Supervised Learning In Quest SLIQ

Jaehyun Lee

Introduction

What is SLIQ?

- SLIQ (Supervised Learning in Quest) is a high speed and flexible decision tree classifier that allows to sort and interpret data.
- SLIQ can reduce costs using efficient and pre-sorting decision trees to sort through large data sets while accounting for differences in data types.
- This maintains competitive accuracy with the ability to scale and interpret larger data sets with multiple classes and attributes.

Advantages of SLIQ

- The algorithm aims to reduce the diversity of the tree at each split, resulting in more efficient and cost-effective sorting of data
- SLIQ does not require data normalization, making it easier to use with a variety of data types and features
- It scales well with data size, making it suitable for large data sets
- SLIQ is an improvement upon existing decision tree algorithms, offering better sorting and pruning of data

Disadvantages of SLIQ

- The algorithm requires more time to train the model compared to other decision tree algorithms.
- SLIQ is not suitable for regression or predictive modeling, limiting its usefulness in certain applications.
- SLIQ may not perform well with imbalanced datasets, where one class has significantly more instances than the others.

Application of SLIQ

- The main application of SLIQ is on classification tasks in data mining. Which can be applied in many domains, such as finance, healthcare, and marketing.
- One real life application is Bidding Decision System of Electricity Market. The SLIQ algorithm is applied to the bidding decision system of the electricity market, where the knowledge of the bidding unit's ability is gained by considering the market's demand, bidding price, and capacity [3].

Procedure

Procedure Overview

- Presorting the data
- Processing evaluation on splits using Gini index
- Updating the class list
- Tree pruning

Gini Index

- SLIQ uses a training set and a Gini index to prepare the data for the decision tree algorithm. These equations are what make SLIQ a, supervised learning, algorithms as the data is pre-sorted and pruned.
- For training set with n distinct classes the equation, where L is left of the the root node and R is the right of the root node. A and B are the class results.

Attribute Value < P	A	В
L	a1	a2
R	b1	b2

$$\begin{aligned} &Gini\ Index = \frac{a1+a2}{n}\left[1-\left(\frac{a1}{a1+a2}\right)^2-\left(\frac{a2}{a1+a2}\right)^2\right] + \\ &\frac{b1+b2}{n}\left[1-\left(\frac{b1}{b1+b2}\right)^2-\left(\frac{b2}{b1+b2}\right)^2\right] (5) \end{aligned}$$

with data classes a and b:

Tree Pruning

- The Minimum Description Length (MDL) principle is used in the tree pruning strategy of SLIQ. According to MDL, the best model for encoding data is the one that minimizes the sum of the cost of describing the data in terms of the model and the cost of describing the model. In the context of decision tree classifiers, the models are the set of trees obtained by pruning the initial decision tree, and the data is the training set [4].
- If M is a model that encodes the data D, the total cost of the encoding, cost(M, D), is defined as:

$$cost(M, D) = cost(D \mid M) + cost(M)$$

Example

TRAINING DATA

Age Salary Class 30 65 G 23 15 B

G

23 15 B 40 75 G 55 40 B 55 100 G



AFTER PRE-SORTING

	List	
Age	Index	
23	2	
30	1	
40	3	
45	6	
55	5	
55	4	

	_		1	۰
ΑO	e	4	ĸ	L
	-	 -	_	-

Salary	List	
15	2	
40	4	
60	6	
65	1_	
75	3	
100	5	

Salary List

,	Class	Leaf
1	G	N1
2	В	N1
3	G	N1
4	В	NI
5	G	N1
6	G	Ni

Class List

```
EvaluateSplits()

for each attribute A do

traverse attribute list of A

for each value v in the attribute list do

find the corresponding entry in the class list, and

hence the corresponding class and the leaf node (say l)

update the class histogram in the leaf l

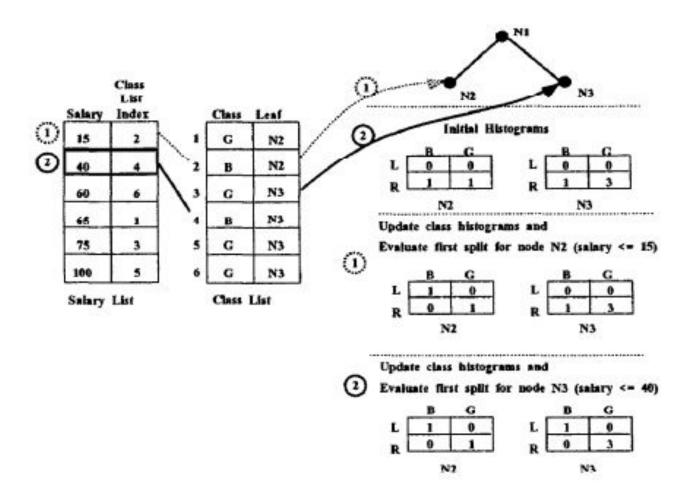
if A is a numeric attribute then

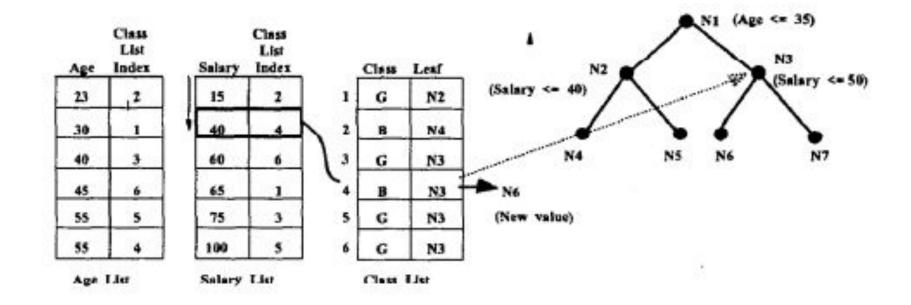
compute splitting index for test (A \leq v) for leaf l

if A is a categorical attribute then

for each leaf of the tree do

find subset of A with best split
```





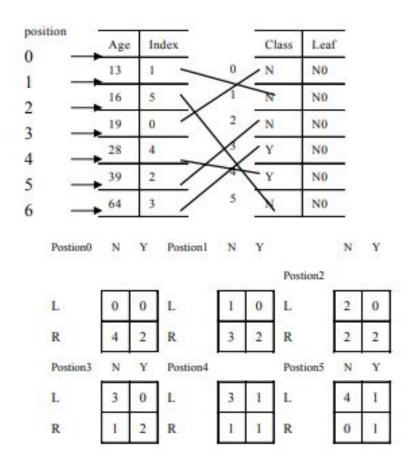
Example 2 [3]

Rid	Aag	Credit-rating	class
0	19	Excellent	N
1	13	Fair	N
2	39	Fair	N
3	64	Excellent	Y
4	28	Medium	Y
5	16	Excellent	N



credit-rating list		Age list		list Age list			class li	st
credit-rating	Index	Age	Index	Rid	Class	Leaf		
Excellent	0	13	1	0	N	N0		
Excellent	3	16	5	1	N	N0		
Excellent	5	19	0	2	N	N0		
Fair	1	28	4	3	Y	N0		
Fair	2	39	2	4	Y	N0		
Medium	4	64	3	5	N	N0		

Example 2 [3]

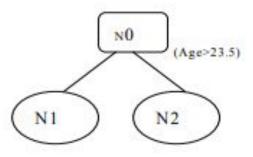


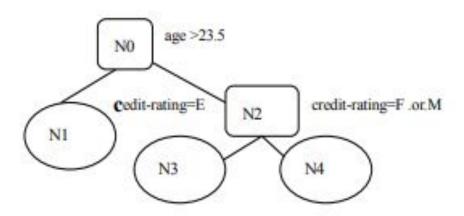
S1:
$$Gini(s_1 < 14.5) = 1 - (\frac{1}{1})^2 = 0$$

S2: $Gini(s_2 > 14.5) = 1 - ((\frac{3}{5})^2 + (\frac{2}{5})^2) = 0.48$
 $Gini_split(14.5) = \frac{1}{6} \times 0 + \frac{5}{6} \times 0.48 = 0.4$
In the same way, $Gini_split(17.5) = 0.33$
 $Gini_split(23.5) = 0.22$; $Gini_split(33.5) = 0.42$

