Rough set approach for Attribute Reduction and Rule generation

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Abstract— Big data presents new prospects for modern society. On the one hand, big data holds great potential for revealing subtle population patterns and heterogeneities that are impossible with small-scale data. On the other hand, the enormous sample size and high dimensionality of Big Data pose particular computational and statistical problems, such as scalability and storage bottleneck, noise accumulation, spurious correlation, and measurement mistakes. A perfect solution to this problem is provided by rough set theory since it can manage incomplete and imprecise data and reduce the data without retaining its original features. Additionally, it has been demonstrated as a powerful tool for pattern identification and developing decision rules. This study seeks to apply the rough set theory approach to create decision rules for classification by reducing the data.The effectiveness of the decision rules produced by RST is validated.
Keywords—Rough set theory, data reduction, decision rules, reduts, Laplace Value, Lift, Support Value

1. INTRODUCTION

The Rough Set Theory, created in 1982 by Zdzislaw Pawlak, constantly evolves. One of the earliest non-statistical techniques for data analysis, its methodology focuses on classifying and analyzing imprecise, ambiguous, or incomplete information and knowledge (Pawlak, 1982). The formal classification of knowledge about the interest area is represented by approximating the bottom and upper spaces of a set, which is the core idea underpinning rough set theory. Objects that will undoubtedly be a member of an interested subset make up the lower approximation's subset. In contrast, objects that may or may not be a part of an interested subset make up the upper approximation's subset. Rough Set refers to any subset defined by upper and lower approximations.

Rough Set Theory has developed into a valuable tool for solving a variety of issues, including representing uncertain or imprecise knowledge, analyzing knowledge, assessing the quality and availability of information about consistency and the presence of data patterns, identifying and evaluating data dependency; and reasoning based on uncertain and reduce of information data. Today's use of rough set applications is significantly more than in the past, especially in process control, database attribute analysis, and medicine. Thissuccess can be attributed in part to the theory's following features: only the facts concealed in the data are analyzed; no extrainformation about the data is necessary; and a minimum knowledgerepresentation isproduced.

Rough set theory is widely applied in many areas as one of the practical feature reduction tools; with the help of rough set theory, one can combine the strengths of a set of decision rules' strength, comprehensibility, and representational effectiveness with the advantages of a decision procedure's simplicity and unambiguity in a tree representation. [1]. Rough sets are the ideal solution, which is why they are so commonly employed in health research and clinical analysis to cope with imprecision in areas like patient diagnosis, healthcare satisfaction survey, and disease classification[2,3, 4,5,6, 22,24]. Rough set-based techniques for data mining in extensive relational databases have recently been presented in many other new areas.By evaluating similar past tasks, project management can make informed decisions to enhance the likelihood of success while effectively managing resources. The most suitable technique for this purpose is Rough set theory[17].Rough Set theory used in energy policy, especially for solar system decision-making. Despite rule adjustment issues, RS improves decision support, reducing costs and simplifying green energy regulations[18].RST decision rules can optimize the aviation and airspace management system and offer pertinent proposals for studying aviation and airspace congestion[19].

Rule-based methods are a famous for data mining and machine learning techniques. One of their common objectives is finding patterns in data that may be described as an IF-THEN rule. As a result of these rules' simplicity, classifiers like these are frequently utilized to produce descriptive models[16]. Accuracy of the Decisional Rules[7] to generate decision rules for traffic vehicles, knowledge is extracted from large amounts of data using rough set theory[8]. The developed and analyzed approximation spaces of the rough set theory are essential for approximate Boolean reasoning, inducing operations on information granules, inclusion and closeness measures, productions and AR schemes, and domain knowledge approximation [10]. Rough set theory is being used for decision rule generation with much improvisation to increase performance and accuracy in classification [11,12,23]. Numerous probabilistic methods, such as decision-theoretic analysis, variable precision analysis, and information-theoretic analysis, have been used to study the theory of rough sets[13].

