

CS 301 – Intro to Data Mining

Algorithms for Constructing Rules from Coverings (continued)

- **PRISM** looked for a covering each time it needed to put together a part of a rule for one particular value of a decision attribute (i.e., class)

Ex: If ? then **Recommended Lenses** = hard

	Correctness
Age = young	2/8
...	
Astigmatism = yes	4/12
...	
Tear Production Rate = normal	4/12

Best is 4/12, so could pick either **Astigmatism** = yes or **Tear Production Rate** = normal

If **Astigmatism** = yes then **Recommended Lenses** = hard

Only correct for 4 of the 12 instances it covers (hardly “perfect”!), so try to add more conditions to the rule

If **Astigmatism** = yes and ? then **Recommended Lenses** = hard

	Correctness
Astigmatism = yes and Age = young	2/4
Astigmatism = yes and Age = pre-presbyopic	1/4
Astigmatism = yes and Age = presbyopic	1/4
Astigmatism = yes and Spectacle Prescription = myope	3/6
...	

Instead you can find one covering from which you can generate the rules for all values of the decision attribute

- **Finding all coverings for a decision attribute**

You might decide you like one covering better than another ☺

Let S be the set of all non-decision attributes

For every non-empty subset P of S compute P^*

where P^* is a partitioning of the instances of the dataset on some attributes such that if instances x_i and x_j are in the same block in P^* it means that they are indistinguishable in their values for the attributes in P

Ex: Decision attribute is f

	a	b	c	d	f	color1	color2
x1	0	L	0	L	0	B	W
x2	0	R	1	L	1	B	W
x3	0	L	0	L	0	W	B
x4	0	R	1	L	1	W	B
x5	1	R	0	L	2	B	W
x6	1	R	0	L	2	W	B
x7	2	S	2	H	3	B	W
x8	2	S	2	H	3	W	B

$$\{a\}^* = \{\{x_1, x_2, x_3, x_4\}, \{x_5, x_6\}, \{x_7, x_8\}\}$$

$$\{b\}^* = \{\{x_1, x_3\}, \{x_2, x_4, x_5, x_6\}, \{x_7, x_8\}\}$$

$$\{c\}^* = \{\{x_1, x_3, x_5, x_6\}, \{x_2, x_4\}, \{x_7, x_8\}\}$$

$$\{a, c\}^* = \{a, b\}^* = \{b, c\}^* = \{a, b, c, d\}^* = \{\{x_1, x_3\}, \{x_2, x_4\}, \{x_5, x_6\}, \{x_7, x_8\}\}$$

$$\{a, b, c, d, \text{color1}, \text{color2}\}^* = \{\{x_1\}, \{x_2\}, \{x_3\}, \{x_4\}, \{x_5\}, \{x_6\}, \{x_7\}, \{x_8\}\}$$

...

Later we're also going to need the partition for the decision attribute

$$\{f\}^* = \{\{x_1, x_3\}, \{x_2, x_4\}, \{x_5, x_6\}, \{x_7, x_8\}\}$$

Attribute dependency inequality:

Let P_1, P_2 be partitions

Then $P_1 \leq P_2$ if for each block B of P_1 there exists a block B' of P_2 such that B is a proper subset of B'

Ex: $\{\{X_1, X_3\}, \{X_2, X_4, X_5, X_6\}, \{X_7, X_8\}\} \leq \{\{X_1, X_3\}, \{X_2, X_4\}, \{X_5, X_6\}, \{X_7, X_8\}\}$ **yes/no?**

$\{\{X_1, X_3\}, \{X_2, X_4\}, \{X_5, X_6\}, \{X_7, X_8\}\} \leq \{\{X_1, X_3\}, \{X_2, X_4, X_5, X_6\}, \{X_7, X_8\}\}$ **yes/no?**

Covering:

Let S be the set of all non-decision attributes and let R be the set of decision attributes

P is a **covering** of R if:

- (1) P is a subset of S ,
- (2) $P^* \leq R^*$, and
- (3) P is minimal.

