Implementation of Association Rule Mining for Bridge Datasets Using Weka

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Abstract: Data mining playing vital information in extracting useful information from large amount of data set. Apriori algorithm generate useful rule by finding frequent itemset from huge data set. In this paper can apply the Apriori Algorithm to generate rules for the given data set (bridge) using Waikato Environment for Knowledge Analysis tool. Bridge dataset is taken from UCI machine learning repository. These articles explore and visualize the apriori technique in data mining concept.

Keywords: Data mining, Apriori technicque, UCI machine

1. INTRODUCTION

The data mining represents mining the knowledge from large data. Topics such as knowledge discovery, query language, decision tree induction, classification and prediction, cluster analysis, and how to mine the Web are functions of data mining. Manual analyses are time consuming in the real world. In this situation, WEKA can use for automating the task.

Weka is a collection of machine learning algorithms for data mining tasks. Classification was performed using WEKA in data mining research. WEKA is a data mining workbench that allows comparison between many different machine learning algorithms. In addition, it also has functionality for feature selection, data pre-processing and data visualization [1]. The algorithms can either be applied directly to a dataset or called from Java code. Weka contains tools for data pre-processing, classification, regression, clustering, association rules and visualization. Well-suited for developing new machine learning schemes. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is also well-suited for developing new machine learning schemes.

2. RELATED WORK

The more associations between accident factors and accident severity were illustrated when applying Apriori algorithm [2]. The predictive Apriori algorithm could derive more number of rules that could be useful when studying the effect of each individual factor to accident severity. These results can help the decision makers in the traffic accident department to take actions based on various hidden patterns from the data. The swarm based techniques to extract association rules for student performance prediction as a multi-objective classification problem is analysis by [3]. In this algorithm takes a low convergence time and it used a few number of parameters. Honeybee Colony Optimization and Particle Swarm Optimization are the



two used metaheuristics to extract association rules. These are used in this investigation and WEKA, Rapidminer and KEEL tools are used for comparing the technique. Various type of analysis is carried out using association rules [4-6] in data mining through WEKA environments.

3. EXPERIMENTS DESIGN

Implementation of Association Rule Mining is carried out in Bridge datasets using Weka tool.

3.1 Dataset description

Association rule works only with nominal type and the data values are discrete in nature. Data set Characteristics: Multivariate Number of Instances:108 Number of Attributes: 13 Attribute Characteristics: Categorical, Integer

3.2 Attributes description

Table.1 shows the list of attributes in bridge dataset. It also represents the data type for each attributes. Bridge datasets attributes are viewed by viewer in the WEKA explorer panel. It is illustrated in Fig. 1

| Attribute | Possible Values | Data type |
|-----------|--|-----------|
| Id | | Nominal |
| River | A,M,O | Nominal |
| Location | 1 to 52 | Numeric |
| Erected | 1818-1986; Crafts, Emerging, Mature, Modern | Numeric |
| Purpose | Walk, Aqueduct, RR, Highway | Nominal |
| Length | 804-4558; Short, Medium, Long | Numeric |
| Lanes | 1,2,4,6 | Numeric |
| Clear-G | N, G | Nominal |
| T-OR-D | Through, Deck | Nominal |
| Material | Wood Iron, Steel | Nominal |
| Span | Short, Medium, Steel | Nominal |
| REL-L | S, S-F, F | Nominal |
| Туре | Wood, Suspen, Simple-T, Arch, Cantilev, Cont-T | Nominal |

