MAGIX: Model Agnostic Globally Interpretable Explanations

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Abstract

Explaining the behavior of a black box machine learning model at the instance level is useful for building trust. However, what is also important is understanding how the model behaves globally. Such an understanding provides insight into both the data on which the model was trained and the generalization power of the rules it learned. We present here an approach that learns simple if-then rules to globally explain the behavior of black box machine learning models that have been used to solve classification problems. Collectively, these rules represent the pattern followed by the model and are useful for gaining insight into its behavior. We demonstrate the power of the approach on three publicly available data sets.

1 Introduction

Machine Learning and Artificial Intelligence have become so widespread as to pervade almost every aspect of our life. The implementation of ‘intelligent’ algorithms is rampant in all verticals of industry. These include but are not restricted to applications in medicine, finance, imaging, operations in e-commerce, audio and so on. In such a situation, it becomes more important than ever to understand and interpret these algorithms.

Broadly, there are two types of machine learning algorithms. The first type are based on relatively straightforward formulations and are hence easily interpretable. Under this category we have algorithms such as Linear Regression, Logistic Regression, Decision Trees and other similar approaches. The main advantage of such algorithms is that they are simple, easy to visualize and hence interpret. For instance, by looking at the weights learned by a Linear Regression model, it is possible to determine the relative importance of different features used by the model. Hence, decisions made by such models are relatively easier to
justify. As a concrete though slightly contrived example, a Decision Tree model used to predict the risk of loan defaulting can provide a justification to the end customer as to why his loan was rejected. The justification can be of the form ‘... because your annual income is less than 5000 dollars and you are married...’. These types of models also provide another interesting insight. They allow the data scientist or end user to discern at a glance the general patterns the model has picked up on. Extending our loan rejection example, bank officials can visualize the resulting decision tree and glean at a glance any spurious patterns that perhaps should not have been a part of the learning process. Concretely, let us assume that the decision tree has a path that says ‘If user is from North Carolina then reject loan’. Now, it is certainly possible that the rule makes sense for some application domains, however it is more likely that there existed certain un-generalizable patterns in the training and test data, and were learned by the machine learning algorithm. In the above example, it is possible that the data used for training the machine learning algorithm had only a few users from North Carolina, all of whose loans had been rejected. To the machine learning algorithm, this highly correlated though relatively infrequent pattern would look ‘causal’.

The second type of algorithms are based on complex formulations that are able to represent highly non-linear functions. Most popular among these are Neural Networks, Random Forests, Gradient Boosted Trees and so on. The key characteristic of these approaches is that they are able to model very complex patterns and hence achieve higher accuracy on most data sets than their simpler counterparts. However, the cost of this gain in accuracy is model interpretability. Neural Networks, for instance often have several hidden layers with different activations and dropout. Random Forests can have thousands of trees, and the final decision is a function of the combination of the individual predictions made by these trees. Now, let’s return to our loan rejection example. If we had used a Random Forest algorithm with say 2000 trees instead of a single Decision Tree, then it would be non-trivial to justify to a particular end user the criteria on which his loan was rejected. Such justifications are often not only ‘good to have’ but also legally essential when deploying the system. Further, even if we could explain to a particular user the grounds for rejection (we will see how later), we still cannot glean the general patterns that the model may have picked up on.

Model Interpretation is important in several industry verticals. It helps provide answers to questions such as ‘Do I understand my model?’ and more importantly, ‘Do I trust my model?’? Unfortunately, the complexity of machine learning algorithms that enables them to perform well, also makes their inner working relatively harder to understand. Hence, there is usually a trade off between accuracy and interpretability. For example, in the case of loan rejection, statutory requirements require transparency. Hence, machine learning models to solve such problems are based on Decision Trees or Linear Regression. In domains where interpretation is not as important, such as facial recognition software, companies use complex black box models such as neural networks to achieve maximum accuracy. What is needed is a way to incorporate the best aspects of both types of algorithms. The accuracy of complex algorithms with the interpretability of simple ones.

We present here an approach that is global, model agnostic and that explains model behavior in a very easy to understand way. We will only be discussing it with respect to understanding models that perform the task of classification.
Hence, our approach learns rules that explain the behavior of a classification model. Each rule is independent, and is of the form ‘If C1 AND C2 AND.... Then Predict class K’. Here, Ci refers to a specific condition such as ‘15 < age < 25’ and K is some class in the data. Our approach currently works only on classification models, however extending to regression models by methods of binning should be straightforward. A more detailed discussion about this is presented in the section 5. Some possible applications of our approach are as follows:

1. In the loan rejection example discussed previously, our approach would allow the algorithm developer to read through the rules that the model has picked up on. This serves two purposes. First, it allows the developer to ascertain and subsequently reject any spurious or incidental patterns in the training data that the model may have picked up on. Second and perhaps equally important, it allows the developer to gain insights about his particular problem domain. For example, in the case of loan rejection, by training a complex model on say the last 5 years of loan rejection data, and by extracting rules from this model using our approach, the developer or analyst could gain unprecedented insight into patterns in his original data set. He may learn for example the role that implicit bias plays in loan rejection, by examining rules related to certain geo-locations.

2. Similarly, for machine learning applications in medicine, our approach can be used to extract rules that represent the behavior of the model. Such rules would assist the physician in both diagnosing the generalizability of the machine learning model and drawing insights regarding the patterns of past diagnoses.

3. For data scientists and machine learning developers, our approach provides a powerful debugging tool. It allows the developer to examine the quality and applicability of the learned rules and take appropriate action.

2 Literature Survey

There has been a wide variety of work in the field of model interpretation. The types of approaches applied can be characterized along several dimensions. They are:

1. The complexity of the response function that we want to explain. These include simple linear functions such as the ones learned by linear regression algorithms. Such functions are the most straightforward to interpret. The advantage of such functions is that it is easy to see what effect (both magnitude and direction) a particular attribute would have on the output variable. Non linear functions on the other hand involve complex combinations of the input features and are hence much harder to interpret.

2. Scope of interpretability. Some approaches allow global interpretation of machine learning models, while others focus on instance level or local explanations. By local explanations, we mean explaining model behavior in a limited region of the input space.
3. Whether the approach depends on the model. There are two types of approaches under this category. The first are model specific, i.e. those approaches that are designed to exploit model specific properties in constructing explanations. The second are model agnostic, i.e. those approaches that do not leverage underlying details of the machine learning model in constructing explanations. Rather, they treat the model as a black box and rely on the predict function of the model.

The following techniques are commonly used to understand model behavior:

1. Partial dependence plots - these plots show how the output of a machine learning model changes as we vary one or two input variables of interest. They are useful to explain model behavior as a function of input variables that are deemed important by domain experts.

2. Residual analysis - Residuals refer to the difference between the recorded value of a dependent variable and the predicted value of a dependent variable for every row in a data set. Generally, the residuals of a well-fit model should be randomly distributed because good models will account for most phenomena in a data set, except for random error. Plotting the residual values against the predicted values is a time-honored model assessment technique and a great way to see all your modeling results in two dimensions. If strong patterns are visible in plotted residuals, it is an indication that there are problems with the data, the model, or both. If models are producing randomly distributed residuals, this a strong indication of a well-fit, dependable, trustworthy model. ([PHA17], [CW82])

3. Generalized Additive Models (GAMs) - Generalized Additive Models (GAMs) enable one to hand-tune a tradeoff between increased accuracy and decreased interpretability by fitting standard regression coefficients to certain variables and nonlinear spline functions to other variables. Also, most implementations of GAMs generate convenient plots of the fitted splines. Depending on your regulatory or internal documentation requirements, you may be able to use the splines directly in predictive models for increased accuracy. If not, you may be able to eyeball the fitted spline and switch it out for a more interpretable polynomial, log, trigonometric or other simple function of the predictor variable that may also increase predictive accuracy. ([PHA17], [HT90])

Please refer [PHA17] for a more comprehensive list of such approaches.

The techniques described above are discussed in more detail in [PHA17] and are useful for models that learn monotonic response functions. However, complex models such as neural networks and gradient boosted trees learn nonmonotonic response functions. In such functions, changes in the input variables in the same direction can lead to the response variable changing in different directions. For example, in a loan rejection model, the age increasing from 20 to 25 may decrease the risk of loan rejection, however the age increasing from 60 to 65 might produce the opposite effect and increase the risk of loan rejection. Interpreting the behavior of such models at a global level is a non-trivial problem. Some approaches that have been used for this are:
1. Surrogate models - these are simpler models that act as surrogates for more complex models. As a concrete example, we can take each training instance and its predicted output for a complex neural network model. Then we can use this data to train a decision tree. Intuitively, the decision tree would capture patterns that the neural network learned from the training data. However, this method suffers from several drawbacks. Firstly, when using a decision tree to capture model behavior, the most obvious shortcoming is that each path to a leaf node goes through the first attribute that the tree splits on. The result being that each rule includes a condition involving this attribute. This holds recursively such that the rules derived from the left subtree would have two common attributes and so on. Further, the tree itself can often be several levels deep, leading to complex paths that are not easy to understand. However, this can be forcefully restricted by setting the max-depth parameter of the decision tree. The trade off as before is between accuracy (in this case accuracy in explaining model behavior) and rule interpretability. Figure 1 shows the decision tree obtained on Breast Cancer Dataset with class as predicted by Random Forest Classifier, max-depth 8 and accuracy 96.4%. Even for a simple dataset, a complex tree is obtained which gives long non-interpretable rules.

2. LIME (Locally Interpretable Model Agnostic Explanations) - [RSG16] show how locally faithful model explanations can be derived in the form of marginal contributions of individual feature values towards the final prediction objective. [LL16] extend a prediction explanation method based on the Shapley value from game theory. They show how different approaches to interpreting model predictions can be reduced to calculating the feature importance values or expectation Shapley (ES) values. Intuitively, say that a particular instance has been classified into some class. Then, we want to understand how the different feature values of this instance contributed to its classification into this class. Hence the analogy to Shapley values. This fascinating insight from their work provides the starting point for our approach.

