REVIEW OF RESEARCH

SYSTEMATIC APPROACH TOWARDS DECISION MAKING

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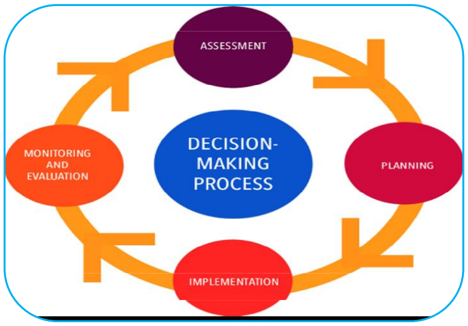

ABSTRACT:

A particular decision is good or bad is not apparent from one occasion. A good decision will benefit in the long run, while a bad decision will lead to a loss in the long run. In this paper the systematic approach to good decision making may be summarized in the form of the five steps in decision making.

KEYWORDS: *Decision tree, Minimax Regret, Maximax, Maximum Average Payoff, Coefficient of Optimism, Miximize Expected Value.*

I. INTRODUCTION

Decision making is an inevitable and unavoidable part of human life. There are two opposite ways of treating the act of decision-making. One is to consider it as a responsibility where the decision-maker has to take the risk of possibly going wrong and eventually having to suffer as a consequence of the wrong decision. The other is to treat it as an opportunity where the decision-maker has to take a chance of making the most appropriate decision so that there will be a great reward as a consequence of the decision. The first approach leads to a conservative decision, while the second approach encourages on optimistic view and often permits the decision-maker make what are known as bold decisions. The conservative way of thinking has the principle of better to be safe than sorry, while the proactive way of thinking asks as to why not try the most rewarding option. Since the reality is not black of while, but has some shades of grey, there is no universal rule for making the right decision in every situation. It is therefore necessary to understand the characteristics of good decisions and bad decisions, so that choosing an available decision will be easy. Decision theory is defined as an analytic and systematic approach to the study of decision making. This allows us to first characterize, then decide, and finally construct good decisions. Good decisions are based on reasoning, consider all available data and possible alternative, and employ a quantitative approach. On the other hand, bad decisions are not based on reasoning, do not consider all available data and possible alternatives, and do not employ a quantitative approach. As a consequence of the uncertainty in prevailing conditions, it should be kept in mind that a good decision may sometimes result in an unexpected outcome, but it is still considered to be a good decision if it is made properly. On the other hand, at the same time, a bad decision may occasionally lead to a good outcome (incidentally), but still it is a bad decision.

II. STEPS IN DECISION MAKING

The systematic approach to good decision making may be summarized in the form of the five steps in decision making as follows:

1. List all the possible alternatives (that is, actions or decisions).

2. Identify the possible outcomes as consequences of every possible action or decision.
3. Identify the profit, payoff, or reward for every possible action, corresponding to each potential outcome.
4. Select one of the decision theory models.
5. Apply the selected model and make your decision accordingly.

It is also necessary to recognize the decision making environments. Is the decision to be made under certainty or uncertainty? It is easier to make decisions under certainty, while it is harder to make decisions under uncertainty. Moreover, the uncertainty can be non-deterministic, where no pattern can be found in the states of nature or probabilistic where states of nature exhibit a certain pattern. As a result of existence of a pattern in states of nature, it is possible to measure the risk posed by the uncertainty in the decision making environment. The situation is then described as in the context of decision making under risk. In the framework of decision making, under assurance the consequences of every decision or action are known, and it is then left to the decision maker to choose the alternative that results in the best possible outcome. By contrast, when decision is to be made under uncertainty, the consequences of the action or decision are not known with certainty. It is then necessary to determine the level of risk one is willing to take in decision making. Accordingly, there are different criteria developed by researchers and experts in decision theory.

III. COMMON CRITERIA

The following are the most common criteria in decision making.

1. Maximax

This is an optimistic criterion. It considers only the best possible outcome corresponding to every possible alternative, and then selects the alternative that has the best of these outcomes. This approach is considered to be very optimistic because the decision maker positively assumes that the most favourable result will occur, no matter which alternative is selected.

