Rule Mining for Many-Valued Implications Using Concept Lattice

Bhavana Jamalpur[1], Nagendar Yamsani[3]
Department of Computer Science and Engineering
S R Engineering College
Warangal Urban, India
bhavana_j@srecwarangal.ac.in, nagendar.y@srecwarangal.ac.in

Prof.SSVN Sarma[2]
Department of Computer Science and Engineering
Vagdevi Engineering College
Warangal Rural, India
ssvn.sarma1@gmail.com

***Abstract*—Every object contains properties/attributes which generally have binary values either on or off. The basic issue is how to manage with multi-valued attributes which consists of different values for a single attribute. Conceptual scaling is used to discretize the attributes such as age, color, shape which contain many values. A concept lattice may contain multi-valued contexts which is an important issue in the theory of concept lattices. This paper discusses on scaling and construction of concept lattice for multi-valued context. Conversion of multi-valued into one-valued is the primary goal of this paper. By analyzing formal contexts, which are obtained after transformation. Construction of lattice and generation of implications with specific support and confidence for the contexts is shown experimentally**

Keywords-Concept Analysis; many-valued concept; concept lattice; implications; data mining

I. INTRODUCTION

Information can be gained in an abstract way using a formal concepts .Numbers of routines are developed to built lattice and their sub-contexts. Pictorial representing of the data can be done using line/nested diagrams to gain knowledge. The main aim is to convert the raw data context into concept lattice using logic scaling. Multi-valued context is transformed by conceptual scaling to a single valued context. Generally, scaling involves human interpretation of the data.

II. FORMAL CONCEPT ANALYSIS – SCALING

Scaling is used in the knowledge acquisition in data for different types of attributes and also using concepts data analysis for learning the behavior of objects. Different kinds of scaling include nominal, interval, ordinal and ratio.

Objects of the scale are the possible values of the multi-valued attributes.

A. *Nominal Scales*

In case of nominal type the attribute significance is rejected with the other.

	a_1	a_2	a_3	a_4
o_1	1	0	0	0
o_2	0	1	0	0
o_3	0	0	1	0
o_4	0	0	0	1

Table 1. Nominal

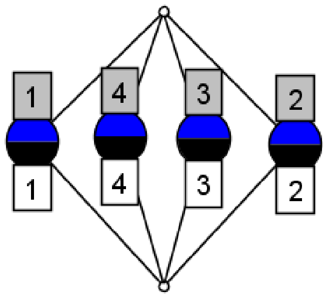


Fig1.Nominal-Scale

B. ***Ordinal Scales:*** In case of ordinal scaling the attributes with sequence set of values. The net result of concept can be analyzed by grading. Examples are :Temperature: low, medium, high

Grades: good, better, best

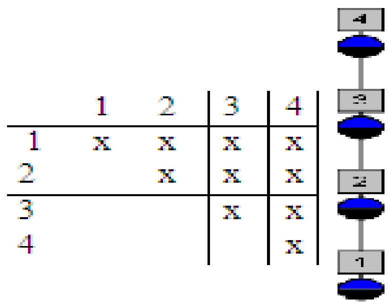


Fig2. Ordinal Scale

C. ***Inter-ordinal Scales :*** This type of scaling is used in questionnaires where one can select values on scale as like active, passive ,agree ,disagree. Generally, the scale values lies in between the relation.

	≤1	≤2	≤3	≤4	≥1	≥2	≥3	≥4
o1	1	1	1	1	1	0	0	0
o2	0	1	1	1	1	1	0	0
o3	0	0	1	1	1	1	1	0
o4	0	0	0	1	1	1	1	1

Table2. Inter Ordinal Scale

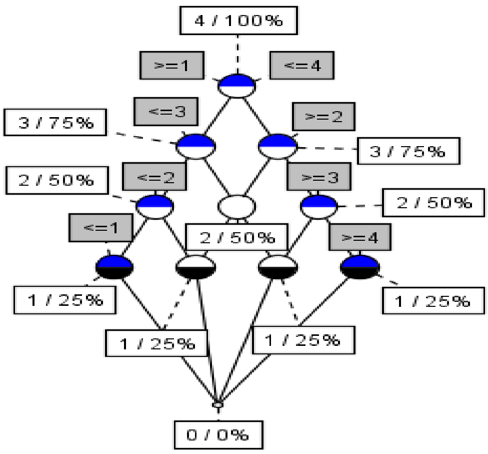


Fig3. Inter Ordinal Scale

D. ***Bi-ordinal Scales:*** This type of scaling is used when objects are assigned to one of the two poles with a different degree such as very silent, silent ,loud ,very loud .

