Fuzzy Temporal Data Mining Algorithms

Venkata Subba Reddy Poli

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June 7, 2020
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 constraints. 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 will perform the computation and write to database. In the following, temporal databases and fuzzy temporal databases are discussed.

II. FUZZY TEMPORAL 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 “t1-t0”, where t0 is starting time and t1 ending time.

For instance “past”=t1-t0, t1 < t0
“Present”= t1 approximately t0
“feature”=t1-t0, t1 > t0

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)
(not(rich), past)=not (rich, past)
(I, t) and (J, t) = (I, t)  (J, t) conjunction
“x was rich and poor”
(rich, past) and (poor, past) = (rich, past)  (poor, past)
(I, t) or (J, t)=(I, t)  (J, t) disjunction
“x was rich or poor”
(rich, past) or (poor, past) = (rich, past)  (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 A may be defined in terms of possibility P as
p→Π_{xЄX}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_{xЄX}rich X past
Definition: The fuzzy temporal set A is characterized by membership function µ_{A}: XxT → [0,1], xЄX and TЄA
Suppose X is a finite set. The fuzzy temporal set A of X may be represented by
A = (µ_{A}(x_1,t_1)/x_1 + µ_{A}(x_2,t_1)/x_2 +…+ µ_{A}(x_n,t_1)/x_n)/t_1
+ (µ_{A}(x_1,t_2)/x_1 + µ_{A}(x_2,t_2)/x_2 +…+ µ_{A}(x_n,t_2)/x_n)/t_2 +…+
(µ_{A}(x_1,t_m)/x_1 + µ_{A}(x_2,t_m)/x_2 +…+ µ_{A}(x_n,t_m)/x_n)/t_m
A =1-{µ_{A}(x_1)}
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= {0.2/x_1+}
0.3/x_2+0.3/x_3+0.3/x_4+0.3/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” → µ_{A}(x) 2
“the flight x comes more or less in time”→ µ_{A}(x) 0.5
“x was rich”
Π_{was rich}(x)=rich X past
where rich X past = min {rich, past}
rich= 0.5/x_1 +0.5/x_2 + 0.7/x_3 +0.75/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/x_2 + 0.7/x_3 +0.75/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 +0.75/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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TABLE I. Arrival

<table>
<thead>
<tr>
<th>Fno</th>
<th>From City</th>
<th>Arrival</th>
</tr>
</thead>
<tbody>
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</tr>
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</tr>
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TABLE II. Departure

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TABLE III. Lossless Join

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<td>6.30</td>
<td>Dubai</td>
<td>8.30</td>
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</tbody>
</table>

**Functional Dependency**

\[
\begin{align*}
\mu_{\text{very rich past}}(x) &= \mu_{\text{rich past}}(x) \\
\mu_{\text{more or less rich past}}(x) &= \mu_{\text{rich past}}(x)^{0.5}
\end{align*}
\]

Concentration

**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 A1, A2, Am with some temporal Attributes and is represented as

\[ R = A_1 \times A_2 \times \ldots \times A_m \]

\[ t_i = a_{i1} \times a_{i2} \times \ldots \times a_{im}, i=1,\ldots,n \text{ are tuples} \]

R(A1, A2, ..., Am), R is relation. A1, A2, ..., Am are domains R(ai1, ai2, ..., aim, i=1, n are tuples)

Consider the flight databases

**TABLE IX. Departure Fuzzy temporal rough set**

<table>
<thead>
<tr>
<th>Fno</th>
<th>To City</th>
<th>Departure</th>
</tr>
</thead>
<tbody>
<tr>
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</tr>
<tr>
<td>F601</td>
<td>Kuala Lumpur</td>
<td>6.30</td>
</tr>
</tbody>
</table>

**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 used to solve the fuzzy problems. The fuzzy map-reducing algorithms read fuzzy rough set as input and write output. The operations on fuzzy rough sets are given below.

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.

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

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

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

\[ \mu_{\text{late}}(x) \rightarrow [0,1], x \in X, x \text{ is minutes.} \]

\[ \text{late} = 0.2/10 + 0.4/20 + 0.5/30 + 0.6/40 + 0.8/50 + 0.9/60 \]

R(A1, A2, ..., A_m). R is relation, A1, A2, ..., Am are domains R(ai1, ai2, ..., aim, i=1, n are tuples).

**TABLE VII. Fuzzy temporal rough set**

<table>
<thead>
<tr>
<th>d1</th>
<th>d2</th>
<th>d3</th>
<th>( \mu )</th>
</tr>
</thead>
<tbody>
<tr>
<td>t1</td>
<td>a_{i1}</td>
<td></td>
<td>\mu_{d(t1)}</td>
</tr>
<tr>
<td>t2</td>
<td>a_{i2}</td>
<td></td>
<td>\mu_{d(t2)}</td>
</tr>
<tr>
<td>\vdots</td>
<td>\vdots</td>
<td>\vdots</td>
<td>\vdots</td>
</tr>
<tr>
<td>\vdots</td>
<td>\vdots</td>
<td>\vdots</td>
<td>\vdots</td>
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</tbody>
</table>

**TABLE VIII. Arrival Fuzzy temporal rough set**

<table>
<thead>
<tr>
<th>Fno</th>
<th>From City</th>
<th>Arrival</th>
<th>late</th>
</tr>
</thead>
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<td>Dubai</td>
<td>0.40</td>
<td>0.2</td>
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<td>Colombo</td>
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<td>0.9</td>
</tr>
<tr>
<td>F402</td>
<td>New York</td>
<td>10.50</td>
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<td>20.45</td>
<td>0.6</td>
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<td>F601</td>
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<td>6.30</td>
<td>0.8</td>
</tr>
</tbody>
</table>

**TABLE IX. Departure Fuzzy temporal rough set**

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

\[ \mu_{\text{late}}(x) \rightarrow [0,1], x \in X, x \text{ is minutes.} \]

\[ \text{late} = 0.2/10 + 0.4/20 + 0.5/30 + 0.6/40 + 0.8/50 + 0.9/60 \]

R(A1, A2, ..., A_m). R is relation, A1, A2, ..., Am are domains R(ai1, ai2, ..., aim, i=1, n are tuples).
Reducing algorithms are

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 0.5
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-C= 1- \( \mu_{C}(x) \) Negation

CUD = 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>
<thead>
<tr>
<th>Fno</th>
<th>From City</th>
<th>Arrival</th>
<th>To City</th>
<th>Departure</th>
<th>late</th>
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<td>Kuala Lumpur</td>
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<td>0.2</td>
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<tr>
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<td>Dubai</td>
<td>8.30</td>
<td>0.6</td>
</tr>
</tbody>
</table>

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>
<thead>
<tr>
<th>Fno</th>
<th>From City</th>
<th>To City</th>
<th>Frequency</th>
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<tr>
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<tr>
<td>F502</td>
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</table>

E. Frequency items

<table>
<thead>
<tr>
<th>Fno</th>
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</tr>
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F. Association rule

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<tr>
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G. Clustering

The Flights which are late for New York.

<table>
<thead>
<tr>
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<th>Coty</th>
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</thead>
<tbody>
<tr>
<td>F402</td>
<td>New York</td>
</tr>
<tr>
<td>F502</td>
<td></td>
</tr>
</tbody>
</table>

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 -> departure)
very less arrival o (min{arrival, departure})
Departure = very less arrival o (arrival )
very less arrival o (arrival \(\rightarrow\) departure)

<table>
<thead>
<tr>
<th>Fno</th>
<th>From City</th>
<th>To City</th>
<th>Zadeh</th>
<th>Mamdani</th>
<th>Proposes</th>
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