3. Interpretation through Decision Lists - [LRM+15] provide an approach that produces predictive models that are not only accurate, but are also interpretable to human experts. The models they generate are decision lists, which consist of a series of 'if...then...else if...then...else' statements (e.g., if high blood pressure, then stroke else ...) that discretize a high-dimensional, multivariate feature space into a series of simple, readily interpretable decision statements. The shortcoming with this and related approaches is that Decision Lists themselves are not easy to interpret for humans. This is because rules cannot be looked at in isolation. The order of the rules in decision lists is crucial and the applicability of each rule is subject to the rules above it being false.

4. Interpretable Decision Sets - [LBL16] provide a Joint Framework for Description and Prediction in the form of interpretable decision sets. What we find particularly useful from this work are the following two points. First, the comparison between the understandability of decision lists and decision sets. They show that Decision sets are more comprehensible to
Figure 1: Interpreting a Random Forest classifier on the Breast Cancer dataset using Decision Tree as the surrogate model
humans because rules apply independently. Whereas, in decision lists, rules implicitly depend on all the rules above it not being true. Thus, while the order of the rules in decision lists is crucial, it does not matter for decision sets. Second, the criteria they have optimized for in their objective function were useful when building the fitness function of our Genetic Algorithm (section 4.3).

3 Notations and Definitions

Please refer to Table 1 for a reference of the notations and definitions used in the paper.

Definition 3.1. Rule Precision: The precision of \( R_i \) is the ratio of number of instances in correct-cover(\( R_i \)) to the number of instances in cover(\( R_i \)).

\[
\text{Precision}(R_i) = \frac{\text{len(correct-cover}(R_i))}{\text{len(cover}(R_i))}
\]

Definition 3.2. Rule Length: The length of \( R_i \) is the cardinality of the precondition set for the rule \( C_i \).

\[
\text{Length}(R_i) = \text{number of conditions in } R_i
\]

Definition 3.3. Rule Class Coverage: The class coverage of \( R_i \) is the ratio of number of instances in correct-cover(\( R_i \)) to the number of instances in the training set that have been predicted by the classifier to have label \( y_i \).

\[
\text{Class-Coverage}(R_i) = \frac{\text{len(correct-cover}(R_i))}{\text{number of instances in the training set having predicted label } y_i}
\]

Definition 3.4. Rule F1-Score: The F1-Score of \( R_i \) is defined as the harmonic mean of Precision(\( R_i \)) and Class-Coverage(\( R_i \)).

\[
\text{F1-Score}(R_i) = \frac{2 \times \text{Precision}(R_i) \times \text{Class-Coverage}(R_i)}{\text{Precision}(R_i) + \text{Class-Coverage}(R_i)}
\]

Definition 3.5. Rule Set Precision: The precision of \( R \) is the ratio of number of instances in correct-cover(\( R \)) to the number of instances in cover(\( R \)).

\[
\text{Precision}(R) = \frac{\text{len(correct-cover}(R))}{\text{len(cover}(R))}
\]

Definition 3.6. Rule Set Class Coverage: The class coverage of \( R \) is the ratio of number of instances in correct-cover(\( R \)) to the number of instances in the training set that have been predicted by the classifier to have label \( y_i \) where \( y_i \) is the class that the rules in \( R \) predict.

\[
\text{Class-Coverage}(R) = \frac{\text{len(correct-cover}(R))}{\text{number of instances in the training set having predicted label } y_i}
\]
Table 1: Notations and Definitions Used

| Symbol | Definition | Example |
|--------|------------|---------|
| X      | training data, consisting of instances | [(1, John, 25), (2, Jane, 30),...]| |
| Y      | set of predicted classes | [approve, reject] |
| x      | Particular instance in the training set | (1, John, 25) |
| y      | Particular predicted class | approve |
| c_i    | Condition, which is a combination of an attribute and a range of values the attribute can take | age<30, state=New York |
| R_i    | A classification rule which classifies an instance to belong to its associated class if a predicate consisting of a conjunction (AND) of conditions holds. | IF age<30 and Income>100 and state=New York Then Predict Class approve |
| C_i    | Set of conditions for rule R_i | IF age<30 and Income>100 |
| y_i    | Associated target class for rule R_i | Predict Class: approve |
| cover(R_i) | Set of instances rule R_i covers in the training data. These are instances for which the conditions of R_i are true. | \{x_1, x_2\} |
| correct-cover(R_i) | Set of instances for which the rule made a correct prediction. Formally, it is the set of instances x_i such that x_i is in cover(R_i) and the predicted label of the rule y_i matches with the class prediction by the classifier for the instance x_i | \{x_1\} |
| incorrect-cover(R_i) | Set of instances that are incorrectly covered by R_i | \{x_2\} |
| R     | Rule set. Consists of a set of rules of the form R_i. | \{R_1, R_2, ...\} |
| correct-cover(R) | Correct cover of rule set R. Not to be confused with correct cover of rule R_i. It is defined as the union of the correct covers of R_i for each rule in R | \{x_1, x_3\} |
| cover(R) | Cover of rule set R. Not to be confused with cover of rule R_i. It is defined as the union of the covers of R_i for each rule in R | \{x_1, x_2, x_3, x_4\} |
Definition 3.7. Rule Set F1-Score: The F1-Score of R is defined as the harmonic mean of Precision(R) and Class-Coverage(R).

\[
F1\text{-Score}(R) = \frac{2 \times \text{Precision}(R) \times \text{Class-Coverage}(R)}{\text{Precision}(R) + \text{Class-Coverage}(R)}
\]

4 Approach

In this section we describe our approach in detail with the help of an example. We first put our approach into context. What we have as an input is a data set (training as well as test) and a model that has been trained on this data set. Further, we do not know anything about the model implementation. The model has a `predict-proba(x_i)` function defined that takes an instance as the input and returns a vector of probabilities. Each element in the vector represents the probability that the instance belongs to the corresponding class. The class selected by the classifier for an instance is the one corresponding to the highest probability in the vector. Our approach is outlined in Algorithm 1 and the subsequent sections explain each step in more detail.

**Algorithm 1** EXPLAIN-MODEL

1: \( \textbf{X} \leftarrow \) training instances
2: \( \textbf{M} \leftarrow \) classification model
3: \( \textbf{Y} \leftarrow \) set of output classes
4: \( \textbf{R} \leftarrow \text{Map<string, set()>} \)
5: \( \text{PreProcessInputData}(\textbf{X}, \textbf{Y}) \)
6: for \( y_i \) in \( \textbf{Y} \) do
7: \hspace{1em} conditions \( \leftarrow \) `GenerateInstanceLevelConditions(\textbf{X}, \textbf{M}, y_i)`
8: \hspace{1em} classLevelRules \( \leftarrow \) `LearnClassLevelRules(\textbf{X}, \textbf{M}, conditions, y_i)`
9: \hspace{1em} classLevelRules \( \leftarrow \) `PostProcessRules(classLevelRules, \textbf{y}_i)`
10: \hspace{1em} optimalRuleSubset \( \leftarrow \) `ExtractOptimalRuleSubset(classLevelRules, \textbf{y}_i)`
11: \hspace{1em} \( \textbf{R}[C_i] \leftarrow \) `FScoreSorting(optimalRuleSubset, \textbf{y}_i)`
12: end for
13: return \( \textbf{R} \)

4.1 Preprocessing the Input Data

In this step we pre-process the input data to make each feature categorical. Concretely, for categorical features we leave them unmodified. For numerical features, we perform entropy based binning to split the feature values into discrete bins [RSG16]. For instance, if the attribute age takes values from 10 to 85 (inclusive), then our binning step might produce the ranges ‘10 ≤ age < 25’, ‘25 ≤ age < 60’ and ‘60 ≤ age ≤ 85’. Post this step, the input data comprises only of categorical features. This corresponds to the `PreProcessInputData(\textbf{X}, \textbf{Y})` function labeled in the algorithm.
Table 2: Hyper Parameters Used

| Parameter                              | Value   | Position of use                  |
|----------------------------------------|---------|----------------------------------|
| train-test-split                       | 80%     | splitting of dataset             |
| no. of estimators                      | 400     | random forest                    |
| criterion                              | entropy | random forest                    |
| no. of jobs                            | 4       | random forest                    |
| max-depth                              | 10      | random forest                    |
| verbose                                | 1       | random forest                    |
| instance-level-skip-tolerance          | 0       | generating instance level condi- |
| discretizer                            | entropy | generating instance level condi- |
| top-labels                             | 1       | choose highest probability class  |
| min-relevance-score-for-single-condi- | 0       | generating instance level condi- |
| population size                        | 600     | first level genetic algorithm    |
| mutation probability                   | 0.5     | first level genetic algorithm    |
| crossover probability                  | 0.5     | first level genetic algorithm    |
| no. to select from population          | 750     | first level genetic algorithm    |
| no. of generations                     | 1000    | second level genetic algorithm   |
| mutation probability                   | 0.05    | second level genetic algorithm   |
| crossover probability                  | 0.5     | second level genetic algorithm   |
| no. to select from population          | 200     | second level genetic algorithm   |
| number-bits-to-mutate                  | 2.5     | genetic algorithm                |
| individual mutation probability       | num-bits-to- |
|                                      | mutate/size-of-individual | genetic algorithm |
| coverage desired                       | 90%     | greedy algorithm                 |
4.2 Generating Instance Level Conditions

The algorithm iterates over each instance in the training data. Now, for each instance we have a particular class that the instance has been classified into. What we want to compute is the marginal contribution of each feature in arriving at this classification. Concretely, say the training instance has 3 features. Let us assume that they are \( 10 \leq \text{age} < 25 \), \( 100 \leq \text{income} < 200 \) and \( \text{state} = \text{NewYork} \). Please note that each feature is categorical, as discussed in section 4.1. Also, let us assume that the output of the classifier for this instance is \((0.69, 0.31)\). What this essentially means is that the classifier assigns a probability of 0.69 for this instance to be in class 1 and 0.31 for this instance to be in class 2. Since this is a classification problem, the instance would be classified to class 1. Now, if we were to compute the true Shapley values for each feature in reaching this classification, the process would be computationally expensive. Hence, we have used the approach described by [RSG16]. The approach perturbs the training instance in question, and trains a locally faithful linear model in the locality of said instance. The weights of the different features then approximate the marginal contribution values. We perform another optimization here. Experiments showed that several conditions were common across instances. Hence, it is not always necessary to visit every instance to generate sufficient rules to describe all instances in our data set. So, when we get a list of conditions from a training instance, we check which instances are
covered by this list, and we remove those instances from further consideration. This approximation greatly speeds up computation at this step. The output of this step is a very large list of conditions. Each condition consists of a single feature and a value (for categorical features) or a range of values (for numerical features). The complete algorithm is outlined in Algorithm 2.

