A Multi-Criteria Approach for the Evaluation of Rule Interestingness.

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Abstract

This paper studies several criteria for evaluating rule interestingness. It first reviews some rule interestingness principles with respect to the widely-used criteria of coverage, completeness and confidence factor of a rule. It then considers several additional factors (or criteria) influencing rule interestingness that have been somewhat neglected in the literature on rule interestingness. As a result, this paper argues that rule interestingness measures should be extended to take into account the additional rule-quality factors of disjunct size, imbalance of the class distribution, attribute interestingness, misclassification costs and the asymmetry of classification rules. The paper also presents a case study on how a popular rule interestingness measure can be extended to take into account the proposed additional rule-quality factors.

1 Introduction.

A crucial aspect of data mining is that the discovered knowledge should be somehow interesting, where the term interestingness arguably has to do with surprisingness (unexpectedness), usefulness and novelty Fayyad[3].

Rule interestingness has both an objective (data-driven) and a subjective (user-driven) aspect. This paper focus on the objective aspect of rule interestingness. For a discussion about subjective aspects of rule interestingness, the reader is referred e.g. to Liu[10]. It should be noted that, in practice, both objective and subjective approaches should be used to select interesting rules. For instance, objective approaches can be used as a kind of first filter to select potentially interesting rules, while subjective approaches can then be used as a final filter to select truly interesting rules.

This paper is organized as follows. Section 2 reviews rule interestingness principles, based mainly on the rule quality factors of coverage, completeness and confidence factor. Section 3 discusses five additional factors that are not explicitly addressed by the factors reviewed in section 2 but that should, we believe, be taken into account by rule interestingness measures. These factors are disjunct size, imbalance of the class distribution, attribute interestingness, misclassification costs and the asymmetry of classification rules. Section 4 presents a case study on how a popular rule interestingness measure can be extended to take these additional factors into account. Finally, section 5 concludes the paper.

2 A Review of Rule Interestingness Principles.

For the purposes of this paper, a classification rule is a knowledge representation of the form A => B, where A is a conjunction of predicting attribute values and B is the predicted class. When evaluating the quality of a rule, three common factors to be taken into account are the coverage, the completeness and the confidence factor of the rule, defined as follows. The coverage of the rule (i.e. the number of tuples satisfied by the rule antecedent) is given by $|A|$. The rule's completeness (or proportion of tuples of the target class covered by the rule) is given by $|A\&B| / |B|$. The rule's confidence factor (or predictive accuracy) is given by $|A\&B| / |A|$.

Piatetsky-Shapiro[15] has proposed three principles for rule interestingness (RI) measures, as follows.

1) $RI = 0$ if $|A \& B| = |A| |B| / N$.

2) RI monotonically increases with $|A\&B|$ when other parameters are fixed.

3) RI monotonically decreases with $|A|$ or $|B|$ when other parameters are fixed.

The first principle says that the RI measure is zero if the antecedent and the consequent of the rule are statistically independent. The second and third principle have a more subtle interpretation. Note that Piatetsky-Shapiro was careful to state these principles in terms of *other* *parameters*, which is a phrase general enough to include any other parameter that we can think of. Let us assume for now that the rule parameters referred to by these principles are the terms |A|, |B|, and |A&B|, which are the terms explicitly used to state the principle. Note that this is an implicit assumption in most of the literature. However, we will revisit this assumption later in this section.

With the above assumption, principle 2 means that, for fixed |A| and fixed |B|, RI monotonically increases with |A&B|. In terms of the above mentioned rule quality factors, for fixed |A| and fixed |B|, the confidence factor and the completeness of the rule monotonically increase with |A&B|, and the higher these factors the more interesting the rule is.

Principle 3 means that: (1) for fixed |A| and fixed |A&B| (which implies a fixed coverage and a fixed confidence factor) RI monotonically decreases with |B| - i.e. the less complete, the less interesting the rule is; and (2) for fixed |B| and |A&B| (which implies a fixed rule completeness) RI monotonically decreases with |A| - i.e. the greater the coverage, the smaller the confidence factor, and the less interesting the rule is.

Major[12] proposed a fourth principle for RI measures, namely:

4) RI monotonically increases with |A| (rule coverage), given a fixed confidence factor greater than the default confidence factor (i.e. the prior probability of the class).

In passing, we mention that Kamber[7] proposed a fifth principle for rule interestingness, but this principle is mainly oriented for characteristic rules, which are beyond the scope of this paper.