Table.1 List of attributes

| Destruction Destruction <thdest< th=""><th>4</th><th></th><th></th><th></th><th></th><th></th><th></th><th>Viewer</th><th></th><th></th><th></th><th></th><th></th><th></th><th>x</th><th>orer</th><th></th><th></th><th></th><th></th><th></th><th>-</th><th>ð ×</th></thdest<> | 4 | | | | | | | Viewer | | | | | | | x | orer | | | | | | - | ð × |
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| Normal Normal Nume | No. | ID | River | Location | Erected | Purpose | Lenath | Lanes | Clear-G | T-OR-D | Material | Span | Rel-L | Type | | | | | | | | | |
| 2 2 k 250 1850-HGWML 1070 2001 PAOL PAO | | | | | | | | | | | | | | | | | Und | do | | Edit | | Save | |
| 3 2 A 39 1839.04/QED. 1.01/v PAO WOOD 5 WOO | 1 | E1 | М | 3.0 | 1818.0 | HIGHW | | 2.0 | N | THRO | WOOD | SHORT | S | WOOD | | | | | | | | | |
| 4 ES A 200 B37.0HGWL. Duo. 2.0H Theo WOOD S S M 3 B B A 28.0 B A 28.0 HBO MOOD S WOOD S S S | 2 | E2 | A | 25.0 | 1819.0 | HIGHW | 1037.0 | 2.0 | N | THRO | WOOD | SHORT | S | WOOD | | | | | | | | | |
| 5 5 M 220 1930, (нрсни: 200, 1930, (нрсни: 200, 100, 100, 100, 100, 100, 100, 100, | 3 | E3 | A | 39.0 | 1829.0 | AQUED | | 1.0 | N | THRO | WOOD | | S | WOOD | 1 | | | | | | | | Apply |
| b c | 1 | E5 | A | 29.0 | 1837.0 | HIGHW | 1000.0 | 2.0 | N | THRO | WOOD | SHORT | S | WOOD | 1 | | | | | | | | |
| p | i | E6 | М | 23.0 | 1838.0 | HIGHW | | 2.0 | N | THRO | WOOD | | S | WOOD | 1 | | | | | | | | |
| 1 100 | 5 | E7 | Α | 27.0 | 1840.0 | HIGHW | 990.0 | 2.0 | N | THRO | WOOD | MEDIUM | S | WOOD | | | | Distinct | 109 | | | 0/1 | |
| 2 Di A 330 1380, Jaquess. 1.0h DECK MOOD S MOOD 0 E11 A 280 ISS0, PIEGHU 20.0h DECK MOOD S MOOD 12 2A 380 ISS0, PIEGHU 20.0h DECK MOOD S MOOD 12 2H M 6.0 ISS0, PIEGHU 20.0h THEO MOOD S MOOD | | | А | 28.0 | 1844.0 | AQUED | 1000.0 | 1.0 | N | THRO | IRON | SHORT | S | SUSPEN |] | issing: 0 (0%) | | Districta | 100 | | Ouidne: 109 (100 | 70) | _ |
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| 01 E11 A 290 1851.0HGPW 1000.0 20/N THRO WOOD 5 WOOD 12 E14 M 6.0 1856.0HGPW 20/N THRO WOOD 5 WOOD 3 E13 A 330 1355.0HGPW 20/N THRO WOOD 5 WOOD 5 1 - - - - - 4 E5 1 - |) | E10 | A | 39.0 | 1848.0 | AQUED | | 1.0 | N | DECK | WOOD | | S | WOOD | | 1 E1 | | | | 1 | | | |
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| 13 E13 A 33.0 135.0-MIG/W 2.0 N THRO WOOD S WOOD 14 E15 A 28.0 1357.0-R 2.0 N THRO WOOD S WOOD 15 E16 A 28.0 1357.0-R 2.0 N THRO WOOD S WOOD 16 E17 M 40 1353.0-R 1200.0 2.0 N THRO WOOD MODD S MOOD 15 E16 A 28.0 1366.0-HIG/W 1000.0 2.0 N THRO WOOD MEDUM S/MP 1 | | | | | | | 1200.0 | | | | | | | | | | | | | 1 | | | |
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| | Ж | | | | | | | | | | | | | | | | | | | | | Log | Ċ |

Fig.1 Weka Database Viewer and front panel

4. **IMPLEMENTATION STEPS**

Since Apriori algorithm works with only nominal data, the data set is preprocessed. Save the intermediate files after each step. The preprocessing WEKA is shown in Fig.2 and Fig.3. The Fig.4 represents the pure data after preprocessing.

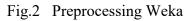
The following preprocessing methods are applied:

• Removing the attribute:

- Remove the attribute id, since it uniquely identifies the tuples. It is done by selecting the remove attribute filter.
- Remove the attribute location, since it does not play a vital role in generating the rules.



| eprocess Classify Cluster Associate | Select attributes Visualize | | | | | | |
|-------------------------------------|-----------------------------------|---|--------------|-------------------------|---------|----------|-------------------------------------|
| Open file | Open URL | Open DB | Gene | rate | Undo | Edit | Save |
| iter | | | | | | | |
| Choose Remove -R 1 | | | | | | | Apply |
| Jurrent relation | 0 | weka.gui.GenericObjectEditor | | × ted attribute | | | |
| Relation: bridges Instances: 108 | weka.filters.unsupervise About | d.attribute.Remove | | ame: ID sing: 0 (0%) | Distinc | :: 108 U | Type: Nominal Jnique: 108 (100%) |
| ittributes | - | a range of attributes from the dataset | Mara | Label | | Count | |
| All | A litter that removes | s a range of attributes from the dataset. | More | 1 E1 | | 1 | |
| <u>^</u> | | | Capabilities | 2 E2 | | 1 | |
| No. Name | | | | 3 E3 | | 1 | |
| 1 🗸 ID | attributeIndices 1 | | | - 5 E6 | | 1 | |
| 2 River | invertSelection Fals | 3 | | v 6 E7 | | 1 | |
| 3 Location | | • | | 7 E8 | | 1 | |
| 4 Erected 5 Purpose | Open | Save OK | Cancel | 8 E9 | | 1 | |
| 6 Length | | | | 9 E10 | | 1 | |
| 7 Lanes | | | | 10 E11 11 E12 | | 1 | |
| 8 Clear-G | | | | 11 E12 12 E14 | | 1 | |
| 9 T-OR-D | | | | 13 E13 | | 1 | |
| 10 Material | | | | | | | |
| 11 Span | | | | Class: Type (Nom) | | | ✓ Visualize / |
| 12 Rel-L 13 Type | | | | | | | |
| | Remove | | | | | | |