Algorithm 2  GENERATE-INSTANCE-LEVEL-CONDITIONS
1:  \( X \leftarrow \) training instances
2:  \( M \leftarrow \) classification model
3:  \( \text{not-yet-covered} \leftarrow X \)
4:  \( \text{conditions} \leftarrow \text{set()} \)
5:  \( \text{for } x_i \text{ in } X \) do
6:    \( \text{instance-level-conditions} \leftarrow \text{ComputeMarginalContributions}(x_i, M) \)
7:    \( \text{for } \text{cond} \text{ in } \text{instance-level-conditions} \) do
8:      \( \text{not-yet-covered} \leftarrow \text{not-yet-covered} - \text{CoveredInstances}(\text{cond}) \)
9:    end for
10:  \( \text{conditions} \leftarrow \text{conditions} \cup \text{instance-level-conditions} \)
11:  \( \text{if } \text{length(} \text{not-yet-covered} \text{)} = 0 \) then
12:    \( \text{break;} \)
13:  end if
14: end for
15: return \( \text{conditions} \)

4.3 Learning Rules From Conditions

The output of the previous step is an exhaustive list of conditions that were important at the instance level. For each class, we have a set of conditions that were important in classifying instances of that class. Now, we want to learn rules for that class. We reiterate the definition of a rule. A rule is an \( '\text{AND}' \) i.e. a conjunction between several conditions that must hold for that class. For example, if \( '10 \leq age < 25' \) and \( '100 \leq income < 200' \) are conditions for class 2, then one candidate rule is \'If \( 10 \leq age < 25 \) AND \( 100 \leq income < 200 \) THEN Predict Class 2'. Each rule has an associated coverage and precision as defined in definitions 3.3 and 3.1 respectively. So, the problem is the following. How can we build rules having high precision and coverage, from these base conditions. It is clear that this could be done in a combinatorially prohibitive manner. For instance, we could first evaluate all rules of length 1, i.e. having only a single condition. This would be followed by evaluating all rules of length 2 (having 2 conditions) and so on. However, if the output of the previous step gives \( N \) conditions, then the complexity of this algorithm would be \( 2^N \). This is not computationally feasible for larger data sets.

The problem then is that we need an approach that can learn optimal combinations of conditions (each combination of conditions is a rule). And we want the notion of optimality to be abstracted away from the particular approach. Concretely, we want an algorithm that can take as input a notion of optimality and subsequently combine conditions to generate rules that are optimal. Another point that needs to be considered is that if there are any categorical
variables in the data then we want the rules to allow these categorical variables to take more than one value. For example, if we had a categorical variable called country and if '10 ≤ age < 25', 'country = US', and 'country = India' are conditions for class 2, then one candidate rule could be 'If 10 ≤ age < 25 AND country = US, India THEN Predict Class 2'. Therefore, the combinations that we need are not only 'AND's of conditions but also 'OR's within a condition involving a categorical variable so that it allows such a variable to take on multiple possible values.

Hence, inspired by the work done in [FLF00] and [GBSS10] we use a Genetic Algorithm to learn such rules under the given conditions. Please note that we run the algorithm independently for each class. Hence, we are trying to learn class level rules from class level conditions. Each individual of the Genetic Algorithm represents a possible rule. For example, if, the number of conditions generated in the previous step (learning instance level conditions) was 100, then, each individual of our population would be a bit string of length 100. One example string might be '100100000....000'. The example individual described represents a rule of the form 'If condition1 AND condition4 THEN predict Class 1'. Each condition that involves a categorical variable has been allowed to take more than one value. The fitness function should capture several requirements:

1. **Precision and Coverage**: F1-Score as defined in definition 3.4, captures this notion of simultaneously trying to optimize for both precision and coverage. The rules having a high F1-Score are neither highly precise with low coverage nor overly generic and imprecise with high coverage. If we want to give more weight to one of the two, we could go for $F_{\beta}$ Score which places more importance on coverage rather than precision and can be manipulated to do the opposite.

2. **Length**: We want the fitness function to add a length factor. The intuition here is that shorter rules are easier to interpret. And while it is true that rule length often inversely correlates with coverage, however we find that making this parameter explicit leads to shorter, more interpretable rules.

3. **Overlap**: It may happen that an instance is covered by one rule that says it should belong to Class 1 and another rule that says it should belong to Class 2. Obviously, only one of these is correct and we want to minimize the amount of ambiguity in our final rule set. Since we plan to go for rules that have high precision, meaning that they were correctly copying model behavior, the amount of overlap in the final rule set will automatically be minimized as we optimize precision.

Keeping all these in mind, we designed the following fitness function for our genetic algorithm:

$$ F(ind) = F1-Score(R_i) - \frac{\text{No. of active bits in ind}}{N} $$

Here, $ind$ stands for individual represented by a bit string, $R_i$ is the rule that this individual represents and $N$ is the length of the bit string. A weight can be given to either of these terms as per the requirement of the user. We take our population to be 1200 individuals with a cross-over probability of 50% and
mutation probability set in such a manner that only 2 bits of an individual are flipped whilst undergoing mutation. This gives a reasonable trade-off between exploration and exploitation. We initialized the population with individuals that have a high probability of being 'fit’. These are individuals with only one bit set in the bit string (such as, 1000, 0100, 0010 and 0001), followed by those with only two bits set (1100, 0110, 0101...) and so on and so forth until the entire population size i.e. 1200 individuals, is reached. We run the algorithm for 600 generations. All the individuals of the last generation are finally selected as our rule set for one class. Hence, the output of this step is an exhaustive rule set for each class. There will be several rules that do not add value to the set and need to be filtered out.

4.4 Post-processing Rules

The Rules generated in the previous step include several redundant rules. This is a straightforward post processing step, where we sort the generated rules in descending order of precision. Then, for each rule, we check if the rule is a subset of an already added, more precise rule. By subset, we mean that \( R_2 \) is a subset of \( R_1 \) if every instance correctly covered by \( R_2 \) is also correctly covered by \( R_1 \). If it is a subset of a more precise rule, then we do not consider this rule for our next step. Otherwise, we retain this rule for consideration. The corresponding procedure is \( PostProcessRules(R) \).

4.5 Optimal Selection of rules to describe each class

In the final step of processing, we want to select an optimal subset of rules for each class that is able to describe model behavior for that class. It is definitely possible to simply list the output of the post processing step for each class. However, the problem is that even after post processing, there are several rules that do not add value to the explanation process. Intuitively, this would happen when three rules collectively explain instances that can be explained by a single rule that is further down the list. Since any set has \( 2^N \) subsets, this is an NP-Hard problem where the best we can try for is a good approximation. However, we wish to make an important point here. Optimality is in the eye of the beholder. It is quite possible that the final consumers of the rules are data scientists and that they prefer an exhaustive set of rules with close to a 100 percent coverage and little regard for precision. Hence, we present three different approaches in this section. No one approach is correct for all use cases. The selected approach depends on the particular requirements of the user.

4.5.1 Greedy Approach that Optimizes for coverage

The complete algorithm is outlined in Algorithm 3. The greedy approach optimizes class level coverage. The input to the algorithm is a coverage threshold and the class level rules learned in section 4.3. For example the coverage threshold might be set at 90% if high coverage is desired. Then, for each class, the algorithm sorts the rules in descending order of precision. Now, each rule is added to the set of final rules until the desired class level coverage is obtained. Please note that we are not considering rule overlap across classes because highly
precise rules, by definition will have low across class overlap as discussed before in section 4.3. The advantage of this approach is that it provides high data set coverage. However, the drawback is that it selects high precision rules, with no regard for individual coverage, proceeding in a greedy manner until overall coverage hits coverage threshold. As a result, the size of the final rule set is much bigger as compared to what can be achieved using other approaches listed below which achieve the same quality rule set with fewer rules, hence preserving interpretability.

Algorithm 3 GREEDY-SELECT-RULES

1: $R \leftarrow$ set of rules partitioned by class
2: $C \leftarrow$ set of classes
3: $\text{Thr} \leftarrow$ required coverage threshold
4: answer $\leftarrow$ empty set
5: for $C_i$ in $C$ do
6:   class-level-rules $\leftarrow$ $\text{getRulesForClass}(R, C_i)$
7:   sort class-level-rules in descending order of precision
8:   for $R_i$ in class-level-rules do
9:     if $\text{class-coverage}(\text{answer}) > \text{Thr}$ then
10:        break;
11:     end if
12:     answer $\leftarrow$ answer $\cup R_i$
13:   end for
14: end for

4.5.2 Dynamic Programming Based Approach

The complete algorithm is outlined in Algorithm 4. To take our approach towards optimality, we follow up with a dynamic programming based approach that optimizes the F1-score of the rule set as defined in definition 3.7. The input to the algorithm is the set of class level rules and the objective is to select an optimal subset. This is done for each class. We use a bottom-up dynamic approach to build this optimal subset, analyzing a single rule first and then, incrementing the number of rules one by one. At each step, we have a new rule and a subset in hand that is optimal for the rules that we were looking at in the previous step. We have to decide if this new rule should be added to the optimal subset or not. We do this by computing F1-Score for two subsets, one that contains this new rule and the other that does not, and retaining the one having a higher measure of the same.