It should be noted that the above principles were designed mainly for considering the widely-used rule quality factors of coverage, completeness and confidence factor. Another widely-used rule quality factor is rule complexity. Although these factors are indeed important when evaluating the quality of a rule, they are by no means the only ones. In this paper we draw attention to five other factors related to rule quality and particularly to rule interestingness. These additional factors are discussed in the next section.

Note that, in theory, Piatetsky-Shapiro's principles still apply to rule interestingness measures considering these additional factors, as long as they remain fixed. (As mentioned before, the principles were carefully defined with the expression "fixed *other* parameters".) The problem is that, in practice, these additional factors do not remain fixed. These additional factors will probably vary a great deal across different rules, and this variation should be taken into account by the rule interestingness measure. This is the central theme of this paper.

3 Additional Rule Interestingness Factors.

3.1 Disjunct Size.

A rule set can be regarded as a disjunction of rules, so that a given rule can be regarded as a disjunct. The size of a disjunct (rule) is the number of tuples satisfied by the rule.

Thus, small disjuncts are rules whose number of covered tuples is small, according to some specified criterion (e.g. a fixed threshold, or a more flexible criterion). At first glance, it seems that small disjuncts are undesirable, and indeed most data mining algorithms have a bias favoring the discovery of large disjuncts.

Unfortunately, however, prediction accuracy can be significantly reduced if all small disjuncts are discarded by the data mining algorithm, as shown by Holte[6]. This is a particularly serious problem in domains where the small disjuncts collectively match a large percentage of the number of tuples belonging to a given class Danyluk[2]. The main problem is that a small disjunct can represent either a true exception occurring in the data or simply noise. In the former case the disjunct should be maintained, but in the latter case the disjunct is error prone and should be discarded. Unfortunately, however, it is very difficult to tell which is the case, given only the data.

Holte[6] suggested that one remedy for the problem of small disjuncts was to evaluate these disjuncts by using a bias different from the one used to evaluate large disjuncts. Hence, they proposed that small disjuncts be evaluated by a maximum-specificity bias, in contrast with the maximum-generality bias (favoring the discovery of more general rules) used by most data mining algorithms. Ting[21] further investigated this approach, by using an instance-based learner (as far as we can go with the maximum-specificity bias) to evaluate small disjuncts.

From a rule interestingness point of view, the lesson is that small disjuncts and large disjuncts should be evaluated in different ways by a rule interestingness measure.

3.2 The Imbalance of the Class Distribution.

A class distribution is imbalanced if tuples belonging to one class are either much more frequent or much rarer than tuples belonging to other classes. To simplify our discussion, let us consider the common case of two-class problems.

Other things being equal, a problem where the two classes have the same relative frequency (or prior probabilities) is more difficult than a problem where there is a great difference between the relative frequencies of the two classes. In the latter case, it is relatively easy to discover rules predicting the majority class, but it is difficult to discover rules predicting the minority class. The smaller the relative frequency of the minority class, the more difficult it is to discover rules predicting it, and thus, intuitively, the more interesting are the rules predicting the minority class and the less interesting are the rules predicting the majority class. This point if often ignored by data mining algorithms.

Kononenko[8] have proposed an information-theoretic measure for evaluating the performance of a classifier by taking into account the problem of imbalanced class distributions, and their measure has some interesting properties. However, their approach was designed to evaluate a classifier as a whole - mainly to compare the performance of different classifiers in the same domain or the performance of a classifier in different problem domains - rather than to compare the interestingness of different rules discovered by the same classifier, which is the focus of this paper.

Note that the problem of imbalanced class distributions interacts with other problems discussed in this paper. For instance, consider the interaction between the problem of imbalanced class distributions and the problem of small disjuncts. Let r_1 and r_2 be two small disjuncts (rules) of the same size (i.e. the same number of covered tuples), where r_1 predicts the minority class and r_2 predicts the majority class for a new tuple. Then r_1 tends to have a much smaller prediction accuracy than r_2 Quinlan[16].

Finally, note that using a rule interestingness measure which takes into account the relative class frequencies is not the only approach to cope with the problem of imbalanced class distributions. For instance, another approach to address this problem consists of selectively removing tuples from the majority class, so that the class distribution becomes less imbalanced Kubat[9]. In this paper however, we are interested only in modifying the rule interestingness measure used by the algorithm, leaving the data being mined intact.