	≤1	≤2	≤3	≤4	≥5	≥6
1	1	1	1	1	1	1
2	0	1	1	1	1	1
3	0	0	1	1	1	1
4	0	0		1	1	1

Table3. Bi-Ordinal Scale

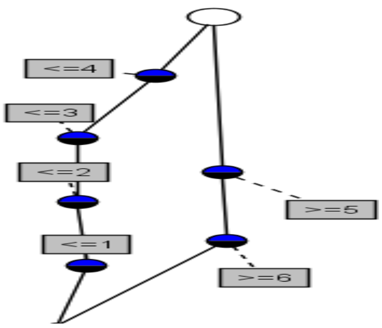


Fig4. Bi- Ordinal Scale

E. ***Dichotomic scale :*** This type of scaling generally contains yes/no values.

	0	1
0	X	
1		x

Table4. Dichotomic scale

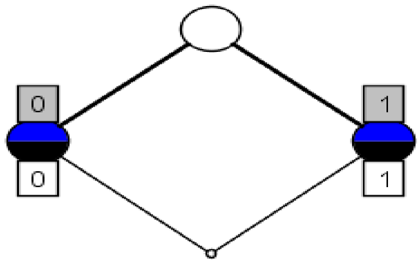


Fig5. Di-scale

III. FORMAL CONCEPT ANALYSIS

A context contains $C_1(G_1,M_1,I_1)$ where G_1 and M_1 are set of objects and attributes in such a way that

$I_1 \square G_1$ X M_1, there exist a relation between objects and attributes. The notation $(g_1, m_1) \square I_1$ is represented as $g_1I_1\, m_1$.

This can be read as “object g_1 has attribute m_1”.

For $A_1 \square\ G_1$, $B_1 \square\ M_1$ then,

$A_1 = \{\ m_1 \square\ M_1 \mid (\text{for every } g_1 \square\ A_1)\ g_1I_1m_1\}$

$B_1 = \{\ g_1 \square\ G_1 \mid (\text{for every } m_1 \square\ B_1)\ g_1I_1m_1\}$

Here the set of objects along with their attributes with a relation form a formal context which is represented in a tabular form with ‘x’ indicating the presence of the attribute and ‘null’ indicate the absence of the attribute for the object.

A. Construction of Concept – Lattice

FCA makes the connections and groups of concepts can be shown in the form of the lattice and also to pictorial representation of the relation that exists.

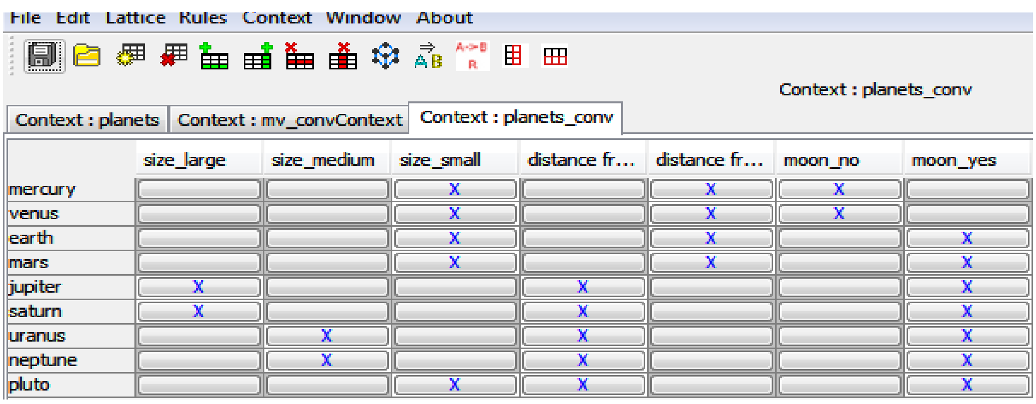
An order if relation for a group of concepts for a context can be written as:

Given two concepts (A1,B1) and (A2,B2) in C1(G1,M1,I1) here (A1,B1) is known as the Subconcept of (A2,B2) or (A2,B2) is known as the SuperConcept of (A1,B1) if A1 subset of A2 , B1 superset B2. Thus, (A1 ,B1) less than or equal to (A2,B2) which is denoted by “≤” is defined as the order of the relation. So, the group of ordered relation is denoted as C1(G1,M1; ≤) is the Galois lattice / Concept Lattice for the context. So, sub-super concept relation and a set of concepts are contained in galois lattice.

IV. MANY VALUED CONTEXTS

Many valued contexts may not only be properties which may or may not be linked to an object but can posses different values. Attributes such as weight, height, gender are examples of multi valued attributes.