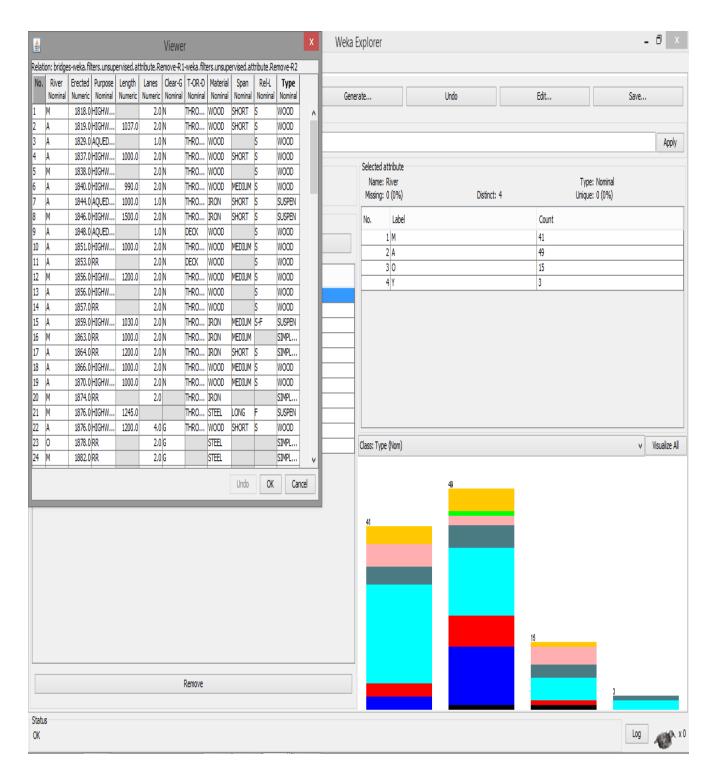


| Preprocess Classify Cluster Associate Select | attributer Vieualize | | Weka | Explo | orer | | | | - | ð X |
|---|-------------------------------------|---------------------------------------|--------------|-------|-------------------------------|------|-----------|------------|-------------------------------|---------------|
| Open file | Open URL | Open DB | Gene | rate | | Undo | | Edit | Save | |
| Filter | | | | | | | | | | |
| Choose Remove -R 2 Current relation | | veka.gui.GenericObjectEditor | | X | ted attribute | | | | | Apply |
| Relation: bridges-weka.filters.unsupervised.a Instances: 108 | weka.filters.unsupervised. About | attribute.Remove | | | ame: Location sing: 1 (1%) | Dis | tinct: 54 | Ty Unic | /pe: Numeric que: 21 (19%) | |
| Attributes | | range of attributes from the dataset. | More | | stic rum | | | Value 1 | | |
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| Status OK | | | | | | | | | Log | 100 |

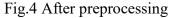
Fig.3 Unwanted attribute removing in Preprocessing Weka



5







Discretization: Association rule mining can be applied on categorical data, so the three numeric attributes erected, length and lanes in the data set are discretized and it shown in Fig.5. The Fig.6 represents the how to modify the normalized value for discretization.