This research will discuss critical applications of rough set theory in numerous fields. We will also present a case study that elaborates on the use of RST in feature selection, pattern recognition, and the creation of decision rules.

2. FUNDAMENTAL CONCEPT

The foundation of the rough set philosophy is that every object in the world of discourse has some information (data, knowledge) attached to it. When compared to the known information, objects with the same characteristics are indistinguishable (similar). Rough set theory's mathematical foundation is the indiscernibility connection that is produced in this way.

In order to express vagueness, rough set theory uses a set's boundary area rather than its membership. A set is said to be crisp if its boundary region is empty and rough (inexact) if it is not. A set's nonempty boundary area might be seen as a sign that we may not know enough about it to describe it precisely [13].

A primary granule (atom) of knowledge about the universe is formed by any collection of all undetectable (similar) items, referred to as an elementary set. A crisp (exact) set is the name given to an arbitrary union of some elementary sets. A set is described as rough (vague, imprecise) if it needs to be crisp. It should be emphasized that the search is typically limited to a viable subset of the family of all possible unions of elementary sets due to the computational difficulty of finding appropriate crisp sets for the topic under consideration [8].

As a result, each rough Set contains borderline cases or things that cannot be categorically identified as belonging to the Set or its complement. There are no ambiguous elements in crisp sets. As a result, the notion that knowledge has a granular structure arises from the presumption that objects can only be "seen" through the information that is available about them. Some objects of interest cannot be distinguished because of the granularity of information and appear the same [15].

It is, therefore, difficult to describe ambiguous conceptions purely in terms of the parts that constitute or satisfy the notion, as opposed to precise concepts. The lower and upper approximations of the unclear notion are, therefore, assumed to replace any vague concepts in the suggested strategy. The things that unquestionably belong to the concept are all included in the lower approximation, while all potential concept members are included in the upper approximation. The border region of this nebulous idea is defined as the difference between the upper and lower approximation. Two fundamental procedures in crude set theory are these approximations [14].

3. CASE STUDY

The dataset may have many attributes of the same or indiscernible features, which unnecessarily increases the volume of the data. Some of the attributes can be superfluous or redundant. Only the qualities that uphold the indiscernibility connection should be kept, and approximation should be set as a result. Usually, there are numerous subsets of attributes, and the smallest of them are referred to as reducts. Therefore, a Reduct is a sufficient set of attributes that can completely characterize the knowledge in the database on its own. The Set of attributes that all reducts share is known as the core. The reduced Set of attributes is then used to build the decision rules.

Figure 1: Classification by rough set approach

A. *Method and Material used*

We utilized our model to analyze a real dataset and categorize the price range of mobile phones based on 12 specific parameters. Various attributes describe distinct qualities of well-known mobile brands, such as camera quality, memory capacity, weight, screen size, battery capacity, and rating. We utilized the 'RoughSets' Package of R program to apply Rough set theory in classifying data based on pricing category. Initially, we assessed reducts and subsequently examined decision rules.

A.1 Information Table

Rough Set uses a table to hold data model information. A dataset containing objects, attributes, and a decision attribute that specifies the class or category to which each object belongs is called as information table. This information is often organized in a decision table, where rows representobjects and columns represent attributes.Table 1 gives details about the data set.

Battery	Battery capacity in mAh
Fast Charging	Fast charging in Wattage
ROM	ROM in GB
RAM	RAM in GB
Telephoto camera	Capabilities of camera
Wide. Angle.camera	
Ultra-wide camera	
Selfie Camera	
Screen Size	Screen size in inches
Refresh Rate	The number of screen refreshes per second is measured in Hertz (Hz).
Antutu	A popular benchmarking app used to assess the performance of mobile devices
Weight	Weight of the mobile in gram
Price	Price in Rupees

Table 1: Data Description

Every attribute is classified into specific groups or categories according to how its values relate to specified benchmarks. This classification procedure helps to determine the attribute's level of precision, improving its description and broadening its possible uses.

