Making Use of Functional Dependencies Based on Data to Find Better Classification Trees

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I. INTRODUCTION

Data mining has shown practicality and utility in various fields, showing several successful use cases [1, 2]. And explainable AI is a hot topic for research nowadays, because, even though their great success, it’s hard to understand how neural networks inference logical decisions [3], likewise other high accuracy algorithms such as SVM [4, 5]. On the other hand, because of their structure decision trees are easy to understand. So, decision trees are considered one of the most important machine learning algorithms [6]. But, as the size of training data become large, which is very common in data mining tasks, the size of tree also tends to be large, as a result, understandability of the tree becomes worse. A simple method to generate smaller decision tree is to stop growing the tree in a certain depth. But, stopping at a certain depth of the tree may not be good enough with respect to the accuracy of the tree, because there would be many instances that are not classified fully [7].

The target datasets of decision trees consist of conditional attributes and decisional attributes. The requirement of conditional attributes is that they are independent each other and dependent on decisional attributes only. Statistical method to check independence between attributes is Chi-square test, but the test can be effective for categorical attributes only. So, the applicability of Chi-square test is limited, because most datasets for data mining have mixed attributes of categorical and numerical. In order to overcome the problem, and as a way to test dependency between conditional attributes, a novel method based on functional dependency based on data that can be applied to any datasets irrespective of data type of attributes is suggested. After removing highly dependent attributes between conditional attributes, we can generate better decision trees. Experiments were performed to show that the method is effective, and the experiments showed very good results.

Keywords—artificial intelligence, machine learning, classification, decision trees, knowledge modelling, preprocessing, information systems, functional dependency.
have some duplicate data. Duplicate data in relations may cause data inconsistency problem if we miss updating any of them. Incorrect design of relation schema may raise other anomalies, like not being able to timely updates, or loss of information for sole tuples after delete operations [12]. As a result, a lot of research has been done to discover functional dependencies based on stored data in relations or data sets in tabular form, and we may use the information of found functional dependencies to improve the structure of relation schema. Because we can have \(2^m - 1\) combinations of attributes for a table having \(m\) attributes, the related algorithms try to find functional dependencies as efficiently as possible. There are several polynomial time algorithms suggested; top-down [13, 14], bottom-up [15], and hybrid algorithms [16]. The found functional dependencies can represent the relationship between attributes in the table.

Therefore, in order to find simpler and better decision trees we want to remove highly dependent attributes in conditional attributes first before we generate decision trees. As a way to do the task we try to do functional dependency test first to find closely related attributes, and use the information to get rid of redundant attributes to obtain smaller but still accurate decision trees.

II. RELATED WORK

Over-fitting and under-fitting in machine learning is a hard-to-solve problem [17]. In conventional decision tree algorithms tree size is determined by two factors – stopping criteria and pruning. If we apply stopping criteria early enough, we may have small and under-fitted decision trees. On the other hand, if we apply stopping criteria as late as possible, we may have large decision trees that are over-fitted to the training data set. After generating an over-fitted tree, we may apply pruning methods to achieve more generalization of the tree. The over-fitted tree is made into a smaller tree by removing sub-branches that are not contributing to the generalization. The pruning method was applied in CART [18], as well as in C4.5 [19], which are the two most well-known decision tree algorithms [20]. It has been shown that employing the pruning can improve the performance of generalization in many experiments.