Ex: Which of the partitions computed earlier qualifies as a **covering** for $R = \{f\}$?

$\{f\}^* = \{\{X_1, X_3\}, \{X_2, X_4\}, \{X_5, X_6\}, \{X_7, X_8\}\}$ $S = \{a, b, c, d, \text{color1}, \text{color2}\}$

$\{a\}^* = \{\{X_1, X_2, X_3, X_4\}, \{X_5, X_6\}, \{X_7, X_8\}\}$ **yes/no?**

$\{b\}^* = \{\{X_1, X_3\}, \{X_2, X_4, X_5, X_6\}, \{X_7, X_8\}\}$ **yes/no?**

$\{c\}^* = \{\{X_1, X_3, X_5, X_6\}, \{X_2, X_4\}, \{X_7, X_8\}\}$ **yes/no?**

$\{a, c\}^* = \{\{X_1, X_3\}, \{X_2, X_4\}, \{X_5, X_6\}, \{X_7, X_8\}\}$ **yes/no?**

$\{a, b\}^* = \{\{X_1, X_3\}, \{X_2, X_4\}, \{X_5, X_6\}, \{X_7, X_8\}\}$ **yes/no?**

$\{b, c\}^* = \{\{X_1, X_3\}, \{X_2, X_4\}, \{X_5, X_6\}, \{X_7, X_8\}\}$ **yes/no?**

$\{a, b, c, d\}^* = \{\{X_1, X_3\}, \{X_2, X_4\}, \{X_5, X_6\}, \{X_7, X_8\}\}$ **yes/no?**

$\{a, b, c, d, \text{color1}, \text{color2}\}^* = \{\{X_1\}, \{X_2\}, \{X_3\}, \{X_4\}, \{X_5\}, \{X_6\}, \{X_7\}, \{X_8\}\}$ **yes/no?**

- **Finding (i.e., “inducing”) rules from coverings - RICO**

Pick the covering you prefer from the ones you found

initialize E to the set of all instances;

initialize rule set to empty;

while E contains instances do

 create rule that uses attribute values of first instance in E for each attribute
 in covering;

 add rule to rule set;

 remove instances in E covered by this rule;

end-while

Ex: If we had picked covering {a, c} what rule set would we get?

	a	b	c	d	f	color1	color2
x1	0	L	0	L	0	B	W
x2	0	R	1	L	1	B	W
x3	0	L	0	L	0	W	B
x4	0	R	1	L	1	W	B
x5	1	R	0	L	2	B	W
x6	1	R	0	L	2	W	B
x7	2	S	2	H	3	B	W
x8	2	S	2	H	3	W	B

If $a = 0$ and $c = 0$ then $f = 0$

If $a = 0$ and $c = 1$ then $f = 1$

If $a = 1$ and $c = 0$ then $f = 2$

If $a = 2$ and $c = 2$ then $f = 3$

Could any conditions be dropped in any of those rules?

If $a = 0$ and $c = 0$ then $f = 0$

If $a = 0$ and $c = 1$ then $f = 1$

If $a = 1$ and ~~$c = 0$~~ then $f = 2$

If ~~$a = 2$~~ and $c = 2$ then $f = 3$ OR If $a = 2$ and ~~$c = 2$~~ then $f = 3$

- **Essential attribute:** attribute that appears in every covering; *what is the significance of this???*
- **Some advantages to this algorithm:** (1) will always find at least one covering and (2) will always generate rules that are 100% correct