| 0 | | | Weka Exp | olorer | | | - 0 × |
|---|---|------------------------|--------------|-----------------------------|--------|------------|--------------------------------|
| Preprocess Classify Cluster Associate Select | t attributes Visualize | | | | | | |
| Open file | Open URL | Open DB | Generat | | Undo | Edit | Save |
| Filter | | | | | | | |
| Choose Discretize -B 4 -M -1.0 -R 5 | · | 10.1011.001 | > | | | | Apply |
| Current relation | | ui.GenericObjectEditor | | ted attribute | | | |
| Relation: bridges-weka.filters.unsupervised.a Instances: 108 | weka.filters.unsupervised.attribute. About | Discretize | | ame: Lanes sing: 16 (15% | 6) Dis | tinct: 4 U | Type: Numeric nique: 0 (0%) |
| Attributes | An instance filter that discretiz | es a range of numeric | More | stic | | Value | |
| All | attributes in the dataset into n | | Capabilities | num | | 1 | |
| | | | Capabilities | mum | | 6 | |
| No. Name | | | | ev | | 2.63 | |
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| 4 Length | de tradition de la companya de la co | | | | | | |
| 5 🗸 Lanes | desiredWeightOfInstancesPerInter | Vai -1.0 | | | | | |
| 6 Clear-G | findNumE | ins False | v | | | | |
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| | Remove | | 9 | | 0 | 0 | 4 |
| | | | 1 | | | 3.5 | |
| Status OK | | | | | | | Log 🐠 x |

Fig.5 Discretization in Bridge datasets



The input file with the above changes is shown below Fig.6.

| 4 | | | | | | Viewe | r | | | | | X | | Weka | Explore | er | | | | | - | . 🛛 🛛 |
|-------------|------------|------------|------------|--------------|-----------|-------------|-----------|----------|---------------|-----------|-------------|-------|----|-------|----------|------------|----|------|----------|-------|---------------|---------------|
| Relati | on: bridge | es.data.ve | rsion2-wel | ka.filters.i | unsupervi | sed.attribu | ute.Remov | ve-R1-we | ka.filters.un | supervisi | ed.attribui | te.Re | | | | | | | | | | |
| No. | River | | Purpose | | | Clear-G | | | | Rel-L | Туре | | Ŀ | | | | | | | | | |
| | Nominal | | | | Nominal | Nominal | Nominal | | Nominal | | Nominal | | | Ger | ierate | | | Undo | | Edit | Save | |
| | М | | HIGHW | | 2 | | THRO | | SHORT | | WOOD | ٨ | | | | | | | | | | |
| | A | | HIGHW | | 2 | | THRO | | SHORT | | WOOD | | E | | | | | | | | | |
| | | | AQUED | | 1 | | | | | | WOOD | | ι. | | | | | | | | | Apply |
| | | | HIGHW | | | | | | SHORT | | WOOD | | E | | Calacta | d attribu | ha | | | | | |
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| | A | | HIGHW | | | | THRO | | MEDIUM | | WOOD | | | NCT12 | | ng: 0 (0% | 3 | Dis | tinct: 4 | | nique: 0 (0%) | |
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| <u> </u> | М | CRAFTS | | MEDIUM | | | THRO | | MEDIUM | | SIMPL | | L | | | | | | | | | |
| <u> </u> | | CRAFTS | | MEDIUM | | | THRO | | SHORT | | SIMPL | | E | | | | | | | | | |
| <u> </u> | A | | HIGHW | | | | THRO | | MEDIUM | | WOOD | | E | | | | | | | | | |
| | | | HIGHW | | _ | | THRO | | MEDIUM | | WOOD | | E | | | | | | | | | |
| | | EMER | | | 2 | | THRO | | | | SIMPL | | E | | | | | | | | | |
| _ | | | HIGHW | | | | THRO | | LONG | | SUSPEN | | Г | | | | | | | | | |
| | | | HIGHW | MEDIUM | | | THRO | | SHORT | | WOOD | | | Г | | | | | | | | |
| | | EMER | | | _ | G | | STEEL | | | SIMPL | | E | | Class: T | ype (Nor |) | | | | v | Visualize All |
| 24 | М | EMER | RR | | 2 | G | | STEEL | | | SIMPL | V | ſ | | 1 | | | | | | jL | |
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| Stati OK | S | | | | | | | | | | | | | | | | | | | | Log | |

8

Fig.6 After Discretization on Bridge datasets

The following Fig.7 depict the labels assigned for the attributes and the changes in the instances (one instance highlighted):

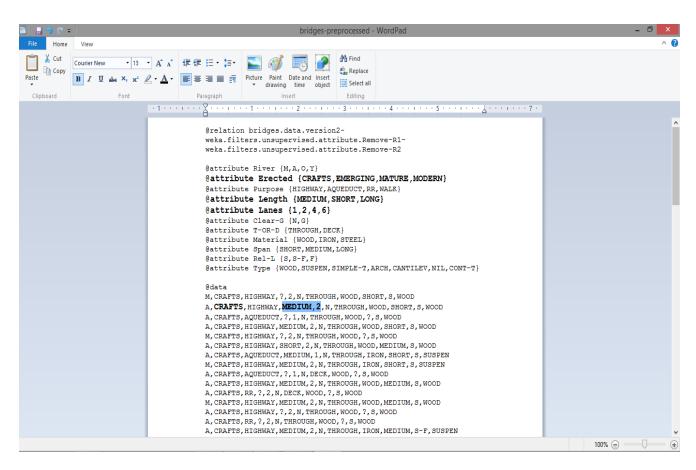


Fig.7 Labels assigned for the attributes and the changes in the instances

Apriori Algorithm Implementation in Weka:

The preprocessed data file is used for Association rule mining (Apriori Algorithm) and the following rules are generated by setting the necessary measures such as support and confidence is shown in Fig.8 and Fig.9.

