

Optimization of Simple Additive Weighting Method Based on Information Gain in Decision Support System

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Abstract:

Decision support systems are an alternative offered in the global era to ease tasks and work by converting the role of humans in making decisions to machines. However, humans still determine the parameters or criteria as an indicator of decision-making considerations. Feature selection is used to determine the best features in the dataset to be used in the decision-making process. This study proposes the use of feature selection in the decision-making process based on feature ranking using information gain and simple additive weighting (SAW) used in the decision-making process. Private data collection is carried out through instruments containing questions that represent the condition of students to produce objective information. The target of filling out this instrument includes all state high school and vocational high school students in the city of Salatiga, while the UCI repository is used as a reference for public resources. Between public data and private data which is influenced by cultural factors belonging to a country. Private data is generated by adjusting the culture and customs that exist in Indonesia. Decision making using the simple additive weighting (SAW) method is considered effective in producing decisions because the resulting decisions are more objective based on ranking data.

Key Word: simple additive weighting (SAW), information gain, ranking

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I. Introduction

The development of information technology is transforming so rapidly and affects the decision-making system mechanism. Mechanisms that originally relied on human abilities shifted to computer-based mechanisms or ways of working. Decision support systems are an alternative offered in the global era to ease tasks and work by converting the role of humans in making decisions to machines. However, not all of the considerations are left to the computer, while humans still determine the parameters or criteria as indicators of decision-making considerations. It is revealed in [1] that in the era of big data, it is possible to use data mining as an effective alternative in doing data modeling using algorithms. However, the reality shows that researchers use various algorithms according to their wishes. This becomes an obstacle for beginners in determining the right algorithm for data modeling. So it is proposed to use a decision support system as a tool in determining the most appropriate algorithm to build the model. Decision support systems play a role in helping provide objective decisions.

In terms of performance measurement, it is necessary to do it objectively with reliable measuring tools. Various kinds of mathematical methods are offered to get optimal results. One of the tools used is a decision support system. According to [2], a decision support system is an interactive application system by combining data and mathematical models to assist management in making a complex decisions. In the world of education, the decision support system plays an important role in assisting the implementation of academic activities. In addition, the decision support system helps in determining the performance of the academic community more objectively and regardless of the subjective views of decision makers if it is done manually. The performance of students needs to be measured to find out the extent of their competence. This can be taken into consideration in determining the award of scholarships or determining other policies that involve the competence of students. What is happening now is that the process of determining and considering is done manually, but it is still being intervened by the subjective views of decision makers. So it is necessary to have an objective tool as the sole decision maker by using mathematical calculations based on predetermined methods. In Portugal, [3] has conducted research on student performance. There is a downward trend in the level of education in Portugal, then a study was conducted using datasets from UCI repository to perform modeling and then the comparison of the effectiveness of each method used was known.

This study proposes the use of feature selection in the decision-making process based on feature ranking. Feature selection is used to determine the best features in the dataset to be used in the decision-

making process. Simple additive weighting (SAW) is used in the decision-making process based on information gain for the feature selection process. The simple additive weighting (SAW) method is also known as the sum method [4]. The ranking method was chosen because of its effectiveness in providing calculation results. The data is clearly presented starting from the highest rank which is assumed to be a weighted feature and has a 100% chance to be used as a decision-making feature to the lowest rank.

The systematics of this paper is divided into (1) an introduction which contains a descriptive description of the problems that occur and a description of the expected results, (2) related research conveys several studies that are relevant to the problems discussed in this paper, (3) the method contains methods or methods. which is used in conducting this research which is divided into two methods, namely data collection methods and problem solving methods, (4) results and discussion explores problem solving steps based on predetermined methods to obtain decision results, (5) closing consists of conclusions from research and suggestions as input or gaps for further research, as well as (6) references containing a list of literature used as a basis for conducting research and writing this paper.

