36	0.36
F601	Kuala Lumpur	Dubai	0.8	0.8	0.8

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