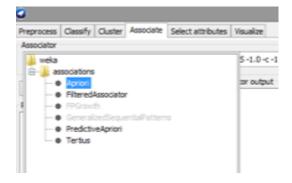


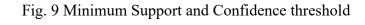
Fig.8 Apriori Algorithm Implementation in Weka

Minimum Support and Confidence threshold:

The following Fig.9 shows the parameters set

| 0 | | | Weka Explorer | - Ō X |
|-------------------|-------------------------------------|--|---------------|---------------|
| Preprocess Clas | ssify Cluster Associate | Select attributes Visualize | | |
| Associator | | | | |
| Choose | 0 | weka.gui.GenericObjectEditor | | |
| Start | weka.associations.Apriori | | | |
| Result list (righ | About Class implementin <u>o</u> | g an Apriori-type algorithm. More Capabilities | | |
| | car | False v | | |
| | dassIndex | -1 | | |
| | delta | 0.05 | | |
| | lowerBoundMinSupport | 0.5 | | |
| | metricType | Confidence v | | |
| | minMetric | 0.9 | | |
| | numRules | 10 | | |
| | outputItemSets | False v | | |
| | removeAllMissingCols | False v | | |
| | significanceLevel | -1.0 | | |
| | upperBoundMinSupport | | | |
| | verbose | False v | | |
| | Open | Save OK Cancel | | |
| | | | | |
| Status OK | | | Log | *** ×0 |





Output-Rules Generated:

The screen shot shows the rules generated by applying Apriori Algorithm for association rule mining is shown in Fig.10.

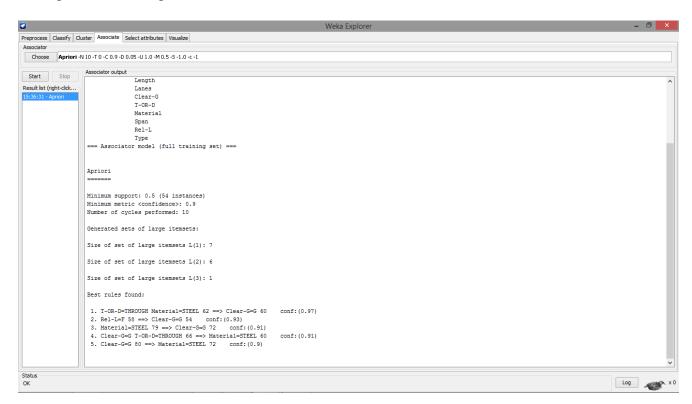


Fig.10. Output rule generated

= Run information = == Scheme: weka.associations.Apriori -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.5 -S -1.0 -c -1 Relation: bridges.data.version2-weka.filters.unsupervised.attribute.Remove-R1weka.filters.unsupervised.attribute.Remove-R2 Instances: 108 Attributes: 11 River Erected Purpose Length Lanes Clear-G T-OR-D Material Span Rel-L Type

=== Associator model (full training set) ===

Apriori

Minimum support: 0.5 (54 instances) Minimum metric <confidence>: 0.9 Number of cycles performed: 10 Generated sets of large itemsets: Size of set of large itemsets L(1): 7 Size of set of large itemsets L(2): 6 Size of set of large itemsets L(3): 1

Best rules found:

1. T-OR-D=THROUGH Material=STEEL $62 \Longrightarrow$ Clear-G=G $60 \mod(0.97)$

2. Rel-L=F 58 ==> Clear-G=G 54 conf:(0.93)

3. Material=STEEL 79 ==> Clear-G=G 72 conf:(0.91)

4. Clear-G=G T-OR-D=THROUGH 66 ==> Material=STEEL 60 conf:(0.91)

5. Clear-G=G 80 ==> Material=STEEL 72 conf:(0.9)

5. CONCLUSION AND FUTURE DIRECTION

The above rules infer that Most of the THROUGH bridges are constructed using the Material STEEL. If Bridges built on Clear Ground and are THROUGH bridges then the Material used to build such bridges is STEEL.

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