II. Related Research

Feature selection has been used in several studies related to data management. It was mentioned in [5] that high data duplication or redundancy can lead to a non-optimal selection process, so an efficient framework model is proposed for feature selection using an unsupervised method. This is in line with that conveyed by [6], where high data dimensions in some machine learning applications require complex computational analysis. It is necessary to decide that the right feature is chosen as a decision-making indicator, so deep feature selection is proposed in this case the relationship between teacher and student. In [7], the ensemble classification method is considered to have better performance than the use of a single classifier method. In this study, a formal comparison of different ensemble methods was conducted in the feature selection domain. This comparison involves five machine learning techniques, namely logistic regression, support vector machine (SVM), extreme learning machine, naive bayes and decision tree. Most feature selection is applied in research to reduce high data dimensionality and reduce duplication or data redundancy, such as the application of feature selection in [8]. Feature selection for text grouping has been carried out by [9] in Improved information gain. Similarly, [10] combines information gain with feature selection for web filtering. The implementation of feature selection in statistical calculations was proposed through research [11]. The application of feature selection was developed to analyze the development of big data, as in the research described in [12] which carried out an online feature selection technique to handle classification in big data. Several studies were conducted to seek novelty regarding decision support systems. Some of them are combined with data mining modeling. [13] suggested that the decision support system is a combination of information systems and decision- making technology. Visual interaction between humans and computers in decision making is a key decision support system technique. His research proposes a decision support system that can be applied in industry. In the study [14] identified a decision model that supports decisions in choosing an information technology system in a company. The study was conducted based on the literature with reference to five basic criteria that influence the selection of an information technology system by an entrepreneur. [15] analyzed the development of spatially based decision support systems over a three- decade time period. It is an attraction and a challenge to conduct research related to decision support systems. The future development of decision support systems is an important point in terms of data mining management. In a study conducted by [16], several decision-making methods were carried out to determine the performance of each method. In this study, the SAW, TOPSIS, GRA methods were used and implemented in Multiple criteria decision- making (MCDM). MCDM is implemented by [17] in a decision support system in providing support tools to tourists in determining hotel choices. The method used in this study using TOPSIS. Comparison between SAW and TOPSIS in the analysis through research conducted [18]. SAW uses several criteria to do calculations using the weights of each criterion with the results in the form of a ranking with advantages that are simple and easy to understand, while TOPSIS uses positive and negative value indicators which indicate the best solution marked positive and negative to indicate discrepancies. The development of a decision support system is very important. [19] develop a decision support system for emergencies.

III. Proposed Method

The proposed method of this paper is divided into two, namely data collection methods and problem solving methods. This study uses a data set or dataset which is divided into private data and public data. The UCI repository is used as a public resource reference. In addition, this research involves partners, in this case students, to generate private data through filling out questionnaires. The data used is about student data where in this study measures the performance of each student in order to determine the achievement rating of students. There are differences in data features between public data and private data used in this study, where these

differences are influenced by cultural factors belonging to a country. Private data is generated by adjusting the culture and customs that exist in Indonesia.

In collecting private data, it is done by distributing instruments containing questions that represent the condition of students. Instruments are arranged in as much detail as possible to produce objective information. The target of filling out this instrument includes all state high school students in the city of Salatiga. The information contained in the data shows indicators of student performance. There are differences in the features contained in private and public datasets. This is influenced by differences in culture and habits of the dataset producing country. The differences in the features of private and public datasets are shown in table 1.