Ex: Decision attribute is **Play**

	Outlook	Temperature	Humidity	Windy	Play
x1	sunny	hot	high	FALSE	no
x2	sunny	hot	high	TRUE	no
x3	overcast	hot	high	FALSE	yes
x4	rainy	mild	high	FALSE	yes
x5	rainy	cool	normal	FALSE	yes
x6	rainy	cool	normal	TRUE	no
x7	overcast	cool	normal	TRUE	yes
x8	sunny	mild	high	FALSE	no
x9	sunny	cool	normal	FALSE	yes
x10	rainy	mild	normal	FALSE	yes
x11	sunny	mild	normal	TRUE	yes
x12	overcast	mild	high	TRUE	yes
x13	overcast	hot	normal	FALSE	yes
x14	rainy	mild	high	TRUE	no

Coverings are {**Outlook**, **Temperature**, **Windy**} and {**Outlook**, **Humidity**, **Windy**}

Rule set for covering {**Outlook**, **Temperature**, **Windy**}:

[[[sunny, hot, TRUE, no], 1], [[sunny, hot, FALSE, no], 1], [[sunny, mild, TRUE, yes], 1], [[sunny, mild, FALSE, no], 1], [[sunny, cool, FALSE, yes], 1], [[overcast, hot, FALSE, yes], 2], [[overcast, mild, TRUE, yes], 1], [[overcast, cool, TRUE, yes], 1], [[rainy, mild, TRUE, no], 1], [[rainy, mild, FALSE, yes], 2], [[rainy, cool, TRUE, no], 1], [[rainy, cool, FALSE, yes], 1]]

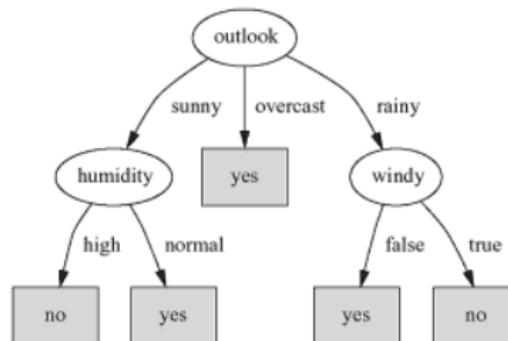
Here **Outlook** and **Windy** would be essential attributes

Without dropping conditions, we get 12 rules as compared to:

6 rules produced by **PRISM**

```
Prism rules
-----
If outlook = overcast then yes
If humidity = normal
  and windy = FALSE then yes
If temperature = mild
  and humidity = normal then yes
If outlook = rainy
  and windy = FALSE then yes
If outlook = sunny
  and humidity = high then no
If outlook = rainy
  and windy = TRUE then no
```

At most 2 decisions required in result produced by **ID3/J48**



Ex: Decision attribute is ***Recommended Lenses***

Table 1.1 Contact Lens Data				
Age	Spectacle Prescription	Astigmatism	Tear Production Rate	Recommended Lenses
young	myope	no	reduced	none
young	myope	no	normal	soft
young	myope	yes	reduced	none
young	myope	yes	normal	hard
young	hypermetrope	no	reduced	none
young	hypermetrope	no	normal	soft
young	hypermetrope	yes	reduced	none
young	hypermetrope	yes	normal	hard
pre-presbyopic	myope	no	reduced	none
pre-presbyopic	myope	no	normal	soft
pre-presbyopic	myope	yes	reduced	none
pre-presbyopic	myope	yes	normal	hard
pre-presbyopic	hypermetrope	no	reduced	none
pre-presbyopic	hypermetrope	no	normal	soft
pre-presbyopic	hypermetrope	yes	reduced	none
pre-presbyopic	hypermetrope	yes	normal	none
presbyopic	myope	no	reduced	none
presbyopic	myope	no	normal	none
presbyopic	myope	yes	reduced	none
presbyopic	myope	yes	normal	hard
presbyopic	hypermetrope	no	reduced	none
presbyopic	hypermetrope	no	normal	soft
presbyopic	hypermetrope	yes	reduced	none
presbyopic	hypermetrope	yes	normal	none

Only covering we would find for this dataset is the entire set of attributes, with a rule for each instance

A downside to using this particular approach ☹