3.3 Attribute Interestingness.

Most rule interestingness measures consider the rule antecedent as a whole, without paying attention to the individual attributes occurring in the rule antecedent. In this sense, theses measure are coarse-grained.

However, two rules with the same value of a coarse-grained rule interestingness measure can have very different degrees of interestingness for the user, depending on which attributes occur in the rule antecedent.

As an example of a particular case where the notion of attribute interestingness is crucial, consider the issue of attribute costs, as follows. In order to classify a new tuple with a given rule, it is necessary to match the rule conditions against the tuple's predicting attributes (i.e. attributes other than the class one). Hence, the algorithm must access the values of the new tuple's predicting attributes. In some application domains, different attributes might have very different "costs" to be accessed. The typical example is medical diagnosis. For example, it is trivial to determine the gender of the patient, but some health-related attributes can only be determined by performing a very costly examination. In this case attribute costs must be taken into account when evaluating a rule. The smaller the cost of the attributes occurring in the rule, the more interesting (the more useful, the less costly) the rule is. Some data mining algorithms that take into account attribute costs are described in Nunez [14], Tan[20], Turney[22].

3.4 Misclassification Costs.

In some application domains, different misclassifications might have very different costs. For instance, in the domain of bank loans, the cost of erroneously denying a loan to a good client (who is likely to pay it back) is usually considerably smaller than the cost of erroneously granting a loan to a bad client (who is unlikely to pay it back). In this case the data mining algorithm must be modified to take misclassification costs into account Roberts[18], Michie[13], Breiman[1]. This implies that the rule induction measure should take misclassification costs into account.

We must make here a comment similar to the one made in the section on imbalanced class distributions. Using a rule interestingness measure which takes into account misclassification costs is not the only approach to cope with this problem. For instance, another approach to address this problem consists of adjusting the relative proportions of each class in the data being mined. Once more in this paper, however, we are interested only in modifying the rule interestingness measure used by the algorithm, leaving the data being mined intact.

3.5 Asymmetry in Classification Rules.

It should be noted that classification is an *asymmetric* task with respect to the attributes in the database. Indeed, we want to discover rules where the value of the predicting attributes determine the value of the goal attribute, not vice-versa. Hence, intuitively a rule interestingness measure should be asymmetric with respect to the rule antecedent and the rule consequent.

It is interesting to note that statistical measures of association, such as the popular χ^2 (chi-squared) measure, which is widely used in data mining systems, were not designed for classification tasks. Rather, they were designed for measuring the association (or dependency) between two attributes in a *symmetric* way, i.e. none of the two rule terms (antecedent and consequent) being analyzed is given special treatment when computing the χ^2 value.

We note in passing that an additional problem associated with the use of statistical significance tests in data mining, as pointed out by Glymour[5], is that these tests were designed to evaluate a single hypothesis, whereas data mining algorithms typically have to evaluate many alternative hypothesis.

4 A Case Study on the Applicability of Additional Rule Interestingness Factors.

The above sections have identified five factors that should be involved in measuring the interestingness of a rule, but that have often been somewhat ignored in the literature on rule interestingness. We now discuss how these factors can be applied to define a rule interestingness measure.

There are several rule interestingness measures proposed in the literature. As a case study, we will focus on one of the most popular ones, introduced by Piatetsky-Shapiro[15] as the simplest measure satisfying the three principles discussed in section 2. This measure, hereafter called PS (Piatetsky-Shapiro's) measure, is defined as:

$$PS = |A\&B| - |A||B|/N. \qquad (1)$$

The remaining of this section is divided into two parts. Section 4.1 discusses how the PS measure addresses the additional rule interestingness factors discussed in section 3. Section 4.2 shows how this measure can be extended to better address those rule rule interestingness factors.

4.1 Analyzing the PS Rule Interestingness Measure.

We now discuss how the PS measure, given by formula (1), addresses the rule quality factors of disjunct size, imbalance of the class distribution, attribute interestingness, misclassification costs and the asymmetry of classification rules.

Disjunct size - The PS measure takes into account the size of the disjunct, since formula (1) contains the term $|A|$. However, this measure treats small disjuncts and large disjuncts in the same way, with the same bias, which is undesirable, as discussed in section 3.1.

Imbalance of the Class Distribution - The PS measure takes into account the relative frequency (prior probability) of the class predicted by the rule, since formula (1) contains the term $|B|$. Other things being equal, the larger the value of $|B|$, the smaller the value of PS, so that the PS measure has the desirable property of favoring rules that predict the minority class.