Feature selection is also an important method to generate simpler trees [21]. Principle component analysis (PCA) is a well-known feature selection method [22]. But, because PCA is mainly designed for numerical attributes, it is not easy to apply PCA for datasets having categorical and numerical attributes together. Note that most datasets for data mining have the two kinds of attributes together. Filter methods [23] try to calculate dependency of attributes to class labels, for example, using Pearson’s correlation coefficient and rank each attributes, so that they can remove most irrelevant attributes with respect to class labels. Wrapper method [24] contains a target machine learning algorithm in the wrapper, and try to find a best subset of attributes by running the algorithm, and supplies or removes attributes one by one until the best result is found. Supplying or removing attributes can be done exhaustively or heuristically. Because of computational nature, wrapper methods are not easy to apply for very large datasets or compute-intensive machine learning algorithms. Moreover, if the size of datasets is not large enough or used machine learning algorithm is deterministic, like decision tree algorithms, the method cannot avoid over-fitting problem [25]. Embed methods try select to subsets of attributes during building machine learning models [26]. Good point of embedded methods is less compute-intensive than the wrapper approach, and a week point is dependency on training data so that instability becomes bigger especially for relatively small training datasets [27, 28].

III. PROBLEM SOLUTION

The definition of functional dependency based on data can be defined as follows [12].

**Definition 1.** Let \( r \) be a relation over the set of attributes \( U \), and \( X, Y \) be any subset of \( U \). Then \( Y \) is functionally dependent on \( X \), \( X \rightarrow Y \), if and only if each \( X \) value in \( r \) is associated with precisely one \( Y \) value. □

If we try to find functional dependencies (FD) based on data, we may find two or more equivalent functional dependencies.

**Definition 2.** Let \( FD_1 \) and \( FD_2 \) are two sets of functional dependency for a relation \( r \). First, if all functional dependencies of \( FD_1 \) can be derived from functional dependencies in \( FD_2 \), we can say that \( FD_2 \supset FD_1 \). Second, if all functional dependencies of \( FD_2 \) can be derived from functional dependencies in \( FD_1 \), we can say that \( FD_1 \supset FD_2 \). If the first and second fact are true, then \( FD_1 \) and \( FD_2 \) are equivalent. □

On the other hand, a relation may not be mature or large enough to contain all the possible values in the domain of attributes, so we need the concept of relation variable. A relation variable is a symbol that can have different values for its attributes at different time, and a relation or relation value is a particular state of the relation variable. If we expand definition 1 for relation variable, we have the following definition 3.

**Definition 3.** Let \( R \) be a relation variable over the set of attributes \( U \), and \( X, Y \) be any subset of \( U \). Then \( Y \) is functionally dependent on \( X \), \( X \rightarrow Y \), if and only if every possible \( X \) value in \( R \) is associated with precisely one possible \( Y \) value. □

If we have very large relations, it is highly possible that the relations approximate corresponding relation variables because they contain many data. So, the idea of trying to find functional dependencies efficiently from data has attracted many researchers’ attention and most researchers want to find functional dependencies from datasets in tabular form [29]. As a result, an open source software called FDTool is available [30]. FDTool is a Python based open source software to mine functional dependencies and candidate keys in tabular datasets. Note that the format of relations is in tabular form. The difference between relations and datasets in tabular form is that the latter can have many functional dependencies in them because they may not be normalized or may be less normalized.

**A. Suggested Method**

We want to check whether a given dataset which has conditional and decisional attributes for data mining has functional dependencies between conditional attributes. In
order to check them, we use FDtool, then, if some functional dependencies are found, we try to eliminate the set of attributes that are dependent to other attributes before we supply the dataset to generate decision trees. The details of procedure is as follows:

**PROCEDURE:**
**INPUT:** a dataset D in tabular form.
**OUTPUT:** a decision tree
**BEGIN**

1. Find functional dependencies based on data in conditional attributes using FDtool;
   /* Make a table having the information of {frequency in LHS, frequency in RHS, (frequency in RHS - Frequency in LHS), (frequency in RHS/Frequency in LHS)} */
2. For each conditional attribute Do
   Calculate {frequency in LHS, frequency in RHS, (frequency in RHS – (Frequency in LHS), (frequency in RHS)/(frequency in LHS));
   End For;
3. Select highly dependent attributes to other attributes and let the set of attributes be A;
4. For all subsets S of A except Ø Do
   Remove the columns of attributes in S from D;
   Generate decision trees;
   End For;
5. Select the best decision tree from the result of 4.
**END.**