Table no 1: Differences between private and public dataset features

| No | Field | |
|----|------------------------------|---|
| | Private | Public |
| 1 | Name | School – student’s school |
| 2 | School | Sex – student’s sex |
| 3 | Sex | Age – student’s age |
| 4 | Address | Address – student’s home address type |
| 5 | Age | Famsize – family size |
| 6 | Family_number | Pstatus – parent’s cohabitation status |
| 7 | residence | Medu – mother’s education |
| 8 | Father_education | Fedu – father’s education |
| 9 | Mother_education | Mjob – mother’s job |
| 10 | Father_job | Fjob – father’s job |
| 11 | Mother_job | Reason – reason to choose this school |
| 12 | choosin_private_school | Guardian – student’s guardian |
| 13 | Travel_time_to_school | Travelttime – home to school travel time |
| 14 | Study_time | Studytime – weekly study time |
| 15 | Stay_class | Failures – number of past class failures |
| 16 | Family_education_support | Schoolsup – extra educational support |
| 17 | Extra_lesson | Famsup – family educational support |
| 18 | extracurricular | Paid – extra paid classes within the course subject |
| 19 | Capacity_building_enthusiasm | Activities – extra-curricular activities |
| 20 | Higher_education_motivation | Nursery – attended nursery school |
| 21 | Internet_facility_at_home | Higher – wants to take higher education |
| 22 | Learning_resource_facility | Internet – Internet access at home |
| 23 | Love_relationship | Romantic – with romantic relationship |
| 24 | Family_relationship | Famrel – quality of family relationships |
| 25 | Free_time | Freetime – free time after school |
| 26 | Hang_out_time | Goout – going out with friends |
| 27 | Healthy | Dalc – work day alcohol consumption |
| 28 | Absence | Walc – weekend alcohol consumption |
| 29 | Worship_intensity | Health – current health status |
| 30 | - | Absences – number of school absences |
| 31 | - | G1 – first period grade |
| 32 | - | G2 – second period grade |
| 33 | - | G3 – final grade |

In solving the existing problems, a mathematical method is needed so that the data obtained from the calculation results are quantitative. This study proposes the Simple Additive Weighting (SAW) method as a decision-making method by combining the feature selection process using information gain and entropy

calculation. The ranking method was chosen because it is considered more effective in determining quality based on ranking. Diagram 1 shows the flow of the data processing process from the start of data collection until the data produces useful information and knowledge for users. Supporting devices for data processing using tools with the following specifications:

- a. Software: Microsoft Excel 2010, XAMP server, Google Form.
- b. Hardware: Laptop Lenovo S10-3, Intel Atom 1,66 GHz, RAM 2 GB, 64-bit OS Windows 7 Ultimate SP 1, HD SATA 300 GB