Definition: A many-valued context (G_0, M_0, W_0, I_0) consists of sets G_0, M_0 and W_0 are sets of elements known as objects(G_0) with many-values and attributes (M_0) and values for attributes (W_0) and I_0 is the relation with I_0 subset equal G_0 X M_0 X W_0 such that (g_0,m_o,v_0) belong I_0 and (g_0,m_0,w_0) belong I_0 implies that $v_0=w_0$.



	size_large	size_medium	size_small	distance fr...	distance fr...	moon_no	moon_yes
mercury			X		X	X	
venus			X		X	X	
earth			X		X		X
mars			X		X		X
jupiter	X			X			X
saturn	X			X			X
uranus		X		X			X
neptune		X		X			X
pluto			X	X			X

Fig 6.Many-valued context

Fig6. Many-valued context where the objects (rows) and attributes (columns) are stored with presence of the attribute for the object by “x” and “null” for absence of the attributes.

Suppose , consider our solar system which consists of nine planents as object placed in the table by rows as :

- mercury(m)
- venus(v)
- earth(e)
- mars(mm)
- jupiter(j)
- saturn(s)
- uranus(u)
- neptune(n)
- pluto(p).

Attributes are size,check the distance from sun and have moon. As these attributes contain multi-values so, size attribute is split into

- small(s)
- medium(m)
- large(l).

Similarly, distance attribute is split into

- near(n)
- far(f)

For moon attribute is divided into

- yes(y)
- no(n).

To allocate concepts to multiple values context , we have to transform the multi-valued to single valued and analyse the concepts of the derived context as the concepts of many-valued .Every multi-valued attribute are converted or replaced by the attribute values which are available in the binary table for each object description for an attribute. Thus, as shown in fig6. Mercury(m) has three single valued attributes such as size(small),distance(near) and has moon(no). So, this can be represented as ss indicating size(small) dn denotes distance(near) and mn denotes has moon(no)

V. EXPERIMENTAL STUDY

From the above fig6. We have the following

Objects with attributes

- mercury(m) {ss,dn,mn}
- venus(v){ss,dn,mn}
- earth(e){ss,dn,my}
- mars(mm){ss,dn,my}
- jupiter(j){sl,df,my}
- saturn(s){sl,df,my}
- uranus(u){sm,df,my}
- neptune(n){sm,df,my}
- pluto(p){ss,df,my}

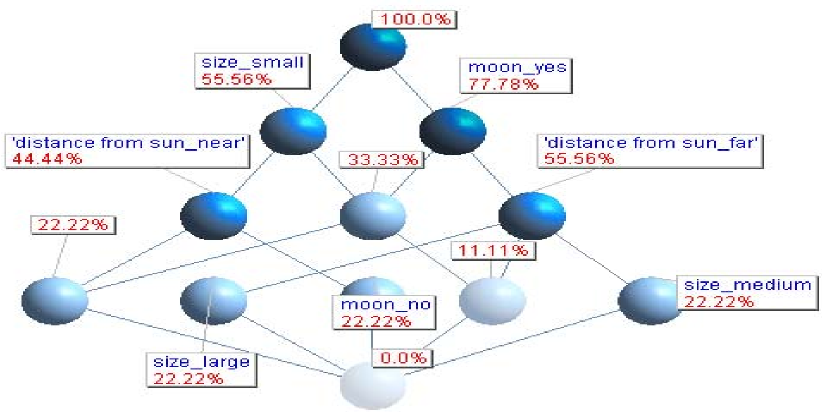


Fig7. Attribute-Values

- We have, the following implications along with support count as:
- The top-node consist of all the objects .
- {m, v, e, mm, j, s, u } -> φ with 100%
- {e, mm, m ,p ,v } -> {ss} with 55%
- {e , j , mm, n, p, s } -> {my} with 77 %
- {e, mm, m, v } -> {dn} with 44.4%
- {j, n, p, s } -> {df} with 55.5%
- {m, v} -> {mn} with 22.2%
- {j , l } -> {sl} with 22.2%
- {n, u} -> {sm} with 22.2%

Context : planets_conv

Min. support : 20.0%

Min. confidence : 70.0%

Rule count : 8

#	Antecedent	=>	Consequence	Support	Confidence
1.	{moon_yes}	=>	{distance from sun_far}	55.55%	71.42%
2.	{size_small}	=>	{distance from sun_near}	44.44%	79.99%
3.	{distance from sun_far}	=>	{moon_yes}	55.55%	100.0%
4.	{distance from sun_near}	=>	{size_small}	44.44%	100.0%
5.	{distance from sun_near, moo...	=>	{size_small}	22.22%	100.0%
6.	{size_large}	=>	{distance from sun_far, moon...	22.22%	100.0%
7.	{size_medium}	=>	{distance from sun_far, moon...	22.22%	100.0%
8.	{moon_no}	=>	{distance from sun_near, size...	22.22%	100.0%