We also maintain another dimension to control the length of the selected subset. Maintaining this dimension allows the user to select the optimal subset for any length that they want. As we discussed before, this will depend entirely on the needs of the user and what they want to do with the rules going further.

It differs from conventional dynamic programming in the aspect that the metric that we use, being the F1-Score of the entire selected subset, lacks optimal substructure. However, it is a good approximation and works for our problem which is NP-Hard. This has been discussed in detail in section 5.
Algorithm 4 DP-SELECT-RULES

1: $R \leftarrow$ set of rules partitioned by class
2: $C \leftarrow$ set of classes
3: finalAnswer $\leftarrow$ Map<string, set()>
4: for $C_k$ in $C$ do
5:     class-level-rules $\leftarrow$ getRulesForClass($R$, $C_k$)
6:     answer $\leftarrow$ Map<(Int, Int) , set()>
7:     for $R_i$ in class-level-rules do
8:         for len in 1 to i do
9:             if $F1$-Score(answer[(i-1, len)]) $\geq$ $F1$-Score(answer[(i-1, len-1)] $\cup$ $R_i$) then
10:                 answer[(i, len)] $\leftarrow$ answer[(i-1, len)]
11:             else
12:                 answer[(i, len)] $\leftarrow$ answer[(i-1, len-1)] $\cup$ $R_i$
13:         end if
14:     end for
15: end for
16: f-Final $\leftarrow$ 0
17: lastRow $\leftarrow$ length($R$)
18: for len in 1 to lastRow do
19:     if $F1$-Score(answer[(lastRow, len)]) $>$ f-Final then
20:         finalAnswer[$C_k$] $\leftarrow$ answer[(lastRow, len)]
21:         f-Final $\leftarrow$ F1-Score(answer[(lastRow, len)])
22:     end if
23: end for
24: end for
25: return finalAnswer

4.5.3 Second Level Genetic Algorithm

Now, our original problem was the following. We wanted to select an optimal subset of class level rules from the exhaustive list generated by the first Genetic Algorithm. We discussed two approaches for this. The greedy approach is straightforward, and optimizes for coverage, generating a large number of rules in the process. The dynamic programming approach is powerful, in that it generates good coverage with a small number of rules. However, it can sometimes be a little restrictive, in not selecting certain rules that might be useful to the end user. Hence, we wanted an approach that lies between the over generosity of the greedy approach and the frugality of the dynamic programming one. This leads us to the second level Genetic Algorithm. The algorithm is run at a per class level. Each individual of the population is a bit string, having length equal to the number of rules in the previous step. For example, the individual '1100000...00' corresponds to a rule set that includes only $R_1$ and $R_2$ and covers all instances that are covered by $R_1$ or $R_2$. A rule set here is an 'OR' across several rules. The mutation level is kept low since we are looking for a single optimal subset of rules. As discussed before, optimality is in the eye of the beholder. The fitness function that we used is F1-Score of the Rule Set.

As our results show, the second level Genetic Algorithm generates more rules than the dynamic programming approach but less than the greedy approach.
However, as we have stated on a couple of occasions, there is no one approach that is right for all users. The particular approach depends on the requirements of the end user.

4.6 Sorting rules by F1-Score

The previous section gives us a combination of ‘OR’s (a subset of rules) among the ‘AND’s (combining clauses into rules) generated by the first level Genetic Algorithm. Once we have the optimal set of rules for a class, we want to sort them so as to provide the user with the most relevant rules at the top and less relevant ones further down the list. This is done as follows. The problem is that we have a set of rules and we need to sort them. We first select the rule with the highest F1-score, and add it to the top of the list. Then, we iterate over all the remaining rules, and add the one which increases the F1-score of the rule set by the highest amount. For example, say \( R_4 \) had the highest F1-score. Then, in the first step we would add \( R_4 \) to the top of the list. Now, in the next step, we iterate over the rules that have not been added so far. Let us assume that they are \( R_1, R_2 \) and \( R_3 \). So, we first add \( R_1 \) to \( R_4 \) and calculate the F1-score of the set \([R_4, R_1]\). This process is repeated for rules \( R_2 \) and \( R_3 \). If the set \([R_4, R_2]\) had the highest F1-score, then we add \( R_2 \) to the next highest position in the list of added rules. The process is then repeated with the remaining rules until all rules have been added.

5 Results

We demonstrate our approach on three publicly available data sets and explain the results across various measures and dimensions to draw interesting insights. These are the ‘Iris’ ([Fis36]) data set, the ‘Wisconsin Breast Cancer data set’([Lic13]), and the ‘Banknote authentication data set’([Lic13]). We train a random forest classifier (with 500 trees) on each dataset and interpret the models as a decision set of independent rules using algorithm 1. We experiment and display the final rules obtained using the three approaches to learn class level rules as discussed in sections 4.5.1, 4.5.2 and 4.5.3.

5.1 Iris Dataset

This data set consists of 3 different types of irises (Setosa, Versicolour, and Virginica). It is an extremely simple data set, however it is popular for first run of many machine learning algorithms. It is a classification data set, having four features which are Sepal Length, Sepal Width, Petal Length and Petal Width. The three classes are Setosa, Versicolour, and Virginica. We trained a Random Forest classifier with 500 trees on the data set. The classifier accuracy was close to 98%.
Table 3: Interpreting a Random Forest classifier on the Iris dataset using the second level Genetic Algorithm

| Setosa | Versic. | Virginica | Rule | Coverage | Precision |
|--------|---------|-----------|------|----------|-----------|
| 43     | 0       | 0         | petal-length $\leq$ 2.45 THEN Predict class: setosa | 100 | 100 |
| 0      | 23      | 0         | 2.45 < petal-length $\leq$ 4.45 THEN Predict class: versicolor | 59  | 100 |
| 0      | 17      | 4         | 1.35 < petal-width $\leq$ 1.75 THEN Predict class: versicolor | 44  | 81  |
| 0      | 21      | 0         | 0.80 < petal-width $\leq$ 1.35 THEN Predict class: versicolor | 54  | 100 |
| 0      | 11      | 1         | 4.45 < petal-length $\leq$ 4.75 THEN Predict class: versicolor | 28  | 92  |
| 0      | 5       | 0         | 1.35 < petal-width $\leq$ 1.75 AND 3.05 < sepal-width $\leq$ 3.25 THEN Predict class: versicolor | 13  | 100 |
| 0      | 0       | 26        | petal-length $> 5.15$ THEN Predict class: virginica | 68  | 100 |
| 0      | 21      | 15        | 2.45 < sepal-width $\leq$ 2.95 THEN Predict class: virginica | 39  | 42  |
| 0      | 1       | 10        | 1.75 < petal-width $\leq$ 1.85 THEN Predict class: virginica | 26  | 91  |
| 0      | 0       | 6         | 6.15 < sepal-length $\leq$ 7.05 AND 1.75 < petal-width $\leq$ 1.85 THEN Predict class: virginica | 16  | 100 |

Table 3 shows the rules extracted from a Random Forest model trained on this dataset using Algorithm 1. The data set though simple, illustrates the
usefulness of the approach. For instance, consider the rule ‘IF petal length (cm) \leq 2.45 THEN Predict class=0’. It has a precision of 1. This means that whenever the classifier saw a flower having petal length less than 2.45cm, it classified it into the setosa. An expert in the domain could easily determine whether such a rule is reasonable in the real world, or is something that inadvertently crept into the data set and is not likely to hold for real world applications. Further, a non expert could analyze such rules to evaluate the extent to which they hold in the data set. The rule in question holds perfectly in the data set, a simple analysis shows that any instance having a petal length less than 2.45cm is indeed of the type setosa. Further, both versicolour and virginica labeled instances have petal lengths greater than 2.45cm. Now, it is unlikely that we would obtain such powerful patterns in more complex data sets, however, even patterns with lower precision are useful for providing insight into both the model behavior as well as the data set under study. Section 5.2 discusses this in more detail. Please refer to the tables in Appendix A for results using the Dynamic Programming based approach and the Greedy Algorithm selection approach.

5.2 Wisconsin Breast Cancer Dataset

This dataset was obtained from the University of Wisconsin Hospitals, Madison from Dr. William H. Wolberg [Lic13]. It includes 699 instances, described by 11 attributes. There are 9 integer-valued attributes ranging from 1-10, along with an id number that is used to refer to patients uniquely and a target variable that indicates whether the tumor is malignant or benign. We trained a Random Forest classifier with 500 trees on the data set. The classifier accuracy was close to 98%.

The rules obtained for this data set are interesting and offer insight into both the workings of the classifier and the original data set. For concerns of conciseness, we have placed the rules for this data set in Appendix B. We discuss a couple of interesting insights here. As we can see from Table 11, the rule ‘IF mitoses \leq 1.50 AND 2.50 < uniformity-of-cell-size \leq 3.50 THEN Predict class=benign’ is a high precision rule. Of the 376 instances this rule covers, it is able to correctly explain model behavior on 370 of them, resulting in a very high value for rule precision. Now, at this point an expert in the domain can examine this and similar rules to gain powerful insight into the training data set. Further, if such rules are due to spurious introductions into the training data and not due to genuine patterns, then the model can be retrained with a more diverse data set to increase its generalization power. It is clear that this level of insight is simply not possible through analysis of model accuracy measures alone. Further, by looking at only instance level justifications, we cannot glean the general patterns that the model derived from the data. Hence, the aggregated view of model behavior that our approach produces is essential to understand how the model works. Further, for larger data sets, the number of such rules generated is large. Hence, we discuss below the experimental results of our F-score sorting approach, which allows us to rank rules by how much they contribute to the F-Score of the rule set.