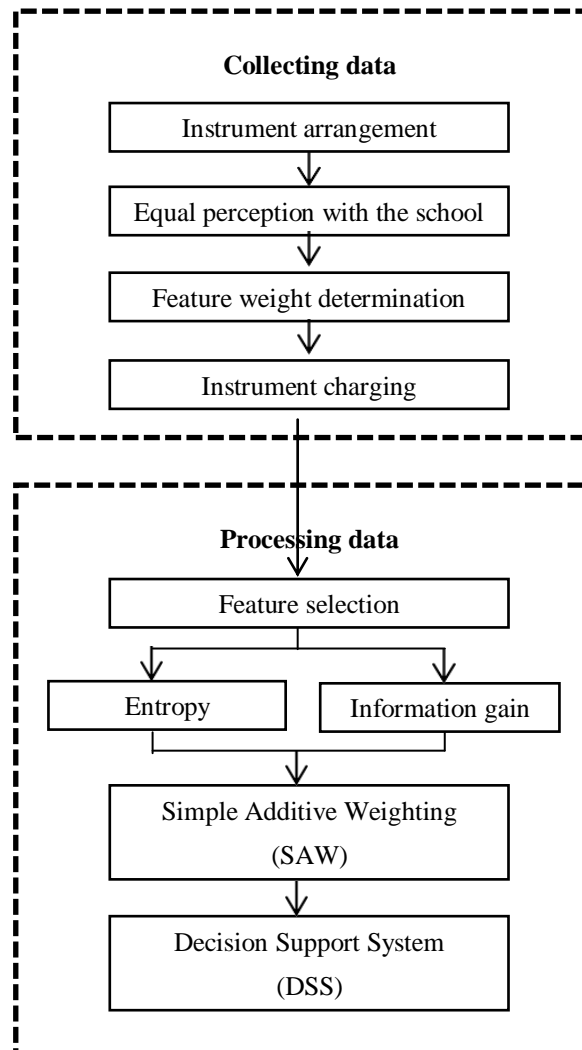


Diagram 1 Data processing flow

IV. Results and Discussion

Feature selection is used to simplify features so that the processed data is of high quality and provides optimal results. Quoted in [20], the main function of feature selection is to select the features that are most relevant to the classification problem. The public dataset of student performance used in this study before feature selection has a total of 33 features and it is necessary to carry out a preprocessing stage with feature selection to produce quality features. The feature selection process using information gain is shown in equation (ii) with entropy calculation shown in equation (i).

$$Entropy(S) = \sum_{i=1}^n -p_i * \log_2 p_i \dots \dots \dots (i)$$

Description:

S = Case set

n = Number of partitions S

P_i = Proportion S_i to S

$$Gain(S, A) = Entropy(S) - \sum_{i=1}^n \frac{|S_i|}{|S|} * Entropy(S_i) \dots \dots \dots (ii)$$

Description:

S = Case set

A = Feature

n = Number of attribute partitions *A*

|S_i| = Proportion *S_i* to *S*

|S| = Number of case in *S*

The calculation in equation (i) will produce an entropy value of 0.998661155289733, while the formula in equation (ii) is used to obtain the most optimal feature based on the weight of each feature that has been determined, so that the resulting data is shown in table 2.

Table 2 Information gain of students performance dataset

| No | Features | Weight |
|-----|------------|-------------|
| 1. | Mjob | 0,597501148 |
| 2. | absences | 0,051268248 |
| 3. | G1 | 0,02035119 |
| 4. | G2 | 0,018395952 |
| 5. | G3 | 0,015893431 |
| 6. | Fedu | 0,007193007 |
| 7. | age | 0,006731174 |
| 8. | Fjob | 0,006683177 |
| 9. | sex | 0,004526564 |
| 10. | reason | 0,003495889 |
| 11. | famrel | 0,003214155 |
| 12. | Dalc | 0,002175279 |
| 13. | studytime | 0,002060688 |
| 14. | Medu | 0,001903606 |
| 15. | famsup | 0,001710373 |
| 16. | goout | 0,001502321 |
| 17. | Walc | 0,001060899 |
| 18. | failures | 0,000942961 |
| 19. | traveltime | 0,000911323 |
| 20. | health | 0,000855747 |
| 21. | freetime | 0,000789435 |
| 22. | higher | 0,000369799 |
| 23. | schoolsup | 0,000310738 |
| 24. | activities | 0,000127759 |
| 25. | internet | 0,000101565 |
| 26. | guardian | 8,80082E-05 |
| 27. | school | 7,79496E-05 |
| 28. | address | 7,75196E-05 |
| 29. | nursery | 6,00963E-05 |
| 30. | paid | 5,79397E-05 |
| 31. | Pstatus | 4,79299E-05 |
| 32. | famsize | 7,56744E-06 |

| | | |
|-----|----------|-------------|
| 33. | romantic | 8,13317E-07 |
|-----|----------|-------------|

Table 2 shows the weights of each feature of the student performance dataset sorted from the highest to the lowest weight. Based on table 2, the mother's job (job) has the highest weight, which means that the mother's job has a big influence on student performance in learning and is followed by the number of student attendance (absence) which is the next influencing factor.

The results obtained from feature selection using information gain are features with the highest to lowest weights. From these features, the most optimal feature is chosen, namely the feature that has the highest weight. In table 3, the most optimal features have been determined which will later be used for the decision-making process.