Example 2 [3]

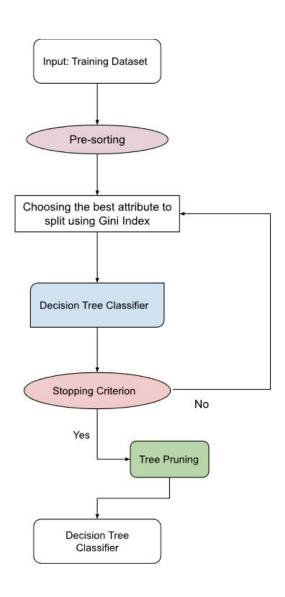
	Class	Leaf				
0	N	N1				
1	N	N1				
2	N	N2				
3	Y	N2				
4	Y	N2				
5	N	N1				



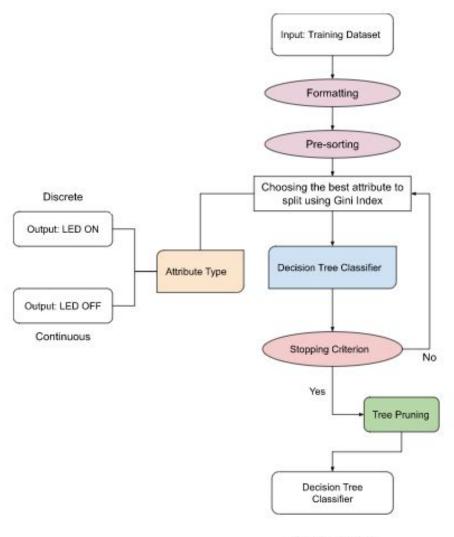


Methodology

Data Flow Graph



Data Flow Graph



Data Flow Graph

Training Data

Status, Married, Dependents, Education, Self_Employed, Applicant_Income, Coapplicant_Income, Loan_Amount, Credit_History Y,0,0,1,0,584900,0,15000000,1