Attribute Interestingness - The PS measure does not take into account the interestingness of individual predicting attribute costs. Actually, this measure considers the rule antecedent as a whole only, without paying attention to individual attributes of the rule antecedent.

Misclassification Costs - The PS measure does not take into account misclassification costs.

Asymmetry of Classification Rules - The PS measure is symmetric with respect to the rule antecedent and the rule consequent. We consider this an undesirable property of this measure, given the clearly asymmetric nature of the classification task.

To summarize, out of the five factors influencing rule interestingness discussed in section 3, the PS measure takes into account only one of them (imbalance of the class distribution).

4.2 Extending the PS Rule Interestingness Measure.

We now discuss how the PS measure can be modified to take into account the four factors not addressed by this measure, namely attribute interestingness, misclassification costs, disjunct size and the asymmetry of classification rules. However, there is a caveat. There is no data mining bias that is universally best across all application domains. This fact has been shown both empirically Michie[13] and theoretically Schaffer[19], Rao[17]. As a result, there is no rule interestingness measure which is universally best across all application domains. The challenge is to define a rule interestingness measure that is the most suitable for the target application domain.

Therefore, our goal here is *not* to propose a new rule interestingness measure, but rather to suggest ideas that can help designers of data mining algorithms to define new rule interestingness measures particularly suitable for the target problem.

4.2.1 Attribute Interestingness.

The PS measure can be extended to consider the interestingness of individual attributes occurring in the rule antecedent by multiplying formula (1) by a new term called AttInt (Attribute Interestingness). AttInt can be defined in several ways, depending on the target problem. Two basic ideas for defining this term are presented here.

First, in domains where attribute costs must be considered, AttInt can be simply defined as the inverse of the sum of the costs of all the attributes occurring in the rule antecedent, that is:

$$\text{AttInt} = 1 / \sum_{i=1}^{k} \text{Cost}(A_i), \qquad (2)$$

where $\text{Cost}(A_i)$ is the cost of the i-th attribute occurring in the rule antecedent, and k is the number of attributes occurring in the rule antecedent.

Note that this formula has the side effect of penalizing “complex” rules, i.e. rules with many attributes in their antecedent. In some cases, however, the number of attributes in the rule is already being taking into account by another term of the rule interestingness measure, such as an explicit measure of rule complexity. In this case, to avoid that a rule be penalized twice for its high complexity, AttInt can be simply defined as the inverse of the arithmetic average of the costs of all the attributes occurring in the rule antecedent, that is:

$$\text{AttInt} = 1 / (\sum_{i=1}^{k} \text{Cost}(A_i) / k), \qquad (3)$$

where $\text{Cost}(A_i)$ and k are as defined above.

Second, in application domains where attribute costs are irrelevant, we suggest that AttInt be defined by an information-theoretic measure, based on the following idea. First, we calculate the information gain of each attribute, defined as the class entropy minus the class entropy given the value of the predicting attribute. Attributes with high information gain are good predictors of class, when these attributes are considered individually, i.e. one at a time. However, from a rule interestingness point of view, it is likely that the user already knows what are the best predictors (individual attributes) for its application domain, and rules containing these attributes would tend to have a low degree of surprisingness (interestingness) for the user.

On the other hand, the user would tend to be more surprised if (s)he saw a rule containing attributes with low information gain. These attributes were probably considered as irrelevant by the users, and they are kind of irrelevant for classification when considered individually, one at a time. However, attribute interactions can render an individually-irrelevant attribute into a relevant one. This phenomenon is associated with surprisingness, and so with rule interestingness. Therefore, all other things (including prediction accuracy, coverage and completeness) being equal, we argue that rules whose antecedent contain attributes with low information gain are more interesting (more surprising) than rules whose antecedent contain attributes with high information gain. This idea can be expressed mathematically by defining the term AttInt in the rule interestingness measure as:

$$\text{AttInt} = 1 / \left(\sum_{i=1}^{k} \text{InfoGain}(A_i) / k\right), \qquad (4)$$

where InfoGain(A_i) is the information gain of the i-th attribute occurring in the rule antecedent and k is the number of attributes occurring in the rule antecedent.

4.2.2 Misclassification Costs.

In domains where misclassification costs vary according to the class, the PS measure must be modified to take misclassification costs into account. A simple way of doing this is to multiply formula (1) by a new term called MisclasCost, defined as:

$$\text{MisclasCost} = 1 / \sum_{j=1}^{k} \text{Prob}(j)\text{Cost}(i,j), \qquad (5)$$

where Prob(j) is the probability that a tuple satisfied by the rule has true class j, class i is the class predicted by the rule, Cost(i,j) is the cost of misclassifying a tuple with true class j as class i, and k is the number of classes.