Conditional Attributes	**Data type**
Battery	Ordinal (1, 2, 3, 4, 5)
Fast Charging	Ordinal (1, 2, 3, 4)
ROM	Ordinal (1, 2, 3, 4)
RAM	Ordinal (1, 2, 3, 4)
Telephoto camera	Ordinal (1, 2, 3, 4, 5)
Wide Angle camera	Ordinal (1, 2, 3, 4, 5)
Ultra-wide camera	Ordinal (1, 2, 3, 4, 5)
Selfie Camera	Ordinal (1, 2, 3, 4)
Screen Size	Ordinal (1, 2, 3, 4)
Refresh Rate	Ordinal (1, 2, 3)
Antutu	Ordinal (1, 2, 3, 4 ,5)
Weight	Ordinal (1, 2, 3, 4, 5)
Price	Ordinal (1, 2,3)

Table 2: Data classes

B. *Experimental Results*

B.1 Reduction of the conditional attributes:

By using the indiscernible equivalence relations, a total of 17 sets of Reducts are identified as given in Table II

Reduct	Number of attributes	Attributes
1.	6	Battery, Fast Charging, Wide angle camera, Ultra wide camera, Antutu, Weigh
2.	6	Battery, Fast Charging, RAM, Wide angle camera, Ultra wide camera, Weight
3.	6	Battery, RAM, Wide angle camera, Ultra wide camera, Refresh Rate, Weight)
4.	7	Battery, Fast Charging, ROM, RAM, Telephoto, Ultra wide camera, Weight
5.	7	Battery, Fast Charging, ROM, Telephoto, Ultra wide camera, Refresh Rate, Weight
6.	7	Battery, Fast Charging, ROM, Telephoto, Ultra wide camera, Antutu, Weight
7.	7	Battery, Fast Charging, ROM, Wide angle camera, Ultra wide camera, Refresh Rate, Weight
8.	7	Battery, Fast Charging, ROM, RAM, Ultra wide camera, Selfie camera, Weight
9.	7	Battery, Fast Charging, ROM, Ultra wide camera, Selfie camera, Refresh Rate, Weight
10.	7	Battery, Fast Charging, ROM, Ultra wide camera, Selfie camera, Antutu, Weight
11.	7	Battery, Fast Charging, ROM, RAM, Ultra wide camera, Screedn size, Weight
12.	7	Battery, Fast Charging, ROM, Ultra wide camera, Screedn size, Refresh Rate, Weight
13.	7	Battery, Fast Charging, ROM, Ultra wide camera, Screedn size, Antutu, Weight
14.	7	Battery, ROM, Wide angle camera, Ultra wide camera, Screedn size, Antutu, Weight
15.	7	Battery, RAM, Wide angle camera, Ultra wide camera, Screedn size, Antutu, Weight
16.	7	Battery, RAM, Wide angle camera, Ultra wide camera, Selfie camera, Antutu, Weight
17.	7	Battery, Telephoto, Wide angle camera, Ultra wide camera, Screedn size, Antutu, Weight

Table 3: Reducts

B.2 Decision Rules By rough set theory

Rules do not reveal an individual's preferences; instead, they uncover connections between the components of each unique transaction. They differ from collaborative filtering in this way.

In rough set theory, decision rules are derived from lower and upper approximations. The lower approximation is the Set of objects for which we are sure they belong to a particular category based on the available information. The upper approximation is the Set of objects that may belong to the category, including those for which the evidence is uncertain.

The resulting decision rules aim to capture patterns and relationships in the data, allowing for accurate classification of objects, especially in situations where the data is imprecise or uncertain. Following are features of decision rules generated by rough set theory

- Rough set theory is a valuable approach for decision rule generation in specific scenarios due to its unique characteristics and advantages. Here is why rough set theory is often considered best for decision rule generation:
- Rough set theory is designed to deal with uncertainty and imprecision in data
- It generates decision rules relevant to the level of detail present in the data, avoiding overly specific or general rules. This adaptability is crucial for accurate classification.
- Rough set theory identifies minimal subsets of attributes (reducts) necessary for classification. This minimizes the number of attributes used in rules, reducing complexity and improving efficiency.
- Rough set theory can handle datasets with missing values or incomplete information. Even when some data points are partially known, it can still generate meaningful decision rules.