N,1,1,1,0,458300,150800,12800000,1

Y,1,0,1,1,300000,0,6600000,1

Y,1,0,0,0,258300,235800,12000000,1

Y,0,0,1,0,600000,0,14100000,1

Y,1,1,1,1,541700,419600,26700000,1

Y,1,0,0,0,233300,151600,9500000,1

N,1,1,1,0,303600,250400,15800000,0

Y,1,1,1,0,400600,152600,16800000,1

N,1,1,1,0,1284100,1096800,34900000,1

Y,1,1,1,0,320000,70000,7000000,1

Y,1,1,1,0,250000,184000,10900000,1

Y,1,1,1,0,307300,810600,20000000,1

N,0,0,1,0,185300,284000,11400000,1

Y,1,1,1,0,129900,108600,1700000,1

Y,0,0,1,0,495000,0,12500000,1

Y,0,1,0,0,359600,0,10000000,0

N,0,0,1,0,351000,0,7600000,0

N,1,0,0,0,488700,0,13300000,1

Y,1,0,1,0,260000,350000,11500000,1

N,1,0,0,0,766000,0,10400000,0

Y,1,1,1,0,595500,562500,31500000,1

N,1,0,0,0,260000,191100,11600000,0

N,1,1,0,0,336500,191700,11200000,0

N.1.1.1.0.371700.292500.15100000.0

Y,1,0,1,1,956000,0,19100000,1

Y,1,0,1,0,279900,225300,12200000,1

Y,1,1,0,0,422600,104000,11000000,1

N,0,0,0,0,144200,0,3500000,1

Y,0,1,1,0,375000,208300,12000000,1

N,1,1,1,0,416600,336900,20100000,0

N.0.0.1.0.316700.0.7400000.1

N,0,1,1,1,469200,0,10600000,1

Y,1,0,1,0,350000,166700,11400000,1

N,0,1,1,0,1250000,300000,32000000,1

Y,1,0,1,0,227500,206700,0,1

N,1,0,1,0,182800,133000,10000000,0

Y,1,0,1,0,366700,145900,14400000,1

Y,0,0,1,0,416600,721000,18400000,1

Y,0,0,0,0,374800,166800,11000000,1

N,0,0,1,0,360000,0,8000000,1

Y,0,0,1,0,180000,121300,4700000,1

Y,1,0,1,0,240000,0,7500000,0

Y,1,0,1,0,394100,233600,13400000,1

Y,1,0,0,1,469500,0,9600000,1

Y,0,0,1,0,341000,0,8800000,1

Presorting the Data

```
# sort the data and save as .csv file
def sort_data(data, attr):
    return sorted(data, key=lambda x: x[attr])

for attr in attributes:
    sorted_attr_data = sort_data(data, attr)
    sorted_file_path = f"sorted_{attr}.csv"
    write_csv_data(sorted_file_path, header, sorted_attr_data)

def write_csv_data(file_path, header, data):
    with open(file_path, "w") as f:
        f.write(",".join(header) + "\n")
        for row in data:
            f.write(",".join([str(row[h]) for h in header]) + "\n")
```

```
index,Loan_Amount,Credit_Status
36.0.Y
17,10000000,Y
37,100000000,N
21,10400000,N
33,10600000,N
12,10900000.Y
28,11000000,Y
40,11000000,Y
24.11200000.N
14,11400000,N
34,11400000,Y
20.11500000.Y
23,11600000,N
4,12000000,Y
30,12000000,Y
49,12000000,N
27,12200000,Y
16,12500000,Y
2,12800000,N
19,13300000,N
44,13400000,Y
5,14100000,Y
38,14400000,Y
48,14400000,Y
1,15000000,Y
25,15100000,N
8,15800000,N
9,16800000,Y
15,1700000,Y
39,18400000,Y
26,19100000,Y
13.20000000.Y
31,20100000,N
6,26700000,Y
22,31500000,Y
35,32000000,N
```

```
# Imported file
file_path = "loan_train_em.csv"
attributes = ["Married", "Dependents", "Education", "Self_Employed", "Applicant_Income", "Coapplicant_Income", "Loan_Amount", "Credit_History"]

# Read and format the imported data file
def read_csv_data(file_path):
    with open(file_path, "r") as f:
        lines = f.readlines()
    header = lines[0].strip().split(",")
    data = [dict(zip(["index"] + header, [i] + line.strip().split(","))) for i, line in enumerate(lines[1:], 1)]
return data

data = read_csv_data(file_path)
header = ["index"] + list(data[0].keys())[1:]
```

```
26 # Class for each node, contains informations about the node and the split on the node
27 class Node:
28
       def __init__(self, data, attributes, target, depth=0):
            self.data = data
29
30
            self.attributes = attributes
            self.target = target
            self.depth = depth
            self.split attr = None
34
            self.children = []
36 # Sort the data
37 def sort_data(data, attr):
38
        return sorted(data, key=lambda x: x[attr])
39
```

```
40 # Count the dependent variable for the gini
41 def count_credit_status(data):
       counts = {"Y": 0, "N": 0}
42
       for row in data:
43
           counts[row["Credit_Status"]] += 1
44
45
       return counts
46
47 # Calculate the gini index for the data and for each attribute
48 def gini_index(data):
       counts = count credit status(data)
49
       total = sum(counts.values())
50
       gini = 1 - sum([(count / total) ** 2 for count in counts.values()])
51
       return gini
53
54 def gini_index_for_attribute(data, attr):
        sorted data = sort data(data, attr)
56
       total gini = 0
       for i in range(len(sorted data) - 1):
57
           left_data = sorted_data[: i + 1]
58
           right data = sorted data[i + 1 :]
59
           left gini = gini index(left data)
60
           right gini = gini index(right data)
61
           total_gini += (len(left_data) * left_gini + len(right_data) * right_gini) / len(sorted_data)
62
       return total_gini / (len(sorted_data) - 1)
63
```

```
65 # Build decision tree classifier using the informations obtained
66 def build_tree(node, max_depth):
       if stopping_criterion(node, max_depth):
67
           return
68
69
       node.split_attr = best_split(node.data, node.attributes, node.target)
70
       for child_data in split_data(node.data, node.split_attr):
71
           child attributes = list(node.attributes)
72
           child_attributes.remove(node.split_attr)
73
           child = Node(child_data, child_attributes, node.target, node.depth + 1)
74
           node.children.append(child)
75
           build tree(child, max depth)
76
77
```

```
78 # LED on if gini exist, LED off if gini does not exist
79 def is_continuous_attribute(attr):
        continuous attributes = ["Applicant Income", "Coapplicant Income", "Loan Amount"]
80
        return attr in continuous_attributes
81
82
    led = machine.Pin(25, machine.Pin.OUT)
83
84
    def delay():
85
        for i in range(0, 195785):
86
87
             pass
88
    def response():
89
        response = sys.stdin.readline()
90
        if response == "\n":
91
92
             pass
03
    for attr in attributes:
94
        response()
95
        if is continuous attribute(attr):
97
            gini = 0
             led.off()
98
             print(f"Gini index for {attr}: {gini}")
99
100
             delay()
101
        else:
             gini = gini_index_for_attribute(data, attr)
102
103
             led.on()
             print(f"Gini index for {attr}: {gini}")
104
105
             delay()
            led.off()
106
        response()
107
108
109
```