For each class, we use the approach explained in section 4.6 to structure the class level rules. We plot the F-score at each step. The plot of F-Score v/s Number of rules has been shown for each approach outlined in section 4.5 and
for each class.

![Graphs](image1.png)

(a) Benign
(b) Malignant

Figure 3: F-Score v/s Number of rules - Greedy Approach

![Graphs](image2.png)

(a) Benign
(b) Malignant

Figure 4: F-Score v/s Number of rules - DP Based Approach

We can see from figures 3, 4, and 5 that as we add more rules to the set of optimal rules, the rate of increase of F-score decreases, as is expected. The first few rules add more to the overall F-score of the set than do subsequent ones. Concretely, if we had three rules in our rule set and to it we add a fourth rule that did not add anything to correct-cover of the rule set and had low precision, then this will cause the F-Score to fall, akin to the law of diminishing marginal utility.

For the subsets selected by the greedy and genetic algorithms (figures 3 and 5), it can be seen that the F-score increases for a while and then saturates for the class 'benign'. For the class 'malignant', the F-score increases for a while, saturates and then sharply falls indicating a point of optimality for rule subset selection. We can also see that the F-Score values do not fall for the dynamic programming based approach (figure 4). This is expected because of the nature of dynamic algorithms in that as they build the rule set they only add rules that improve the overall F-score of the set.

It is also apparent from the figure that most of the F-score value for the rule set can be achieved by just selecting the first few rules. This is akin to the Pareto Rule in that, 80% of the value can be obtained using just 20% of the rules. This insight is interesting because it helps in designing the user interface for our approach. For instance, if we only had space to show the top ten rules to the users, we could show them the rules sorted as described above and also
Figure 5: F-Score v/s Number of rules - Genetic Algorithm

indicate a 'percentage' of F-score that these rules achieve.

We stated before that our dynamic programming based approach lacks optimal substructure. To take the solution closer to optimality, we modified this approach a bit. Instead of maintaining just one answer subset at each step and for each length, we maintain top n answer subsets. To decide if a new rule should be added to the optimal subset or not we choose n best answer subsets out of 2n answer subsets: n that contain this new rule and n that do not. This has been done for two purposes. One, to see how good an approximation is the metric that we’re using and two, to take the subset as close to optimality as possible.

Figure 6: F-Score v/s Number of candidates maintained

We vary n from 5-200 in steps of 5 and plot the value of the f-score of the selected subset at each step. Further, for each value of n, we re-order the rules randomly. We can observe in figure 6 that there is no increment in the F-score for class 'benign'. For class 'malignant', there is a slight increment. The same trend holds on other datasets and models justifying that the metric used is a good approximation for an NP-Hard problem.

5.3 Banknote Authentication Dataset

This dataset was extracted from images taken from genuine and forged banknote-like specimens [Lic13]. Wavelet Transform tool was used to extract features from these images. The dataset has 1372 instances, described by 5 attributes. Four
out of these are continuous values and one is the target variable that indicates whether a particular instance is genuine or fake. We trained a Random Forest classifier with 500 trees on the data set. The classifier accuracy was close to 99%. For conciseness, we have placed the rules for this data set in Appendix C.

5.4 Car Evaluation Dataset

Each instance of this dataset describes a car [Lic13]. This dataset has 1728 instances, described by 6 attributes: buying cost, maintenance cost, number of doors, number of persons, size of lug boot, safety indication. All of these are categorical taking values like high, medium, low and etc. The target variable indicates whether a particular instance i.e. a car is unacceptable, acceptable, good or very good. We trained a Random Forest classifier with 400 trees on the data set. The classifier accuracy was close to 96%. For such categorical datasets, the kind of rules that we got using dynamic programming based method of subset selection have been displayed in table 4.

Table 4: Interpreting a Random Forest classifier on the Car Evaluation dataset using the Dynamic Programming Algorithm

| Acc | Good | Unacc | Very Good | Rule                                                                                     | Coverage | Precision |
|-----|------|-------|-----------|------------------------------------------------------------------------------------------|----------|-----------|
| 316 | 58   | 203   | 42        | persons = more, 4 AND safety = med, high THEN Predict class: acc                         | 100      | 51        |
| 16  | 41   | 4     | 21        | maint = low AND persons = more, 4 AND buying = med, low AND safety = med, high THEN Predict class: good | 71       | 50        |
| 134 | 0    | 546   | 11        | maint = vhigh, high THEN Predict class: unacc                                            | 57       | 79        |
| 0   | 0    | 462   | 0         | safety = low THEN Predict class: unacc                                                   | 48       | 100       |
| 0   | 0    | 456   | 0         | persons = 2 THEN Predict class: unacc                                                    | 47       | 100       |
| 30  | 0    | 205   | 0         | buying = vhigh, high AND lug-boot = small THEN Predict class: unacc                      | 21       | 87        |
| 8   | 0    | 11    | 18        | safety = high AND lug-boot = big AND buying = low THEN Predict class: vgood              | 43       | 49        |
Looking at the first rule in table 4 we can see that more and 4 have been grouped together as two possible values that the variable persons can take. Similarly, med and high are two possible values for the variable safety. The rules for this data set obtained using Greedy Rule Selection and second level Genetic Algorithm have been placed in Appendix D.

6 Validation

So far we have a set of rules that have been constructed and selected in a manner that optimizes for coverage and precision simultaneously. Although these two are themselves good measures of how well equipped the rules are at capturing model behavior, we believed an explicit matching of behaviors was necessary for validation of our algorithm. So we took a segment of input data for testing, i.e. this data belonged to the same distribution as the input data. This data was never fed into or used by either the model or our algorithm. We used the rules, discovered by our method, to build a predictive model for this data. to predict the class variable for this data. If an instance of this unseen data was covered by more than one rule, the rule with the highest precision was chosen. We also used the model to make predictions on this data. We then compared the predictions made by our rules to the predictions made by the model and computed the fraction of predictions that matched. Tables 5, 6, 7, and 8 list the validation accuracies for our three datasets.

Table 5: Validation Accuracy for Iris dataset

| Algorithm for Optimal Subset Selection | Validation Accuracy |
|---------------------------------------|---------------------|
| Greedy Algorithm                      | 96.67%              |
| Dynamic Programming Based Algorithm   | 96.67%              |
| Second Level Genetic Algorithm        | 96.67%              |

Table 6: Validation Accuracy for Breast Cancer dataset

| Algorithm for Optimal Subset Selection | Validation Accuracy |
|---------------------------------------|---------------------|
| Greedy Algorithm                      | 93.00%              |
| Dynamic Programming Based Algorithm   | 96.40%              |
| Second Level Genetic Algorithm        | 96.40%              |
Table 7: Validation Accuracy for Banknote Authentication dataset

| Algorithm for Optimal Subset Selection | Validation Accuracy |
|---------------------------------------|----------------------|
| Greedy Algorithm                      | 90.90%               |
| Dynamic Programming Based Algorithm   | 90.90%               |
| Second Level Genetic Algorithm        | 90.90%               |

Table 8: Validation Accuracy for Car Evaluation dataset

| Algorithm for Optimal Subset Selection | Validation Accuracy |
|---------------------------------------|----------------------|
| Greedy Algorithm                      | 65.80%               |
| Dynamic Programming Based Algorithm   | 59.50%               |
| Second Level Genetic Algorithm        | 65.60%               |

We can see that our rules are quite a good approximation for model behavior for the first three datasets. The approach may need some refinement to give good results in case of categorical attributes. We would also want to stress on the point that if we were to perform no optimal subset selection at all, we would get the highest validation accuracy. However, the rules are too many and we would lose interpretability. Hence, intelligent filtering is a necessary part of our approach.

7 Conclusion

We have presented here an approach that explain a black box model globally. Our experiments on different data sets demonstrate the power and flexibility of our approach. The potential applications of our approach are diverse. The most obvious one being to understand model behavior and subsequently improve the generalizability of models. Further, by understanding models trained on large data sets, we can extract patterns inherent in the original data sets. This gives us a new way to understand large and complex data sets. Now, by understanding the model, we are indirectly understanding the patterns in the original data set. This is useful both for understanding the data and for possibly learning spurious patterns in the data set that do not hold in the real world. Another interesting direction of research is using our approach to understand how models themselves learn. What ‘really’ happens as models iterate and reduce the error in their objective functions? Do they first learn more generic, low precision rules and then combine them to make better ones? Or, do they start off with overly specific, highly precise rules and then break them down to learn more generic ones while maintaining precision. Further, what do processes like simulated annealing ‘really’ do? Does a model go from having reasonable rules to very poor ones before jumping to very good rules? Or, is something else at play here? The same questions could be asked at an algorithm level. How does a Neural Network learn? Is it different from how a Random Forest learns? What about
Gradient Boosted Trees? What happens when a new tree is added to the existing trees in gradient boosting? Does it actually learn rules that explain previously unexplained instances? These are just some of the fascinating questions that can be possibly explored further using our approach.

8 Future Work

The current version of the approach is based on classification problems. One possible direction of future research would be to extend our approach to predicting continuous variables. A very simple extension is to simply cluster the continuous predicted values and then simply treat each cluster as a class label. In that case, the problem reduces to a classification problem. However, other approaches to solve this type of problem should be explored. Further, we have not applied our existing approach to image classification problems. It would be interesting to extend the approach to explain models that work with images. As model interpretation approaches become more prevalent, another extremely important direction of research is to devise metrics that can compare two different model interpretation approaches. This reduces to the classic problem of not why the approach chose to show certain rules (that can be argued using precision and recall) but rather why the approach chose to ignore certain others? Concretely, is there any reasonably efficient way to say that there did not exist any other combination of feature values that would have added to the quality of the existing Rule Set? This would constitute a very valuable direction of research.