- Rough set theory can handle both quantitative and qualitative attributes, making it suitable for diverse types of data.

For the generation of decision rules, various algorithms are available. In this study, we generated rules using the "LEM2" algorithm. LEM2 generates rules in the following ways.

- LEM2 operates iteratively. Each iteration selects an uncovered object from the boundary region.
- The selected object is used to generate a new decision rule. The rule is constructed by considering the attributes of the selected object and specifying conditions that distinguish it from objects in other classes.
- If multiple objects from the boundary region share the same attribute conditions, a rule covering all of them is generated.

By applying the 'Roughsets' package of R with the LEM2 algorithm, a total of 38 rules are generated.

B.3 Rules mining

Rule mining is a data mining technique to discover exciting relationships or associations between items in large datasets.

To check the accuracy of association rules generated through association rule mining, metrics like support, confidence, and lift. These metrics help you assess the quality and significance of the rules.

i. **Support Value**

This metric provides an indication of how frequently a given item set appears in all instances.

Support is defined mathematically as the percentage of all instances in which the item set appears.

$$support\ of\ X\ to\ Y = \frac{Instances\ containing\ both\ X\ \&\ Y}{Total\ Number\ of\ instances}$$

When calculating support, the prediction (THEN-part) is not essential. Higher support values indicate that the rule is based on more occurrences, making it more reliable.

ii. **Confidence of a rule**

A rule's accuracy is a measure of how well it predicts the correct class for the instances to which its condition applies.

It is described as the percentage of instances in which the association rule is valid or as the proportion of times the items in the antecedent (the "if" part of the rule) and the items in the consequent (the "then" part of the rule) exist in the same transaction.

$$Confidence\ X\ to\ Y\ = \frac{Transactions\ containing\ X\ and\ Y}{Transactions\ containing\ X}$$

The rule is reliable and consistent if the confidence level is high. Higher confidence values suggest a stronger association between the antecedent and the consequent. Typically, you set a minimum confidence threshold to consider a rule valid.

iii. **Lift of a Rule**

Lift measures how much more likely a rule's consequent will occur when the antecedent is present than when it is not. It is the ratio of the rule's certainty to the resultant's frequency throughout the dataset.

$$Lift\ = \frac{confidence}{consequentsupport}$$

A lift value larger than 1 attests to a strong relationship between Y and X. The likelihood of favoring Y because of X increases with lift value. RST shows effectiveness

Sr. no	Lift	Number of rules
1.	Greater than 1	37
2.	Greater than 2	20
3.	Greater than 3	9
4.	Greater than 4	7
5.	Greater than 5	6
6.	Greater than 6	3

Table 4: Number of Rules as per Lift value

iv. **Laplace value**

Laplace value is often used to assess the performance or quality of decision rules, especially when dealing with incomplete or uncertain data. The interpretation of the Laplace value in this context relates to decision rules' reliability and generalization ability. Here is how to interpret the Laplace value for the performance of decision rules in rough set theory:

Laplace value helps to check the robustness of rules in handling uncertainty and make informed choices when selecting rules for decision-making in situations where data may be imperfect or incomplete.

Support, lift, confidence, and Laplace values are essential metrics in association rule mining, each with its merits and potential limitations is given in Table:5.