Alternative Code

```
# Get the sorted indices of the target attribute values
sorted_indices = sorted(range(len(dataset[target_attribute])), key=lambda i: dataset[target_attribute][i])

for attribute in dataset:
    if attribute != target_attribute:
        # Initialize the attribute list for the current attribute
        values = [dataset[attribute][i] for i in sorted_indices]
        classes = [dataset[target_attribute][i] for i in sorted_indices]
        attribute_lists[attribute] = AttributeList(attribute, values, classes)
return attribute_lists
```

Result

Result

```
Shell ×
>>> %Run -c $EDITOR_CONTENT
 Gini index for Married: 0.4624609
 Gini index for Dependents: 0.4569524
 Gini index for Education: 0.4588546
 Gini index for Self Employed: 0.4560198
 Gini index for Applicant Income: 0
 Gini index for Coapplicant_Income: 0
 Gini index for Loan Amount: 0
 Gini index for Credit_History: 0.4034547
>>>
```

References

- Huacheng Zhang, Wu Xie, "Improvement of SLIQ Algorithm and its Application in Evaluation", Genetic and Evolutionary Computing 2009. WGEC '09. 3rd International Conference on, pp. 77-80, 2009.
- [2] Xie Wu, Huacheng Zhang, Huimin Zhang, "Study of comprehensive evaluation methoof undergraduates based on data mining", Intelligent Computing and Integrated Systems (ICISS) 2010 International Conference on, pp. 541-543, 2010.
- [3] Hongwen Yan, Rui Ma and Xiaojiao Tong, "SLIQ in data mining and application in the generation unit's bidding decision system of electricity market," 2005 International Pow Engineering
- [4] Mehta, M., Agrawal, R., Rissanen, J. (1996). SLIQ: A fast scalable classifier for data mining. In: Apers, P., Bouzeghoub, M., Gardarin, G. (eds) Advances in Database Technology — EDBT '96. EDBT 1996. Lecture Notes in Computer Science, vol 1057. Springer, Berlin, Heidelberg.
- [5] S. Sivagama Sundhari, "A knowledge discovery using decision tree by Gini coefficient 2011 International Conference on Business, Engineering and Industrial Applications, 2011, pp. 232-235.
- [6] N. Prasad, P. K. Reddy and M. M. Naidu, "A Novel Decision Tree Approach for the Prediction of Precipitation Using Entropy in SLIQ," 2013 UKSim 15th International Conference on Computer Modelling and Simulation, 2013, pp. 209-217
- [7] Hongwen Yan, Rui Ma and Xiaojiao Tong, "SLIQ in data mining and application in the generation unit's bidding decision system of electricity market," 2005 International Power Engineering Conference, 2005, pp. 1-137.
- [8] B. Chandra and V. P. Paul, "A Robust Algorithm for Classification Using Decision Trees," 2006 IEEE Conference on Cybernetics and Intelligent Systems, 2006, pp. 1-5

Demo

Thank You