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Appendices

A Appendix A - Iris Dataset Model Explanations

Tables 9 and 10 show the results obtained for model interpretation using the dynamic programming based approach and the greedy rule selection approach respectively.

Table 9: Interpreting a Random Forest classifier on the Iris dataset using the Dynamic Programming Algorithm

| Setosa | Versic. | Virginica | Rule | Coverage | Precision |
|--------|---------|-----------|------|----------|-----------|
| 43     | 0       | 0         | petal-length $\leq$ 2.45 THEN Predict class: setosa | 100 | 100 |
| 0      | 23      | 0         | 2.45 $<$ petal-length $\leq$ 4.45 THEN Predict class: versicolor | 59  | 100 |
| 0      | 17      | 4         | 1.35 $<$ petal-width $\leq$ 1.75 THEN Predict class: versicolor | 44  | 81  |
| 0      | 21      | 0         | 0.80 $<$ petal-width $\leq$ 1.35 THEN Predict class: versicolor | 54  | 100 |
| 0      | 0       | 26        | petal-length $>$ 5.15 THEN Predict class: virginica | 68  | 100 |
| 0      | 21      | 15        | 2.45 $<$ sepal-width $\leq$ 2.95 THEN Predict class: virginica | 39  | 42  |
| 0      | 1       | 10        | 1.75 $<$ petal-width $\leq$ 1.85 THEN Predict class: virginica | 26  | 91  |
Table 10: Interpreting a Random Forest classifier on the Iris dataset using the Greedy Rule Selection Algorithm

| Setosa | Versic. | Virginica | Rule                                                                 | Coverage | Precision |
|--------|---------|-----------|----------------------------------------------------------------------|----------|-----------|
| 43     | 0       | 0         | petal-length \( \leq \) 2.45 \( \text{THEN} \) Predict class: setosa  | 100      | 100       |
| 0      | 23      | 0         | 2.45 < petal-length \( \leq \) 4.45 \( \text{THEN} \) Predict class: versicolor | 59       | 100       |
| 0      | 17      | 4         | 1.35 < petal-width \( \leq \) 1.75 \( \text{THEN} \) Predict class: versicolor | 44       | 81        |
| 0      | 21      | 0         | 0.80 < petal-width \( \leq \) 1.35 \( \text{THEN} \) Predict class: versicolor | 54       | 100       |
| 0      | 11      | 1         | 4.45 < petal-length \( \leq \) 4.75 \( \text{THEN} \) Predict class: versicolor | 28       | 92        |
| 0      | 5       | 0         | 1.35 < petal-width \( \leq \) 1.75 AND 3.05 \( \text{AND} \) \( \leq \) sepal-width \( \leq \) 3.25 \( \text{THEN} \) Predict class: versicolor | 13       | 100       |
| 0      | 1       | 0         | 5.55 < sepal-length \( \leq \) 5.85 AND 4.45 \( \text{AND} \) \( < \) petal-length \( \leq \) 4.75 \( \text{THEN} \) Predict class: versicolor | 3        | 100       |
| 0      | 0       | 26        | petal-length \( > \) 5.15 \( \text{THEN} \) Predict class: virgnica | 68       | 100       |
| 0      | 21      | 15        | 2.45 < sepal-width \( \leq \) 2.95 \( \text{THEN} \) Predict class: virgnica | 39       | 42        |
| 0      | 1       | 10        | 1.75 < petal-width \( \leq \) 1.85 \( \text{THEN} \) Predict class: virgnica | 26       | 91        |
| 0      | 0       | 6         | 6.15 < sepal-length \( \leq \) 7.05 AND 1.75 \( \text{AND} \) \( < \) petal-width \( \leq \) 1.85 \( \text{THEN} \) Predict class: virgnica | 16       | 100       |
| 0      | 12      | 19        | 6.15 < sepal-length \( \leq \) 7.05 \( \text{THEN} \) Predict class: virgnica | 50       | 61        |
## Appendix B - Wisconsin Breast Cancer Dataset

Model Explanations

Tables 11, 12 and 13 show the results obtained for model interpretation using the dynamic programming based approach, the second level Genetic Algorithm approach, and the greedy rule selection approach respectively.

**Table 11: Interpreting a Random Forest classifier on the Breast Cancer dataset using the Dynamic Programming Algorithm**

| Benign | Malignant | Rule | Coverage | Precision |
|--------|-----------|------|----------|-----------|
| 310    | 14        | 0.50 < bare-nuclei <= 1.50 THEN Predict class: benign | 85 | 96 |
| 300    | 3         | mitoses <= 1.50 AND uniformity-of-cell-size <= 1.50 THEN Predict class: benign | 82 | 99 |
| 256    | 4         | normal-nucleoli <= 1.50 AND mitoses <= 1.50 AND 1.50 < single-epithelial-cell-size <= 2.50 THEN Predict class: benign | 70 | 98 |
| 224    | 1         | 1.50 < single-epithelial-cell-size <= 2.50 AND uniformity-of-cell-shape <= 1.50 THEN Predict class: benign | 62 | 100 |
| 2      | 114       | bare-nuclei > 8.50 THEN Predict class: malignant | 58 | 98 |
| 15     | 98        | 3.50 < single-epithelial-cell-size <= 7.50 THEN Predict class: malignant | 50 | 87 |
| 7      | 89        | 4.50 < uniformity-of-cell-shape <= 8.50 THEN Predict class: malignant | 46 | 93 |
| 10     | 64        | 3.50 < normal-nucleoli <= 8.50 THEN Predict class: malignant | 33 | 86 |
| 0      | 66        | clump-thickness > 8.50 THEN Predict class: malignant | 34 | 100 |
| 0      | 65        | normal-nucleoli > 8.50 THEN Predict class: malignant | 33 | 100 |
| 2      | 49        | marginal-adhesion > 8.50 THEN Predict class: malignant | 25 | 96 |
Table 12: Interpreting a Random Forest classifier on the Breast Cancer dataset using the Second Level Genetic Algorithm

| Benign | Malignant | Rule | Coverage | Precision |
|--------|-----------|------|----------|-----------|
| 300    | 3         | mitoses $\leq 1.50$ AND uniformity-of-cell-size $\leq 1.50$ THEN Predict class: benign | 82 | 99 |
| 298    | 17        | mitoses $\leq 1.50$ AND marginal-adhesion $\leq 1.50$ THEN Predict class: benign | 82 | 95 |
| 255    | 0         | 0.50 $< \text{bare-nuclei} \leq 1.50$ AND 1.50 $< \text{single-epithelial-cell-size} \leq 2.50$ THEN Predict class: benign | 70 | 100 |
| 256    | 4         | normal-nucleoli $\leq 1.50$ AND mitoses $\leq 1.50$ AND 1.50 $< \text{single-epithelial-cell-size} \leq 2.50$ THEN Predict class: benign | 70 | 98 |
| 280    | 2         | normal-nucleoli $\leq 1.50$ AND mitoses $\leq 1.50$ AND 0.50 $< \text{bare-nuclei} \leq 1.50$ THEN Predict class: benign | 77 | 99 |
| 276    | 2         | uniformity-of-cell-shape $\leq 1.50$ THEN Predict class: benign | 76 | 99 |
| 280    | 1         | normal-nucleoli $\leq 1.50$ AND uniformity-of-cell-size $\leq 1.50$ THEN Predict class: benign | 77 | 100 |
| 272    | 4         | normal-nucleoli $\leq 1.50$ AND mitoses $\leq 1.50$ AND marginal-adhesion $\leq 1.50$ THEN Predict class: benign | 75 | 99 |
| 270    | 0         | 0.50 $< \text{bare-nuclei} \leq 1.50$ AND uniformity-of-cell-size $\leq 1.50$ THEN Predict class: benign | 74 | 100 |
| 253    | 1         | normal-nucleoli $\leq 1.50$ AND uniformity-of-cell-shape $\leq 1.50$ THEN Predict class: benign | 70 | 100 |
|    | N  | Condition                                                                 | Value | Predict       |
|----|----|---------------------------------------------------------------------------|-------|---------------|
| 250| 1  | \(1.50 < \text{single-epithelial-cell-size} <= 2.50\) AND \(\text{uniformity-of-cell-size} <= 1.50\) |       | Predict class: benign |
| 248| 0  | \(\text{normal-nucleoli} <= 1.50\) AND \(\text{marginal-adhesion} <= 1.50\) AND \(\text{uniformity-of-cell-size} <= 1.50\) |       | Predict class: benign |
| 243| 1  | \(\text{uniformity-of-cell-shape} <= 1.50\) AND \(\text{marginal-adhesion} <= 1.50\) |       | Predict class: benign |
| 224| 1  | \(1.50 < \text{single-epithelial-cell-size} <= 2.50\) AND \(\text{uniformity-of-cell-shape} <= 1.50\) |       | Predict class: benign |
|    | 2  | \(\text{bare-nuclei} > 8.50\) |       | Predict class: malignant |
| 7  | 89 | \(4.50 < \text{uniformity-of-cell-shape} <= 8.50\) |       | Predict class: malignant |
| 0  | 53 | \(\text{uniformity-of-cell-shape} > 8.50\) |       | Predict class: malignant |
| 10 | 64 | \(3.50 < \text{normal-nucleoli} <= 8.50\) |       | Predict class: malignant |
| 0  | 65 | \(\text{normal-nucleoli} > 8.50\) |       | Predict class: malignant |
| 0  | 66 | \(\text{clump-thickness} > 8.50\) |       | Predict class: malignant |
| 2  | 49 | \(\text{marginal-adhesion} > 8.50\) |       | Predict class: malignant |
| 3  | 45 | \(4.50 < \text{bland-chromatin} <= 7.50\) AND \(3.50 < \text{single-epithelial-cell-size} <= 7.50\) |       | Predict class: malignant |
| 14 | 29 | \(3.50 < \text{bare-nuclei} <= 5.50\) |       | Predict class: malignant |
| 0  | 54 | \(\text{uniformity-of-cell-size} > 9.50\) |       | Predict class: malignant |
| Benign | Malignant | Rule | Coverage | Precision |
|--------|----------|------|----------|-----------|
| 270    | 0        | 0.50 < bare-nuclei <= 1.5 AND uniformity-of-cell-size <= 1.5 THEN Predict class: benign | 74 | 100 |
| 255    | 0        | 0.50 < bare-nuclei <= 1.5 AND 1.5 < single-epithelial-cell-size <= 2.5 THEN Predict class: benign | 70 | 100 |
| 248    | 0        | normal-nucleoli <= 1.5 AND marginal-adhesion <= 1.5 AND uniformity-of-cell-size <= 1.5 THEN Predict class: benign | 68 | 100 |
| 247    | 0        | normal-nucleoli <= 1.5 AND marginal-adhesion <= 1.5 AND 0.5 < bare-nuclei <= 1.5 THEN Predict class: benign | 68 | 100 |
| 247    | 0        | 0.50 < bare-nuclei <= 1.5 AND uniformity-of-cell-shape <= 1.5 THEN Predict class: benign | 68 | 100 |