In the procedure, LHS and RHS means the left hand side and the right hand side of the found functional dependencies respectively. Note that attributes in RHS of functional dependencies role as dependent attributes, and LHS as independent attributes. So, the meaning of the ratio, (frequency in RHS divided by frequency in LHS), is the ratio of the role as dependent attribute and independent attribute in the found functional dependencies. Moreover, the meaning of difference between frequency in RHS and LHS is the amount of positive or negative role of the attribute as dependent attributes in the found functional dependencies. When we select highly dependent attributes, we use the calculated information on the whole. Please see the experiments for details.

**IV. EXPERIMENTS**

Two datasets, called adult and bank dataset in UCI machine learning repository were used for our experiments [31]. The datasets consist of several conditional attributes and one decisional attribute. We want to find functional dependencies between conditional attributes, and we expect many functional dependencies based on stored data in each dataset.

**A. Adult Dataset**

The task of adult dataset is to predict whether income exceeds $50K/year based on census income data. The data set has 48,842 records and has 14 conditional attributes and one decisional attribute, named ‘class’ having two different values, >50K or <=50K. There are 11,687 records having the class value of >50K, and 37,155 records having the class value of <=50K. The 14 conditional attributes consist of numerical and categorical attributes as in table 1. Categorical attributes have limited number of nominal values, while numerical attributes do not.

| attribute   | values                                                                 |
|-------------|------------------------------------------------------------------------|
| age         | numeric                                                                |
| workclass   | Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked |
| fnlwgt      | numeric                                                                |
| education num | Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse |
| marital-status | Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried |
| occupation  | Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspect, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces |
| relationship | Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried |
| race        | White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black |
| sex         | Female, Male                                                            |
| capital-gain | numeric                                                                |
| capital-loss | numeric                                                                |
| hours-per-week | numeric                                                                |
| native-country | United-States, Cambodia, England, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinidad&Tobago, Peru, Hong, Holand-Netherlands |

1) **Checking Functional Dependencies for Adult Dataset**

38 functional dependencies in the conditional attributes were found. Some examples of the found functional dependencies are as follows:

{ education} -> { educationNum}  
{ educationNum} -> { education}  
{ age}, { relationship}, { education}, { fnlwgt} -> { sex}  
{ age}, { relationship}, { HoursPerWeek}, { fnlwgt} -> { sex}  

......
Based on the found functional dependencies between conditional attributes, we can calculate the frequency of each attributes in left and right hand side of the found functional dependencies and other values as in the table 2.

Table 2. Frequency of attributes in the found functional dependencies in adult dataset

| attribute         | frequency in LHS | frequency in RHS | f.RHS/f.LHS | f.RHS/ f.LHS |
|-------------------|------------------|------------------|-------------|-------------|
| race              | 1                | 26               | 25          | 26          |
| sex               | 4                | 10               | 6           | 2.5         |
| educationNum      | 1                | 1                | 0           | 1           |
| education         | 28               | 1                | -22         | 0.04        |
| fnlwgt            | 36               | 1                | -36         | 0           |
| age               | 1                | 28               | -28         | 0           |
| occupation        | 1                | 20               | -20         | 0           |
| workclass         | 1                | 18               | -18         | 0           |
| marital-status    | 1                | 18               | -18         | 0           |
| relationship      | 1                | 17               | -17         | 0           |
| hoursPerWeek      | 1                | 16               | -16         | 0           |
| nativeCountry     | 1                | 16               | -16         | 0           |
| capitalLoss       | 8                | 0                | -8          | 0           |
| capitalGain       | 2                | 0                | -2          | 0           |

In the table f.RHS and f.LHS means frequency in RHS and frequency in LHS respectively. The attributes having zero frequency in the RHS of the found functional dependency means that the attributes have no effect in dependency in the conditional attributes, so that we don’t need to consider as candidates to remove. Based on the value of (the frequency of RHS – the frequency of LHS), and the ratio between the frequency of RHS divided by the frequency of LHS (that is, f.RHS/f.LHS), we may choose three candidate attributes to remove, race, sex, and educationNum, whose corresponding values are {25, 26}, {6, 2.5} and {0, 1} respectively. Because two attributes educationNum and education make an equivalent functional dependency, we try to remove one of them alternately in order to see the effect of removing in the decision trees.