Assuming a two class problem, a natural estimate for Prob(j) would be

$$\text{Prob}(j) = |A\&{\sim}B|/|A|, \qquad (6)$$

where ~B denotes the logical negation of the rule consequent B. One problem with this estimate is that, if the rule covers few tuples, this estimate is not reliable. A solution for this problem will be given in the next subsection.

4.2.3 Disjunct Size.

The size of the disjunct is a factor that strongly interacts with other rule interesting factors discussed in this paper. For instance, consider the interaction between disjunct size and misclassification costs. As mentioned above, a natural estimate for Prob(j) in formula (5) would be formula (6). However, this estimate is not reliable when the rule is a small disjunct. In this case, the reliability of the probability estimate can be improved by using the Laplace correction Roberts[18], so that

$$\text{Prob}(j) = (1 + |A\&{\sim}B|) / (2 + |A|). \qquad (7)$$

(This correction can be easily generalized to an n-class problem by replacing the "2" in the denominator with n.) Note how the Laplace correction improves the reliability of a probability estimate for small disjuncts without significantly affecting this reliability for large disjuncts. This is a good example to support the claim that small and large disjuncts ought to be treated differently, when measuring the interestingness of a rule.

4.2.4 Asymmetry of Classification Rules.

As mentioned before, the PS measure, as defined by formula (1), has the undesirable property of being symmetric with respect to the rule antecedent and rule consequent. However, the modifications to formula (1) proposed above have the nice side effect of rendering the formula asymmetric, so that this point needs no further elaboration here.

5 Conclusion.

This paper has discussed five factors influencing the interestingness of a rule, namely disjunct size, imbalance of class distributions, attribute interestingness, misclassification costs and the asymmetry of classification rules. These factors are often neglected by the literature on rule interestingness, which often focuses on factors such as the coverage, completeness and confidence factor of a rule.

As a case study, we focused on a popular rule interesting measure, defined by formula (1). We have shown that this measure takes into account only one of the five rule quality factors discussed in this paper, namely imbalanced class distributions. Then we discussed how this measure could be extended to take into account the other four factors. In particular, the extended rule interestingness measure has the form:

$$(|A\&B| - |A|\,|B| / N) * \text{AttInt} * (1 / \text{MisclasCost}), \qquad (8)$$

where the term AttInt measures attribute interestingness - computed e.g. by one of the formulas (2), (3) or (4) - and the term MisclasCost measures the misclassification cost - computed e.g. by formula (5) and one of the formulas (6) or (7). The exact choice of the formula to be used for the terms AttInt and MisclasCost depends both on the target problem and on the interaction of these terms with other rule quality factors, particularly disjunct size. For instance, the use of formula (7) has the advantage of improving the reliability of a probability estimate for small disjuncts, while formula (6) does not have this advantage. Finally, the problem that formula (1) is symmetric, whereas classification rules should be asymmetric, was solved by adding the asymmetric terms AttInt and MisclasCost to the extended formula (8).

As mentioned before, the main goal of this paper was not to introduce yet another rule interestingness measure. Rather this paper had the twofold goal of: (1) drawing attention to several rule factors related to rule interesting that have been somewhat neglected in the literature; (2) showing some ways of modifying rule interestingness measures to take these factors into account, which will hopefully inspire other researches to do the same.

We cannot overemphasize that a rule interestingness measure is a bias, and so there is no universally best rule interestingness measure across all application domains. Each researcher or practitioner must adapt a rule interestingness measure (or invent a new one) to his/her particular target problem.

One limitation of this paper is that we have, implicitly, largely focused on how to measure the interestingness of different rules discovered by the same data mining algorithm, mining the same data. An open problem is how to extend our arguments for comparing the interestingness of different rules discovered by different data mining algorithms, or discovered from different data sets. Another limitation is that our discussion has not taken into account the interaction between rules in the induced rule set. In principle, however, the issue of rule interaction is somewhat orthogonal to the issue of individual rule interestingness, in the sense that the measure of rule interaction (typically a measure of rule overlapping) is often independent of the measure of individual rule interestingness. The reader interested in rule selection procedures taking into account rule interaction is referred to Gebhardt[4], Major[11], Major[12].

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