Fig8. Rules generated with support (20%) and confidence (70%)

From the above fig8. We infer that,

No.	**Implications**	**Support**	**Confidence**
1.	{my} ->{df}	55%	71.4%
2.	{ss} ->{dn}	44.4%	79.9%
3.	{df }->{ my}	55.5%	100%
4.	{dn }->{ss}	44.4%	100%
5.	{dn,mn} ->{ss}	22.2%	100%
6.	{sl} ->{df,my}	22.2%	100%
7.	{sm}->{df,my}	22.2%	100%
8.	{mn}-> {dn,ss}	22.2%	100%
my - moon-yes, df –distance-far, ss-size small, .dn-distance –near, mn-moon-no, sl- size-large .sm-size-medium.			

Table4. Support and Confidence

Many-Valued Attributes – With Missing Values

name	gender	age
Ada	m	21
Bevan	f	50
Chris	?	66
Do	f	88
Eva	f	17
Folly	m	90
Kris	m	50

Table5. Many-valued-Miss values

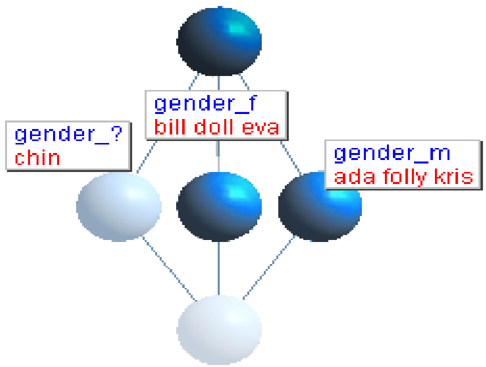


Fig9. Subcontext of Many-valued(gender)

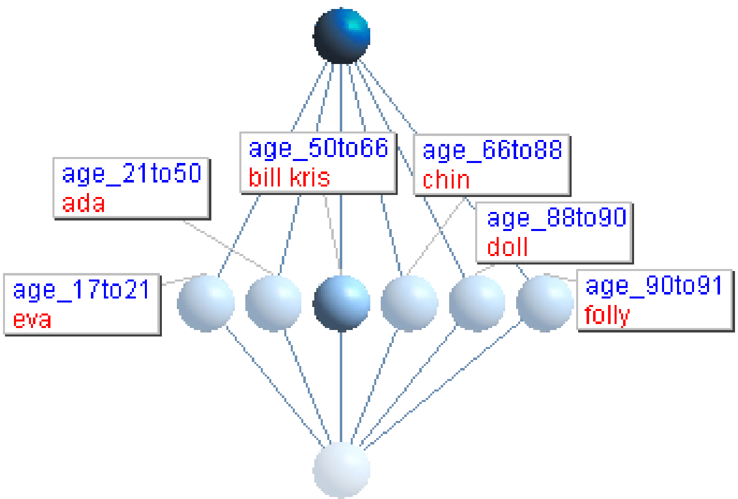


Fig10. Subcontext of Many-valued attributes (age)

Nested line diagrams for contexts derived from multi-valued contexts.

VI. CONCLUSION

Knowledge Discovery is the process of retrieval of information which is hidden inside the data in abstraction. It includes not only various techniques for identifying the patterns in data but also focuses on the visualization of information through Galois connections to find relations among objects and attributes. This paper describes Formal Concept Analysis and many-valued context is transformed into a single-valued is shown experimentally through concept lattice and exaction of implications with minimum support and confidence.

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AUTHORS PROFILE

Bhavana Jamalpur received Master's degree in Computer Science and Engineering in 2013 from Jawaharlal Nehru Technological University, Hyderabad, India. She has 15 years of teaching experience. Currently She is working Assistant Professor in the Department of Computer Science and Engineering in S R Engineering College (Autonomous), Telangana, India . Her research areas include Data Mining and Data Warehousing,

Nagendar Yamsani received Master's degree in Computer Science and Engineering in 2009 from Jawaharlal Nehru Technological University, Hyderabad, India. He has 8 years of teaching experience. Currently he is working Assistant Professor in the Department of Computer Science and Engineering in S R Engineering College (Autonomous), Telangana, India and Coordinator, S R R & D Center. He has published Eleven International Journals and Three International Conference Papers . His research areas include Networks Security, Automata and Data Mining