2) Generating Decision Trees

Table 3 shows the property of decision tree generated by J4.8 which is Java version of C4.5 in Weka machine learning package [32] from the original adult dataset. C4.5 is one of the most popular decision tree algorithms [20]. All experiments are performed in 10-fold cross-validation.

We try to generate decision trees for dataset having select attributes only. We’ll try to remove attributes from the original dataset in the following order; educationNum, education, race, sex, {educationNum, race}, {education, race}, {educationNum, sex}, {education, sex}, {educationNum, race, sex}, {education, race, sex}.

Table 4 shows the property of decision tree generated from the adult dataset of which attribute educationNum is omitted.

Table 5 shows the property of decision tree generated from the adult dataset of which attribute education is omitted.

Table 6 shows the property of decision tree generated from the adult dataset of which attribute race is omitted.
Table 7 shows the property of decision tree generated from the adult dataset of which attribute sex is omitted.

### Table 7. Decision tree from adult dataset – sex attribute

| Number of leaves | 662  |
|------------------|------|
| Size of the tree | 845  |
| Accuracy         | 86.9%|

### Confusion matrix

| Actual | Predicted >50K | Predicted ≤50K |
|--------|----------------|----------------|
| >50K   | 6958           | 4729           |
| ≤50K   | 2104           | 35051          |

Table 8 shows the property of decision tree generated from the adult dataset of which attribute educationNum and race are omitted.

### Table 8. Decision tree from adult dataset – educationNum and race attribute

| Number of leaves | 369  |
|------------------|------|
| Size of the tree | 506  |
| Accuracy         | 86.0018%|

### Confusion matrix

| Actual | Predicted >50K | Predicted ≤50K |
|--------|----------------|----------------|
| >50K   | 6875           | 4812           |
| ≤50K   | 2025           | 35130          |

Table 9 shows the property of decision tree generated from the adult dataset of which attribute education and race are omitted.

### Table 9. Decision tree from adult dataset – education and race attribute

| Number of leaves | 517  |
|------------------|------|
| Size of the tree | 775  |
| Accuracy         | 86.1533%|

### Confusion matrix

| Actual | Predicted >50K | Predicted ≤50K |
|--------|----------------|----------------|
| >50K   | 6932           | 4755           |
| ≤50K   | 2008           | 35147          |

Table 10 shows the property of decision tree generated from the adult dataset of which attribute educationNum and sex are omitted.

### Table 10. Decision tree from adult dataset – educationNum and sex attribute

| Number of leaves | 405  |
|------------------|------|
| Size of the tree | 553  |
| Accuracy         | 85.926%|

### Confusion matrix

| Actual | Predicted >50K | Predicted ≤50K |
|--------|----------------|----------------|
| >50K   | 6849           | 4838           |
| ≤50K   | 2036           | 35119          |

Table 11 shows the property of decision tree generated from the adult dataset of which attribute education and sex are omitted.

### Table 11. Decision tree from adult dataset – education and sex attribute

| Number of leaves | 482  |
|------------------|------|
| Size of the tree | 699  |
| Accuracy         | 86.0591%|

### Confusion matrix

| Actual | Predicted >50K | Predicted ≤50K |
|--------|----------------|----------------|
| >50K   | 7002           | 4685           |
| ≤50K   | 2124           | 35031          |

Table 12 shows the property of decision tree generated from the adult dataset of which attribute educationNum, race and sex are omitted.