Table 13: Interpreting a Random Forest classifier on the Breast Cancer dataset using the Greedy Rule Selection Algorithm
| Rule                                                                 | Support | Confidence |
|----------------------------------------------------------------------|---------|------------|
| bare-nuclei > 8.50 THEN Predict class: malignant                     | 38      | 98         |
| normal-nucleoli > 8.50 THEN Predict class: malignant                 | 34      | 100        |
| clump-thickness > 8.50 THEN Predict class: malignant                 | 33      | 100        |
| uniformity-of-cell-size > 9.50 THEN Predict class: malignant         | 28      | 100        |
| single-epithelial-cell-size > 7.50 THEN Predict class: malignant     | 21      | 100        |
| uniformity-of-cell-shape > 8.50 THEN Predict class: malignant        | 27      | 100        |
| 2.50 < mitoses <= 3.50 AND 4.50 < bland-chromatin <= 7.50 THEN Predict class: malignant | 8       | 100        |
| 1.50 < mitoses <= 2.50 AND 4.50 < uniformity-of-cell-shape <= 8.50 THEN Predict class: malignant | 7       | 100        |
| bare-nuclei > 8.50 AND 4.50 < bland-chromatin <= 7.50 THEN Predict class: malignant | 30      | 100        |
| bare-nuclei > 8.50 AND 4.50 < uniformity-of-cell-shape <= 8.50 THEN Predict class: malignant | 26      | 100        |
| bare-nuclei > 8.50 AND marginal-adhesion > 8.50 THEN Predict class: malignant | 19      | 100        |
| bare-nuclei > 8.50 AND 3.50 < single-epithelial-cell-size <= 7.50 AND 3.50 < normal-nucleoli <= 8.50 THEN Predict class: malignant | 13      | 100        |
| bare-nuclei > 8.50 AND 1.50 < mitoses <= 2.50 THEN Predict class: malignant | 7       | 100        |
C Appendix C - Bank Note Authentication Dataset
Model Explanations

Tables 14, 15 and 16 show the results obtained for model interpretation using the dynamic programming based approach, the second level Genetic Algorithm approach, and the greedy rule selection approach respectively.

Table 14: Interpreting a Random Forest classifier on the Banknote dataset using the Dynamic Programming Algorithm

| Genuine | Fake | Rule | Coverage | Precision |
|---------|------|------|----------|-----------|
| 384     | 542  | -3.68 < curtosis <= 8.84 THEN Predict class: fake | 90 | 59 |
| 1       | 327  | variance > 2.39 THEN Predict class: fake | 55 | 100 |
| 34      | 169  | 6.25 < skewness <= 9.62 THEN Predict class: fake | 28 | 83 |
| 0       | 99   | skewness > 9.62 THEN Predict class: fake | 17 | 100 |
| 303     | 196  | -2.30 < skewness <= 5.21 THEN Predict class: genuine | 61 | 61 |
| 147     | 1    | variance <= -2.80 THEN Predict class: genuine | 30 | 99 |
| 246     | 57   | -2.80 < variance <= -0.40 THEN Predict class: genuine | 49 | 81 |
| 6       | 0    | -0.40 < variance <= 0.32 AND 1.02 < entropy <= 1.92 THEN Predict class: genuine | 1 | 100 |

Table 15: Interpreting a Random Forest classifier on the Banknote dataset using the second level Genetic Algorithm

| Genuine | Fake | Rule | Coverage | Precision |
|---------|------|------|----------|-----------|
| 384     | 542  | -3.68 < curtosis <= 8.84 THEN Predict class: fake | 90 | 59 |
| 0       | 99   | skewness > 9.62 THEN Predict class: fake | 17 | 100 |
| Class | Num | Skewness | Condition | Variance | Entropy | Num | Num |
|-------|-----|----------|------------|----------|---------|-----|-----|
| fake  | 34  | 6.25     | $< \text{skewness} \leq 9.62$ THEN Predict class: fake | 28       | 83      |
| fake  | 0   | -3.68    | $-3.68 < \text{curtosis} \leq 8.84$ AND $\text{variance} > 2.39$ THEN Predict class: fake | 46       | 100     |
| genuine | 303 | -2.30   | $-2.30 < \text{skewness} \leq 5.21$ THEN Predict class: genuine | 61       | 61      |
| genuine | 147 | 1        | $\text{variance} \leq -2.80$ THEN Predict class: genuine | 30       | 99      |
| genuine | 246 | 57       | $-2.80 < \text{variance} \leq -0.40$ THEN Predict class: genuine | 49       | 81      |
| genuine | 6   | 0        | $-0.40 < \text{variance} \leq 0.32$ AND $1.02 < \text{entropy} \leq 1.92$ THEN Predict class: genuine | 1        | 100     |
| genuine | 153 | 9        | $-2.80 < \text{variance} \leq -0.40$ AND $-2.30 < \text{skewness} \leq 5.21$ THEN Predict class: genuine | 31       | 94      |
| genuine | 81  | 0        | $\text{skewness} \leq -6.95$ THEN Predict class: genuine | 16       | 100     |
| genuine | 51  | 0        | $\text{variance} \leq -2.80$ AND $-2.30 < \text{skewness} \leq 5.21$ THEN Predict class: genuine | 10       | 100     |
| genuine | 42  | 8        | $-0.40 < \text{variance} \leq 0.32$ AND $-2.30 < \text{skewness} \leq 5.21$ THEN Predict class: genuine | 8        | 84      |
| genuine | 41  | 0        | $-2.80 < \text{variance} \leq -0.40$ AND $-6.95 < \text{skewness} \leq -5.44$ THEN Predict class: genuine | 8        | 100     |
| genuine | 21  | 1        | $-2.80 < \text{variance} \leq -0.40$ AND $1.02 < \text{entropy} \leq 1.92$ THEN Predict class: genuine | 4        | 95      |
| genuine | 12  | 0        | $\text{variance} \leq -2.80$ AND $-6.95 < \text{skewness} \leq -5.44$ THEN Predict class: genuine | 2        | 100     |
Table 16: Interpreting a Random Forest classifier on the Banknote dataset using the Greedy Rule Selection Algorithm

| Genuine | Fake | Rule | Coverage | Precision |
|---------|------|------|----------|-----------|
| 384     | 542  | -3.68 < curtosis <= 8.84 THEN Predict class: fake | 90 | 59 |
| 1       | 327  | variance > 2.39 THEN Predict class: fake | 55 | 100 |
| 34      | 169  | 6.25 < skewness <= 9.62 THEN Predict class: fake | 28 | 83 |
| 0       | 99   | skewness > 9.62 THEN Predict class: fake | 17 | 100 |
| 0       | 278  | -3.68 < curtosis <= 8.84 AND variance > 2.39 THEN Predict class: fake | 46 | 100 |
| 0       | 81   | 6.25 < skewness <= 9.62 AND variance > 2.39 THEN Predict class: fake | 14 | 100 |
| 31      | 58   | 1.02 < entropy <= 1.92 THEN Predict class: fake | 10 | 65 |
| 303     | 196  | -2.30 < skewness <= 5.21 THEN Predict class: genuine | 61 | 61 |
| 147     | 1    | variance <= -2.80 THEN Predict class: genuine | 30 | 99 |
| 246     | 57   | -2.80 < variance <= -0.40 THEN Predict class: genuine | 49 | 81 |
| 6       | 0    | -0.40 < entropy <= 0.32 AND 1.02 < entropy <= 1.92 THEN Predict class: genuine | 1 | 100 |
| 153     | 9    | -2.80 < variance <= -0.40 AND -2.30 < skewness <= 5.21 THEN Predict class: genuine | 31 | 94 |
| 81      | 0    | skewness <= -6.95 THEN Predict class: genuine | 16 | 100 |
| 51      | 0    | variance <= -2.80 AND -2.30 < skewness <= 5.21 THEN Predict class: genuine | 10 | 100 |
|   |   |   | -0.40 ≤ variance ≤ 0.32 AND -2.30 ≤ skewness ≤ 5.21 THEN Predict class: genuine |
|---|---|---|---|
| 42 | 8 | -0.40 < variance ≤ 0.32 AND -2.30 < skewness ≤ 5.21 THEN Predict class: genuine | 8 | 84 |
| 41 | 0 | -2.80 ≤ variance ≤ -0.40 AND -6.95 ≤ skewness ≤ -5.44 THEN Predict class: genuine | 8 | 100 |
| 21 | 1 | -2.80 ≤ variance ≤ -0.40 AND 1.02 ≤ entropy ≤ 1.92 THEN Predict class: genuine | 4 | 95 |
| 12 | 0 | variance ≤ -2.80 AND -6.95 ≤ skewness ≤ -5.44 THEN Predict class: genuine | 2 | 100 |
| 7  | 0 | 1.02 ≤ entropy ≤ 1.92 AND -6.95 ≤ skewness ≤ -5.44 THEN Predict class: genuine | 1 | 100 |
| 54 | 9 | -6.95 ≤ skewness ≤ -5.44 THEN Predict class: genuine | 11 | 86 |
### Appendix D - Car Evaluation Dataset Model Explanations

Tables 17 and 18 show the results obtained for model interpretation using the second level Genetic Algorithm and the greedy rule selection approach respectively.