2. Maximin (or Minimax)

This is a pessimistic criterion. It considers the worst possible outcome corresponding to every possible alternative, and then selects the alternative that has the best of these outcomes. This criterion is considered to be very pessimistic because the decision maker assumes that the state of nature will be least favorable to whatever alternative is selected.

3. Minimax Regret

This is also pessimistic criterion. This criterion uses the notion of regret or opportunity loss. The concept of regret is defined as the difference between the expected or desired reward and the reward actually received. This criterion evaluates the maximum regret for every alternative, and then selects the alternative that has the smallest of these (maximum) regrets. This criterion essentially chooses an alternative that minimizes the maximum regret associated with every alternative.

4. Coefficient of Optimism (Hurwicz Rule)

This criterion leaves it to the decision maker to select how much optimistic or pessimistic decision is desired. A number r is to be selected between 0 (purely pessimistic) and 1 (purely optimistic) in order to compute the weight of an alternative by the formula weight = r (best outcome) + (1 –r) (worst outcome). The alternative having the highest weight is the selected. This criterion is a compromise between an optimistic and a pessimistic decision.

5. Maximum Average Payoff (Likelihood Criterion)

This criterion computes the average of all possible outcomes corresponding to every alternative, and then selects the alternative that has the best average. It is taken for granted that various states of nature are equally likely to occur in varying context. Hence the average reward corresponding to an alternative is obtained by dividing the total of all rewards by the number of states of nature. The alternative that has the highest average reward is selected.

6. Miximize Expected Value

This criterion requires the knowledge of the probability distribution of the staes of nature, so that the probability of every state of nature is known. This situation is also known as decision creation under risk. It is used for analyzing decision trees. The payoff of every outcome is multiplied by the probability of that outcome before taking the sum of these quantities to obtain the expected payoff for every alternative. The alternative that has the highest expected value is selected.

Some researchers have developed utility theory, where an additional layer of utility over rewards is proposed. In utility theory, risk aversion is described by the consideration that a high negative reward has much higher utility than a high positive reward. On the other hand, risk prone decision making takes an opposite stand.

Payoffs are used in preparing payoff tables when decisions are simple in the sense that they are one-step decisions. When decision situations require series of decisions, then the payoff table method cannot accommodate the multiple layers of decision making process. In such cases, the decision tree approach is the best choice. Moreover, the expected value criterion can be applied at every decision node and the expected value of every route leading from the root towards a leaf node can be calculated. This can be used to identify the optimal path having the highest expected value.

IV. REQUIREMENTS FOR DEVELOPING A DECISION TREE

Decision tree induction is an inductive approach used to study classification from data. Instead of partitioning the state apace using theoretical criteria, decision trees partition the data space using the evidence that is available in the form of data to arrive at the classification rules. Developing a decision tree requires the following:

- **Attribute-value description**

An observation of a case should be expressed in terms of a specified set of qualities or properties. This involves discretization of continuous variable. Alternatively, the algorithm must make a provision for this.

- **Target attribute value (that is, predefined classes)**

The categories to which every observation is to be assigned must be identified before beginning the procedure. If the target attribute is a continuous variable, then it must be appropriately discretized.

- **Distinguishable and exhaustive classes**

Every observation either belongs or does not belong to a particular class. On the other hand, there must be a unique class to which a particular observation belongs. Finally, the number of observations must exceed the number of classes.

- **Sufficient amount of data**

As a matter of fact, even though this is a theoretical requirement, in practice the number of observations runs into hundreds or even thousands.

V. ADVANTAGES OF DECISION TREE

Decision Trees have several advantages over alternative methods of classification. Following is a short list of such advantages:

- Decision trees are self explanatory and are simple to go after even when they are compacted. As a result, even non-professional users can grasp the decision tree as long as it has a reasonably small number of leaf nodes. Moreover, a decision tree may be shown as an equivalent set of rules. This representation, therefore, can be measured to be comprehensive.
- Decision trees are competant of managing nominal and numerical input attributes.
- A representation of decision trees is sufficiently rich to cover any discrete-value classifier.

- Decision trees are sufficiently flexible to have capacity to handle datasets that are likely to have errors.
- Decision trees are sufficiently robust to be able to handle datasets which are likely to have missing values.