### Table 12. Decision tree from adult dataset – educationNum, race, and sex attribute

| Number of leaves | 381  |
|------------------|------|
| Size of the tree | 516  |
| Accuracy         | 85.9506%|

### Confusion matrix

| Actual | Predicted >50K | Predicted ≤50K |
|--------|----------------|----------------|
| >50K   | 6836           | 4851           |
| ≤50K   | 2011           | 35144          |

Table 13 shows the property of decision tree generated from the adult dataset of which attribute education, race and sex are omitted.

### Table 13. Decision tree from adult dataset – education, race, and sex attribute

| Number of leaves | 407  |
|------------------|------|
| Size of the tree | 597  |
| Accuracy         | 86.1328%|

### Confusion matrix

| Actual | Predicted >50K | Predicted ≤50K |
|--------|----------------|----------------|
| >50K   | 6915           | 4772           |
The following table 14 summarizes the experiments with respect to accuracy and size of trees as attributes are dropped from the dataset before generating decision trees.

Table 14. The summary of experiments of decision tree from adult dataset

| Dropped attributes | Accuracy (%) | Tree size |
|--------------------|--------------|-----------|
| none               | 86.0428      | 911       |
| educationNum       | 85.967       | 547       |
| education          | 86.0735      | 838       |
| race               | 86.0796      | 810       |
| sex                | 86.9         | 845       |
| educationNum, race | **86.0018**  | **506**   |
| education, race    | 86.1533      | 775       |
| educationNum, sex  | 85.926       | 553       |
| education, sex     | 86.0591      | 699       |
| educationNum, race, sex | 85.9506 | 516       |
| education, race, sex| 86.1328     | 597       |

As we see in the table, dropping two attributes, educationNum and race, generates the tree of 506/911=56% size with similar accuracy compared to the tree from the original dataset, which enhances comprehensibility a lot without losing accuracy. Comparing the confusion matrix of the two trees in table 8 (from dropping the two attributes, educationNum and race) and table 3 (from original dataset), we have the loss of -100 cases of correct prediction of '>50K' while the gain of +80 cases of correct prediction of '≤50K', which causes a slight prediction rate change in the trees.

B. Bank Dataset

The purpose of bank dataset is to predict if the client will subscribe a term deposit or not. There are 521 records having class value of yes, and 4,000 records having class value of no. The 16 conditional attributes have variety of values as in table 15.

Table 15. Conditional attributes of bank dataset

| attribute   | values                                      |
|-------------|---------------------------------------------|
| age         | numeric                                     |
| job         | admin., unknown, unemployed, management, housemaid, entrepreneur, student, blue-collar, self-employed, retired, technician, services |
| marital     | divorced, married, single, unknown          |
| education   | basic.4y, basic.6y, basic.9y, high.school, illiterate, professional.course, university.degree, unknown |

1) Checking Functional Dependencies for Bank Dataset

1,040 functional dependencies were found in the conditional attributes based on the dataset. That is, we found 21, 132, 331, 261, 224, 42, 20, 9 functional dependencies of length 4, 5, 6, 7, 8, 9, 10, 11 respectively. Some examples of found functional dependencies are as follows:

\[ \text{balance, poutcome, duration} \rightarrow \{ \text{previous} \} \]
\[ \text{balance, age, duration} \rightarrow \{ \text{default} \} \]
\[ \text{balance, campaign, age, housing, marital, duration, loan, housing, previous} \rightarrow \{ \text{day} \} \]
\[ \text{education, default, marital, job, contact, duration, loan, housing, day, previous} \rightarrow \{ \text{month} \} \]

Based on the found functional dependencies between conditional attributes, we can calculate the frequency of each
attribute in the left and right hand side of the found functional dependencies and other values as in the table 16.