**Table 17: Interpreting a Random Forest classifier on the Car Evaluation dataset using the second level Genetic Algorithm**

| Acc | Good | Unacc | Very Good | Rule                                                                 | Coverage | Precision |
|-----|------|-------|-----------|----------------------------------------------------------------------|----------|-----------|
| 228 | 42   | 95    | 42        | persons = more,4 AND lug-boot = med,big AND safety = med,high THEN Predict class: acc | 72       | 56        |
| 173 | 23   | 67    | 42        | persons = more,4 AND safety = high THEN Predict class: acc           | 55       | 57        |
| 103 | 20   | 24    | 12        | persons = more,4 AND safety = med,high AND buying = med THEN Predict class: acc | 33       | 65        |
| 122 | 21   | 44    | 26        | persons = more,4 AND safety = med,high AND lug-boot = big THEN Predict class: acc | 39       | 57        |
| 118 | 23   | 38    | 25        | persons = more,4 AND doors = 5more,4 AND lug-boot = med,big AND safety = med,high THEN Predict class: acc | 37       | 58        |
| 113 | 20   | 40    | 23        | lug-boot = med,big AND safety = med,high AND persons = more THEN Predict class: acc | 36       | 58        |
| 91  | 14   | 30    | 19        | safety = high AND persons = 4 THEN Predict class: acc                | 29       | 59        |
| 74  | 15   | 4     | 12        | persons = more,4 AND lug-boot = med,big AND safety = med,high AND buying = med THEN Predict class: acc | 23       | 70        |
|    |   |   |   | buying = med, high AND persons = more, 4 AND doors = 5more, 4 AND lug-boot = med, big AND safety = med, high THEN Predict class: acc |
|----|---|---|---|---------------------------------------------------------------------------------------------------------------|
| 72 |  8| 11|  8| buying = med, high AND persons = more, 4 AND safety = med, high AND lug-boot = big THEN Predict class: acc |
| 72 |  7| 15|  8| buying = med, high AND safety = high AND persons = more, 4 AND lug-boot = med, big THEN Predict class: acc |
| 71 |  3| 11| 12| safety = med, high AND doors = 5more, 4 AND persons = 4 THEN Predict class: acc |
| 86 | 16| 43| 12| persons = more, 4 AND doors = 5more, 4 AND safety = med, high THEN Predict class: acc |
| 169| 31| 84| 25| safety = med, high AND persons = more, 4 AND doors = 5more, 4 AND safety = med, high THEN Predict class: acc |
| 100| 11| 35|  8| buying = med, high AND persons = more, 4 AND doors = 5more, 4 AND safety = med, high THEN Predict class: acc |
| 166| 31|101| 19| safety = med, high AND persons = 4 THEN Predict class: acc |
| 16 | 41|  4| 21| maint = low AND persons = more, 4 AND buying = med, low AND safety = med, high THEN Predict class: good |
|  3 | 12|  0|  6| maint = low AND persons = more, 4 AND buying = med, low AND safety = med, high AND doors = 5more THEN Predict class: good |
| 43 | 23| 12|  0| safety = med AND persons = more, 4 AND buying = low THEN Predict class: good |
37 21 4 17 persons = more,4 AND doors = 5more,3 AND safety = med,high AND buying = low THEN Predict class: good

0 0 462 0 safety = low THEN Predict class: unacc

0 0 456 0 persons = 2 THEN Predict class: unacc

0 0 172 0 maint = vhigh,high AND buying = vhigh THEN Predict class: unacc

0 0 173 0 buying = vhigh,high AND maint = vhigh THEN Predict class: unacc

30 0 205 0 buying = vhigh,high AND lug-boot = small THEN Predict class: unacc

33 0 206 0 maint = vhigh,high AND lug-boot = small THEN Predict class: unacc

32 0 141 0 buying = vhigh,high AND doors = 2 THEN Predict class: unacc

8 0 11 18 safety = high AND lug-boot = big AND buying = low THEN Predict class: vgood

13 6 4 16 safety = high AND persons = more AND buying = low THEN Predict class: vgood

4 0 0 9 safety = high AND persons = more AND lug-boot = big AND buying = low THEN Predict class: vgood
Table 18: Interpreting a Random Forest classifier on the Car Evaluation dataset using the Greedy Rule Selection Algorithm

| Acc | Good | Unacc | Very | Good | Rule | Coverage | Precision |
|-----|------|-------|------|------|------|----------|-----------|
| 184 | 20   | 89    | 12   | 58   | buying = med,high AND persons = more,4 AND safety = med,high THEN Predict class: acc | 60 |
| 122 | 21   | 44    | 26   | 39   | persons = more,4 AND safety = med,high AND lug-boot = big THEN Predict class: acc | 57 |
| 113 | 20   | 40    | 23   | 36   | lug-boot = med, big AND safety = med, high AND persons = more THEN Predict class: acc | 58 |
| 91  | 14   | 30    | 19   | 29   | safety = high AND persons = 4 THEN Predict class: acc | 59 |
| 89  | 8    | 27    | 25   | 28   | persons = more,4 AND doors = 5 AND safety = high THEN Predict class: acc | 60 |
| 118 | 23   | 38    | 25   | 37   | persons = more,4 AND doors = 5 AND lug-boot = med, big AND safety = med, high THEN Predict class: acc | 58 |
| 137 | 15   | 36    | 12   | 43   | buying = med, high AND persons = more,4 AND lug-boot = med, big AND safety = med, high THEN Predict class: acc | 69 |
| 107 | 8    | 21    | 12   | 34   | buying = med, high AND persons = more,4 AND safety = high THEN Predict class: acc | 72 |
| 103 | 20   | 24    | 12   | 33   | persons = more, 4 AND safety = med, high AND buying = med THEN Predict class: acc | 65 |
100  11  35  8  buying = med,high AND persons = more,4 AND doors = 5more,4 AND safety = med,high
THEN Predict class: acc

97   11  44  5  buying = med,high AND safety = med,high AND persons = 4
THEN Predict class: acc

74   15   4  12  persons = more,4 AND lug-boot = med,big AND safety = med,high AND buying = med
THEN Predict class: acc

72   8  11  8  buying = med,high AND persons = more,4 AND doors = 5more,4 AND lug-boot = med,big AND safety = med,high
THEN Predict class: acc

72   7  15  8  buying = med,high AND persons = more,4 AND safety = med,high AND lug-boot = big
THEN Predict class: acc

71   3  11  12  buying = med,high AND safety = high AND persons = more,4 AND lug-boot = med,big
THEN Predict class: acc

68   7  16  7  buying = med,high AND lug-boot = med,big AND safety = med,high AND persons = more
THEN Predict class: acc

16  41   4  21  maint = low AND persons = more,4 AND buying = med,low AND safety = med,high
THEN Predict class: good

16  24  2  0  maint = low AND persons = more,4 AND buying = med,low AND safety = med
THEN Predict class: good
maint = low AND persons = more,4 AND doors = 5more,3 AND buying = med,low AND safety = med,high THEN Predict class: good

43 23 12 0 safety = med AND persons = more,4 AND buying = low THEN Predict class: good

0 0 462 0 safety = low THEN Predict class: unacc

0 0 456 0 persons = 2 THEN Predict class: unacc

0 0 172 0 maint = vhigh,high AND buying = vhigh THEN Predict class: unacc
|        |   |   |   |                       |   |   |
|--------|---|---|---|-----------------------|---|---|
| 0      | 0 | 173| 0 | buying = vhigh, high  | 18| 100 |
|        |   |    |   | AND maint = vhigh     |   |    |
|        |   |    |   | THEN Predict class:   |   |    |
|        |   |    |   | unacc                 |   |    |
| 8      | 0 | 11 | 18| safety = high AND     | 43| 49 |
|        |   |    |   | lug-boot = big AND    |   |    |
|        |   |    |   | buying = low THEN     |   |    |
|        |   |    |   | Predict class: vgood  |   |    |
| 13     | 6 | 4  | 16| safety = high AND     | 38| 41 |
|        |   |    |   | persons = more AND    |   |    |
|        |   |    |   | buying = low THEN     |   |    |
|        |   |    |   | Predict class: vgood  |   |    |
| 4      | 0 | 0  | 9 | safety = high AND     | 21| 69 |
|        |   |    |   | persons = more AND    |   |    |
|        |   |    |   | lug-boot = big AND    |   |    |
|        |   |    |   | buying = low THEN     |   |    |
|        |   |    |   | Predict class: vgood  |   |    |
| 29     | 0 | 10 | 13| safety = high AND     | 31| 25 |
|        |   |    |   | persons = more AND    |   |    |
|        |   |    |   | lug-boot = big THEN   |   |    |
|        |   |    |   | Predict class: vgood  |   |    |
| 27     | 15| 39 | 30| safety = high AND     | 71| 27 |
|        |   |    |   | buying = low THEN     |   |    |
|        |   |    |   | Predict class: vgood  |   |    |
| 59     | 0 | 74 | 26| safety = high AND     | 62| 16 |
|        |   |    |   | lug-boot = big THEN   |   |    |
|        |   |    |   | Predict class: vgood  |   |    |