Table 3 Optimal features from feature selection

| No | Features | Description |
|----|-----------|----------------------------|
| 1 | Mjob | Mother job |
| 2 | G1 | Grades on the first level |
| 3 | G2 | Grades on the second level |
| 4 | G3 | Grades on the third level |
| 5 | Fedu | Father education |
| 6 | age | Age |
| 7 | Fjob | Father job |
| 8 | famrel | Family relationship |
| 9 | studytime | Study time |
| 10 | sex | Sex |
| 11 | reason | Reason for choosing school |

The next step is the decision-making process. In this study using the Simple Additive Weighting (SAW) method. The SAW method is a method used in the decision-making process based on the ranking and weighting of each feature used. In the calculation process using the SAW method, there are several stages that are correlated with each other. The data to be used for the ranking process needs to be normalized first, as shown in equation (iii). Normalization is done to minimize the occurrence of data redundancy and ensure the data is in the right table with values that comply with data processing standards. In addition, normalization is carried out to handle the occurrence of anomalies or data deviations and data inconsistencies.

$$r_{ij} = \begin{cases} \frac{x_{ij}}{\text{Max } i x_{ij}} & \text{if } j \text{ is a benefit} \\ \frac{\text{Min } i x_{ij}}{x_{ij}} & \text{if } i \text{ is a cost} \end{cases} \dots\dots\dots(iii)$$

- Description:
- r = Data normalization
- x_{ij} = Case set
- $\text{Max } i x_{ij}$ = Highest value
- $\text{Mini } x_{ij}$ = Lowest value

Benefit is a value or criterion that is beneficial in the calculation process, while cost is the opposite. This means that the data is considered a benefit if the value is higher, it will have a positive impact, while the data is considered a cost if the value is higher, it will have a negative or bad impact. Based on the features shown in table 3, Job, G1, G2, G3, Fedu, age, Fjob, Famrel, studytime are classified into benefits. While absences, sex, reason are classified into costs. Each data is divided by the largest value of the total data on each feature for benefits. Cost is calculated by dividing the smallest value of each feature by all data on each feature. The ranking stage is the core of the SAW method, in which the data that has been normalized is carried out a ranking process. The calculation uses the formula shown in equation (iv).

$$V_i = \sum_{j=1}^n w_j r_{ij} \dots\dots\dots(iv)$$

- Description:
- V_i = Ranking
- w_i = Weight
- r_{ij} = Data normalization

The normalized data is multiplied by the weight of each feature, so that a number is obtained which will be used for the ranking process. Table 4 shows the sample data from the calculation process using the SAW method. The data is sorted by rank from highest to lowest value. The resulting value represents the performance of students.

Table 4 Rangking using the Simple Additive Weghting (SAW)