Table 16. Frequency of attributes in the found functional dependencies in bank dataset

| attribute | frequency in LHS | frequency in RHS | f.RHS/f.LHS | f.RHS/f.LHS |
|-----------|-----------------|-----------------|-------------|-------------|
| pdays     | 174             | 203             | 29          | 1.167       |
| poutcome  | 206             | 122             | -84         | 0.592       |
| previous  | 262             | 103             | -159        | 0.393       |
| default   | 48              | 101             | 53          | 2.104       |
| contact   | 274             | 90              | -184        | 0.328       |
| housing   | 331             | 71              | -260        | 0.215       |
| loan      | 271             | 68              | -203        | 0.251       |
| month     | 400             | 63              | -337        | 0.158       |
| marital   | 323             | 50              | -273        | 0.155       |
| education | 366             | 49              | -317        | 0.134       |
| job       | 421             | 30              | -391        | 0.071       |
| day       | 519             | 26              | -493        | 0.050       |
| campaign  | 517             | 16              | -501        | 0.301       |
| balance   | 154             | 12              | -142        | 0.078       |
| age       | 521             | 11              | -510        | 0.021       |
| duration  | 723             | 11              | -712        | 0.015       |

Based on the value of (the frequency of RHS – the frequency of LHS), and the ratio between the frequency of RHS and the frequency of LHS (that is, f.RHS/f.LHS), we may choose two candidate attributes to remove, default and pdays, whose corresponding values are {53, 2.104} and {29, 1.167} respectively. Additionally, we may try to remove other two attributes, poutcome and previous, whose corresponding values are {-84, 0.592} and {-159, 0.393} respectively, because even though their values of (the frequency of RHS – the frequency of LHS) are negative, which means that there are more attributes that role as independent attributes rather than dependent attributes, but the values of the ratio, (the frequency of RHS)/(the frequency of LHS), are the third and fourth respectively, and frequency of RHS is relatively high. Note that attributes in RHS of functional dependencies role as dependent attributes.

2) Generating Decision Trees

Table 17 shows the property of decision tree from the original bank dataset. All experiments are performed with 10-fold cross-validation.

Table 17. Decision tree from bank dataset

| Number of leaves | 104 |
|------------------|-----|
| Size of the tree | 146 |
| Accuracy         | 88.8963% |

Confusion matrix

| Actual yes | Predicted yes | Actual no | Predicted no |
|------------|---------------|-----------|--------------|
| 187        | 334           | 168       | 3832         |

We'll try to remove attributes from the original dataset in the following order; pdays, default, poutcome, previous, {pdays, default}, {pdays, poutcome}, {pdays, previous}, {default, poutcome}, {default, previous}, {pdays, default, poutcome}, {pdays, default, previous}, {pdays, poutcome, previous}, {default, poutcome, previous}, {pdays, default, poutcome, previous}. Table 18 shows the property of decision tree generated from the bank dataset of which attribute pdays is omitted.

Table 18. Decision tree from bank dataset – pdays attribute

| Number of leaves | 102 |
|------------------|-----|
| Size of the tree | 142 |
| Accuracy         | 88.852% |

Confusion matrix

| Actual yes | Predicted yes | Actual no | Predicted no |
|------------|---------------|-----------|--------------|
| 185        | 336           | 166       | 3832         |

Table 19 shows the property of decision tree generated from the bank dataset of which attribute default is omitted.

Table 19. Decision tree from bank dataset – default attribute

| Number of leaves | 102 |
|------------------|-----|
| Size of the tree | 140 |
| Accuracy         | 88.9847% |

Confusion matrix

| Actual yes | Predicted yes | Actual no | Predicted no |
|------------|---------------|-----------|--------------|
| 186        | 335           | 163       | 3837         |

Table 20 shows the property of decision tree generated from the bank dataset of which attribute poutcome is omitted.

Table 20. Decision tree from bank dataset – poutcome attribute

| Number of leaves | 92 |
|------------------|----|
| Size of the tree | 136 |
| Accuracy         | 88.4318% |

Confusion matrix

| Actual yes | Predicted yes | Actual no | Predicted no |
|------------|---------------|-----------|--------------|
| 175        | 346           | 177       | 3823         |

Table 21 shows the property of decision tree generated from the bank dataset of which attribute previous is omitted.