Decision trees belong to nonparametric methods. This indicates that decision trees do not have to make any assumption about the state space distribution and the structure of a classifier.

As a consequence of being a non-paramedic method, decision tree induction does not require tuning of parameters.

- Decision trees do not make any assumptions about independence of attributes.
- Decision trees do not require any transformation of variables. Further, even if some transformations are carried out for some other reasons, any monotone transformation of a variable will still result in the same trees.
- The optimality of decision trees ensures that decision trees automatically select a subset of features which are related to the decision or classification.
- Decision trees are not unduly sensitive to outliers because the selection of a split value of decision variable depends on the relative ordering of attribute values and not on the absolute magnitudes of those attribute values.
- The decisions represented by decision trees can be easily extended to observations containing missing values for some attributes.
- Decision trees are presented graphically, where it is possible to represent decision alternatives, possible outcomes, and chance events schematically. Sequential decisions and outcome dependencies can be easily comprehended due to the visual approach to decision trees.
- Regarding efficiency of a decision tree, complex alternatives can be quickly and easily expressed in decision trees. A decision tree can be used to compare how changes in input values affect various decision alternatives. It is easy to adopt the standard decision tree notation.
- It is not only possible but also easy to compare challenging and competing alternatives, even though total information is not available in terms of the risk and probable value. The term indicating the expected value combines in itself relative investment costs, potential or expected payoffs, and hidden uncertainties into a single numerical value. The expected value highlights the overall merits of competing alternatives.
- Decision trees are complementary in the sense that they can be used in conjunction with other project management tools.
- Decision trees generalize very naturally and hence are extremely fast in classifying unknown observations.
- Decision trees work very efficiently in the presence of redundant attributes.
- If provisions are made for methods to avoid over fitting, then decision trees are reasonably robust in the presence of noise.
- Decision trees clearly indicate which attributes are most important for classification or prediction.
- A decision tree can be applied in a simple and natural way to data structures that include ordered as well as categorical attributes. The recursive partitioning method, in particular, is exceptionally efficient in handling categorical input attributes.
- It helps face the curse of dimensionality. The conventional non-parametric smoothing methods are found to be computationally infeasible when the data dimension exceeds 2. Parametric models also encounter problems as the dimensionality increases. Some examples of these problems are selection of variables, transformations of variables, and handling any interactions that may be present among input attributes.
- A decision tree selects variables stepwise, reduces complexity, and implicitly handles interaction in an automatic manner.
- A decision tree generates, as a by-product, variable importance rankings.

- The information in the output of a decision tree is easily understood and interpreted. One of the main advantages that decision trees have over some of the 'black box' methods like neural networks. The output of decision trees has a visible 'precedence-consequence' relationship, even though it cannot automatically be interpreted as a 'cause-and-effect' relationship.
- The hierarchical and often binary, tree structure segregates data automatically and optimally. This feature makes it an excellent tool in medical diagnosis and prognosis.
- Decision trees, by segregating data into homogenous subsets represented by leaf nodes, provide a natural way of handling be heterogeneity in the data. As a consequence, different data models can be fitted to subsets of data comprising different leaf nodes.
- Decision tree do not require an explicit criterion for selecting input variables in the analysis, as is the case with some other algorithms like regression.
- Decision trees are easy to understand and explain. As a matter of fact, they are even easier than linear regression to explain and interpret.
- Some researchers have argued that decision trees resemble decision making in human beings more closely than regression and other approaches such as and support vector machines and discriminant analysis.
- Trees may be displayed graphically, rather than in a verbal or tabular form, and hence are easily interpreted even by non-experts. This is more relevant when trees are small.
- Decision trees are capable of handling qualitative data without having to report to creating dummy variables.

VI. CONCLUSION

The literature on decision tree induction often focuses more on the algorithmic development, discretization of continuous variables, criteria for selecting a decision variable at a decision node, or optimality properties of the recommended algorithm. As a consequence of the focus of most of the research articles being on some specific aspect of decision trees, it is not very common to find a comprehensive assessment of decision trees as a methodology, technology, or discipline on its own merits. This paper highlights some of the prominent and noticeable points of strength or advantages of decision trees.

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