Metric	Merits	Demerits
Support	● Simple and Intuitive ● Useful for Filtering	● Insensitive to Rule Strength ● May Miss Important Patterns
Confidence	● Reflects Rule Strength ● Helps Filter Rules ● Useful in Recommender Systems	● May Not Detect All Associations ● Sensitive to Dataset Size
Lift	● Accounts for Randomness ● Indicates True Association	● Dependent on Support ● May Not Work for All Cases
Laplace	● Robustness to Sparse Data ● Fairness in Small Samples	● Bias Toward Uniform Distribution ● Lack of Discrimination ● Not Suitable for All Distributions

Table 5: Merits & Demerits of Rule induction method

A total 38 rules are extracted from RST given by Table: 6

Condition	**Price category**
IF ss.category is 4 and bat.category is 3 THEN	3
IF mem.category is 3 and SC.category is 3 and ss.category is 3 and fast.char..category is 3 THEN	1
IF ram.category is 2 and RR.categ is 2 and fast.char..category is 3 THEN	2
IF ss.category is 4 and antutu.category is 4 THEN	3
IF bat.category is 4 and wide.angle.category is 2 and weight.category is 3 THEN	1
IF telephoto.category is 5 and mem.category is 3 and RR.categ is 1 and antutu.category is 3 THEN	2
IF telephoto.category is 5 and mem.category is 3 and fast.char..category is 2 and SC.category is 3 THEN	1
IF wide.angle.category is 2 and fast.char..category is 2 and ram.category is 1 THEN	1
IF telephoto.category is 5 and wide.angle.category is 3 and SC.category is 4 THEN	1
IF wide.angle.category is 2 and ram.category is 2 and ss.category is 4 and RR.categ is 1 THEN	3
IF antutu.category is 3 and UW.category is 5 THEN	2
IF weight.category is 4 and fast.char..category is 3 and bat.category is 4 and ss.category is 3 THEN	1
IF ram.category is 1 and ss.category is 3 and antutu.category is 2 THEN	2
IF ram.category is 1 and mem.category is 4 and ss.category is 4 and weight.category is 4 THEN	2
IF antutu.category is 2 and weight.category is 3 and wide.angle.category is 1 THEN	1
IF mem.category is 4 and antutu.category is 1 and telephoto.category is 5 THEN	2
IF telephoto.category is 2 and mem.category is 4 and ss.category is 4 THEN	3
IF antutu.category is 2 and bat.category is 4 and ss.category is 4 and weight.category is 3 THEN	2
IF fast.char..category is 4 and bat.category is 3 THEN	1
IF bat.category is 4 and RR.categ is 1 and ss.category is 4 and fast.char..category is 1 THEN	2
IF mem.category is 3 and antutu.category is 2 and RR.categ is 3 THEN	3

IF antutu.category is 1 and fast.char..category is 4 THEN	2
IF mem.category is 4 and bat.category is 3 and ram.category is 2 THEN	1
IF telephoto.category is 5 and mem.category is 3 and antutu.category is 3 and ram.category is 3 and RR.categ is 3 THEN	2
IF ram.category is 1 and antutu.category is 3 and wide.angle.category is 2 and mem.category is 4 THEN	3
IF antutu.category is 1 and bat.category is 3 and weight.category is 3 THEN	2
IF mem.category is 3 and fast.char..category is 2 and antutu.category is 3 and wide.angle.category is 1 THEN	3
IF bat.category is 4 and ram.category is 1 and wide.angle.category is 3 and ss.category is 4 THEN	2