Table 21. Decision tree from bank dataset – previous attribute

| Number of leaves | 104 |
|------------------|-----|
| Size of the tree | 146 |
| Accuracy         | 88.8741% |
Table 22 shows the property of decision tree generated from the bank dataset of which attribute pdays and default are omitted.

Table 22. Decision tree from bank dataset – pdays and default attribute

| Number of leaves | 100 |
|------------------|-----|
| Size of the tree | 136 |
| Accuracy         | 88.9405% |

Confusion matrix

|                      | Predicted yes | Predicted no |
|----------------------|---------------|--------------|
| Actual yes           | 188           | 333          |
| Actual no            | 170           | 3830         |

Table 23 shows the property of decision tree generated from the bank dataset of which attribute pdays and poutcome are omitted.

Table 23. Decision tree from bank dataset – pdays and poutcome attribute

| Number of leaves | 102 |
|------------------|-----|
| Size of the tree | 159 |
| Accuracy         | 88.3433% |

Confusion matrix

|                      | Predicted yes | Predicted no |
|----------------------|---------------|--------------|
| Actual yes           | 172           | 349          |
| Actual no            | 178           | 3822         |

Table 24 shows the property of decision tree generated from the bank dataset of which attribute pdays and previous are omitted.

Table 24. Decision tree from bank dataset – pdays and previous attribute

| Number of leaves | 104 |
|------------------|-----|
| Size of the tree | 144 |
| Accuracy         | 88.8299% |

Confusion matrix

|                      | Predicted yes | Predicted no |
|----------------------|---------------|--------------|
| Actual yes           | 186           | 335          |
| Actual no            | 170           | 3830         |

Table 25 shows the property of decision tree generated from the bank dataset of which attribute default and poutcome are omitted.

Table 25. Decision tree from bank dataset – default and poutcome attribute

| Number of leaves | 87 |
|------------------|----|
| Size of the tree | 126 |
| Accuracy         | 88.4318% |

Confusion matrix

|                      | Predicted yes | Predicted no |
|----------------------|---------------|--------------|
| Actual yes           | 175           | 346          |
| Actual no            | 177           | 3823         |

Table 26 shows the property of decision tree generated from the bank dataset of which attribute default and previous are omitted.

Table 26. Decision tree from bank dataset – default and previous attribute

| Number of leaves | 102 |
|------------------|-----|
| Size of the tree | 140 |
| Accuracy         | 88.9405% |

Confusion matrix

|                      | Predicted yes | Predicted no |
|----------------------|---------------|--------------|
| Actual yes           | 186           | 335          |
| Actual no            | 165           | 3835         |

Table 27 shows the property of decision tree generated from the bank dataset of which attribute poutcome and previous are omitted.

Table 27. Decision tree from bank dataset – poutcome and previous attribute

| Number of leaves | 101 |
|------------------|-----|
| Size of the tree | 144 |
| Accuracy         | 88.476% |

Confusion matrix

|                      | Predicted yes | Predicted no |
|----------------------|---------------|--------------|
| Actual yes           | 172           | 349          |
| Actual no            | 172           | 3828         |

Table 28 shows the property of decision tree generated from the bank dataset of which attribute pdays, default and poutcome are omitted.

Table 28. Decision tree from bank dataset – pdays, default, and poutcome attribute

| Number of leaves | 104 |
|------------------|-----|
| Size of the tree | 149 |
| Accuracy         | 88.3433% |
Table 29 shows the property of decision tree generated from the bank dataset of which attribute pdays, default and previous are omitted.

Table 29. Decision tree from bank dataset – pdays, default, and previous attribute

|                | Predicted yes | Predicted no |
|----------------|---------------|--------------|
| Actual yes     | 173           | 348          |
| Actual no      | 179           | 3821         |

Table 30 shows the property of decision tree generated from the bank dataset of which attribute pdays, poutcome and previous are omitted.