| Mjob | G1 | G2 | G3 | Fedu | age | Fjob | famrel | studytime | sex | reason | SAW |
|------|------|------|------|------|------|------|--------|-----------|------|--------|-------------|
| 0.05 | 0.13 | 0.12 | 0.17 | 0.06 | 0.04 | 0.05 | 0.08 | 0.14 | 0.08 | 0.20 | 1.11 |
| 0.06 | 0.13 | 0.13 | 0.18 | 0.04 | 0.04 | 0.06 | 0.08 | 0.14 | 0.08 | 0.15 | 1.11 |
| 0.06 | 0.15 | 0.15 | 0.20 | 0.06 | 0.04 | 0.05 | 0.06 | 0.14 | 0.04 | 0.15 | 1.10 |
| 0.05 | 0.14 | 0.14 | 0.18 | 0.08 | 0.04 | 0.08 | 0.06 | 0.04 | 0.08 | 0.20 | 1.09 |
| 0.08 | 0.12 | 0.13 | 0.18 | 0.06 | 0.03 | 0.05 | 0.08 | 0.11 | 0.04 | 0.20 | 1.07 |
| 0.08 | 0.10 | 0.10 | 0.14 | 0.08 | 0.04 | 0.05 | 0.08 | 0.11 | 0.08 | 0.20 | 1.05 |
| 0.02 | 0.15 | 0.14 | 0.19 | 0.08 | 0.04 | 0.02 | 0.08 | 0.11 | 0.08 | 0.15 | 1.05 |
| 0.05 | 0.13 | 0.14 | 0.18 | 0.06 | 0.04 | 0.02 | 0.08 | 0.11 | 0.04 | 0.20 | 1.03 |
| 0.05 | 0.13 | 0.13 | 0.17 | 0.08 | 0.04 | 0.05 | 0.08 | 0.07 | 0.08 | 0.15 | 1.03 |
| 0.05 | 0.13 | 0.14 | 0.18 | 0.06 | 0.04 | 0.02 | 0.05 | 0.07 | 0.08 | 0.20 | 1.02 |
| 0.05 | 0.13 | 0.11 | 0.15 | 0.04 | 0.03 | 0.05 | 0.08 | 0.14 | 0.04 | 0.20 | 1.02 |
| 0.05 | 0.13 | 0.12 | 0.16 | 0.08 | 0.04 | 0.08 | 0.08 | 0.04 | 0.04 | 0.20 | 1.01 |
| 0.08 | 0.14 | 0.15 | 0.19 | 0.08 | 0.03 | 0.08 | 0.08 | 0.04 | 0.04 | 0.10 | 1.01 |
| 0.08 | 0.12 | 0.11 | 0.14 | 0.08 | 0.04 | 0.08 | 0.05 | 0.07 | 0.04 | 0.20 | 1.01 |
| 0.05 | 0.14 | 0.14 | 0.18 | 0.02 | 0.04 | 0.02 | 0.05 | 0.14 | 0.08 | 0.15 | 1.00 |
| 0.06 | 0.13 | 0.13 | 0.16 | 0.06 | 0.04 | 0.02 | 0.06 | 0.07 | 0.08 | 0.20 | 1.00 |
| 0.06 | 0.12 | 0.11 | 0.15 | 0.04 | 0.03 | 0.05 | 0.05 | 0.11 | 0.08 | 0.20 | 1.00 |
| 0.06 | 0.12 | 0.12 | 0.15 | 0.06 | 0.04 | 0.05 | 0.06 | 0.11 | 0.08 | 0.15 | 1.00 |
| 0.08 | 0.12 | 0.10 | 0.15 | 0.08 | 0.04 | 0.08 | 0.08 | 0.07 | 0.04 | 0.15 | 0.99 |
| 0.06 | 0.11 | 0.12 | 0.16 | 0.04 | 0.04 | 0.05 | 0.06 | 0.07 | 0.08 | 0.20 | 0.99 |

Ranking is useful for decision making in terms of finding the best from a set of objects. An example of its application is in determining the award of scholarships and selecting outstanding student ambassadors. The attributes possessed by the candidate determine the decisions taken. The objectivity and validity of the data at the data collection stage greatly affect the value generated in the ranking process.

V. Results and Discussion

Decision support systems play an important role in assisting the process of making a decision where with the existence of a systematic decision-making mechanism it can produce decisions that are more objective and easy to make considerations. The feature selection provides a better alternative in determining the optimal features to be used as data to support decision making. The ranking-based decision-making method is considered effective in carrying out the decision-making process. In terms of ranking, this research uses information gain for the feature selection process and simple additive weighting (SAW) for the decision support system method.

The cultural differences of a country determine the type of data used for the decision-making process. So in this study two types of data were used, namely public data sourced from other countries and private data collected through filling out instruments for SMA N 2 students in the city of Salatiga.

VI. Suggestion

The application of the ranking-based Simple Additive Weighting (SAW) method is very effective as a decision-making method. Furthermore, this method can be developed for measuring the performance of teachers or instructors as a basis for consideration in providing performance rewards or job competency assessments.

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