Table 6: Decision Rules

Performance of RST rules by different metrics is given in Table: 7

	Support	**Confidence**	**Lift**	**Laplace value**
Rule_1	0.299	1	1.556	0.966
Rule_2	0.059	1	1.380	0.857
Rule_3	0.032	1	1.252	0.778
Rule_4	0.241	1	1.543	0.958
Rule_5	0.021	1	1.150	0.714
Rule_6	0.086	1	1.441	0.895
Rule_7	0.128	1	1.491	0.926
Rule_8	0.011	1	0.966	0.600
Rule_9	0.139	1	1.499	0.931
Rule_10	0.043	1	1.317	0.818
Rule_11	0.027	1	1.208	0.750
Rule_12	0.016	1	1.073	0.667
Rule_13	0.059	1	3.257	0.857
Rule_14	0.027	1	2.850	0.750
Rule_15	0.021	1	2.714	0.714
Rule_16	0.027	1	2.850	0.750
Rule_17	0.021	1	2.714	0.714
Rule_18	0.005	1	1.900	0.500
Rule_19	0.011	1	2.280	0.600
Rule_20	0.005	1	1.900	0.500
Rule_21	0.005	1	1.900	0.500
Rule_22	0.032	1	2.956	0.778
Rule_23	0.016	1	2.533	0.667
Rule_24	0.011	1	2.280	0.600
Rule_25	0.005	1	1.900	0.500
Rule_26	0.011	1	2.280	0.600
Rule_27	0.005	1	1.900	0.833
Rule_28	0.048	1	3.167	0.500
Rule_29	0.005	1	1.900	0.500
Rule_30	0.027	1	2.850	0.750
Rule_31	0.027	1	2.850	0.750

Rule_32	0.032	1	6.717	0.778
Rule_33	0.027	1	6.477	0.750
Rule_34	0.016	1	5.758	0.667
Rule_35	0.011	1	5.182	0.600
Rule_36	0.021	1	6.169	0.714
Rule_37	0.016	1	5.758	0.667
Rule_38	0.005	1	4.318	0.500

Table 7: Support, lift, confidence and Laplace value of Decision Rule

The rules derived from RST (Rough Set Theory) provide robust performance regarding support, confidence, lift, and Laplace value. Specifically, Rule_1, Rule_4, Rule_9, Rule_7, and Rule_6 are the most outstanding rules because they have strong support, moderate to high lift, and high Laplace values. These values indicate both the frequency and reliability of their relationships. In addition, Rule_32 and Rule_33, despite having little support, demonstrate remarkably high lift, indicating robust but infrequent interactions. The observed decline in the number of rules as lift values increase is anticipated, as greater lift values signify less frequent but more robust linkages. Thus, these rules provide a harmonious blend of frequency, association strength, and dependability, rendering them helpful for precise predictions and profound insights in data analysis.

v. **Comparison of accuracy of RST decision rules**

Accurate decision rules are the backbone of effective decision-making, resource optimization, risk management, and many other facets of contemporary enterprises and industries. They promote success over the long run, reduce errors, and generate positive outcomes.

Accuracy of the judgment for the rules produced by rough set theory are tested, it is found that 82%.

Popular machine learning techniques simultaneously examine the classification accuracy for the whole data without using decision rules. The outcomes are shown in Table 4.

Technique	**Accuracy**
K-fold cross-validation	0.71
Repeated k-fold Cross-validation	0.79
Leave one out of cross-validation	0.71
Bootstrap	0.53
RST Decision Rule	0.82

Table 8: Performance of ML Techniques

The accuracy of the rule-based classifier is relatively good; according to the results, RST decision rules are based on reducts, i.e., they depend on the most critical traits rather than all attributes. RST decision rules still provide a more accurate assessment than all other machine learning algorithms.

4. CONCLUSION

Rough set theory is a novel mathematical method for data reduction and decision rules. Its unique strategy for managing data uncertainty and imprecision helps build actionable decision models.

We used a real dataset of mobile phones to categorize their pricing categories by device features. The dataset had 12 conditional attributes: battery life, screen size, processor type, and one decisional attribute-pricing category.

We obtained 17 reducts through this method. Reducts are the most minor subsets of attributes that can explain the original dataset without losing information. These reducts reduced the initial 12 features to six or seven, simplifying the data while keeping its core properties.

Support, lift, confidence, and Laplace value are metrics used for rule mining. These metrics help choose the most essential and reliable decision-making criteria. Clear and straightforward decision rules make them more useful.

The performance of classification by the RST decision rules was tested against famous machine-learning categorization algorithms over the original data. The results showed that RST decision rules were more accurate and reliable.

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