Table 30. Decision tree from bank dataset – pdays, poutcome, and previous attribute

|                | Predicted yes | Predicted no |
|----------------|---------------|--------------|
| Actual yes     | 184           | 337          |
| Actual no      | 165           | 3835         |

Table 31 shows the property of decision tree generated from the bank dataset of which attribute default, poutcome and previous are omitted.

Table 31. Decision tree from bank dataset – default, poutcome, and previous attribute

|                | Predicted yes | Predicted no |
|----------------|---------------|--------------|
| Actual yes     | 171           | 350          |
| Actual no      | 172           | 3828         |

Table 32 shows the property of decision tree generated from the bank dataset of which attribute pdays, default, poutcome and previous are omitted.

Table 32. Decision tree from bank dataset – pdays, default, poutcome, and previous attribute

|                | Predicted yes | Predicted no |
|----------------|---------------|--------------|
| Actual yes     | 192           | 329          |
| Actual no      | 158           | 3842         |

The following table 33 summarizes the experiments with respect to accuracy and size of trees as attributes are dropped before generating decision trees.

Table 33. The summary of experiments of decision tree from bank dataset

| Dropped attributes | Accuracy (%) | Tree size |
|--------------------|--------------|-----------|
| none               | 88.8963      | 146       |
| pdays              | 88.852       | 142       |
| default            | 88.9847      | 140       |
| poutcome           | 88.4318      | 136       |
| previous           | 88.8741      | 146       |
| pdays, default     | 88.9405      | 136       |
| poutcome           | 88.3433      | 159       |
| pdays, previous    | 88.8299      | 144       |
| default, poutcome  | 88.4318      | 126       |
| pdays, previous    | 88.9405      | 140       |
| poutcome, previous | 88.476       | 144       |
| pdays, default, poutcome | 88.3433 | 149 |
| pdays, default, previous | 88.8963 | 138 |
| pdays, poutcome, previous | 88.1376 | 133 |
| default, poutcome, previous | 88.4539 | 134 |
| pdays, default, poutcome, previous | 89.228 | 123 |

As we see in the table, dropping the four attributes, {pdays, default, poutcome, and previous}, generates the best result with respect to tree size as well as accuracy. Comparing the confusion matrix of the two trees in table 32 (from dropping four attributes, pdays, default, poutcome, and previous) and table 17 (from original dataset), we have the gain of +5 cases of correct prediction of ‘yes’ while the gain of +10 cases of correct prediction of ‘no’, that cause better accuracy of the trees.

V. CONCLUSION

When we do data mining task of classification using machine learning algorithms, independence between conditional attributes in datasets is a precondition for the success of the task. And, because their understandability is very good, decision
trees that are used for classification tasks are considered one of the most important machine learning algorithms. But, as the size of training data becomes large, which occurs often for data mining task, the size of tree also tends to be large, as a result, the understandability of the tree becomes worse. Moreover, if we have some dependency or lack of independency between conditional attributes, we can have more complex trees. So, it is recommended to get rid of dependency between conditional attributes before we generate decision trees. Chi-square test is a well-known statistical method to check dependency between attributes. But, its applicability is limited to categorical attributes only, while target datasets of data mining usually consist of categorical and numeric attributes mixed. So, in order to overcome the problem, and as a way to do independence test between conditional attributes irrespective of the type of attributes, a novel functional dependency-based method is suggested. Experiments based on two real world datasets were done using open source software called FDtool to find functional dependencies based on data, and showed very good results. Future works may be the improvement of FDtool. Because the tool is based on polynomial time algorithm, it may take some long time to find all functional dependencies especially if the size of datasets is very large consisting of millions of records. Note that because our functional dependencies are based on data, the more data the better. So, parallelization of it is desirable.

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