Data Mining

Part 3

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Output: Knowledge representation

- Decision tables
- Decision trees
- Decision rules
- Association rules
- Rules with exceptions
- Rules involving relations
- Linear regression
- Trees for numeric prediction
- Instance-based representation
- Clusters

Output: representing structural patterns

Many different ways of representing patterns

Decision trees, rules, instance-based, …

Also called "knowledge" representation

Representation determines inference method

Understanding the output is the key to understanding the underlying learning methods

Different types of output for different learning problems (e.g. classification, regression, …)

Decision tables

Simplest way of representing output:

Use the same format as input!

Decision table for the weather problem:

Outlook	Humidity	Play
Sunny	High	No
Sunny	Normal	Yes
Overcast	High	Yes
Overcast	Normal	Yes
Rainy	High	No
Rainy	Normal	No

Main problem: selecting the right attributes

Decision trees

"Divide-and-conquer" approach produces tree

Nodes involve testing a particular attribute

Usually, attribute value is compared to constant

Other possibilities:

- Comparing values of two attributes
- Using a function of one or more attributes

Leaves assign classification, set of classifications, or probability distribution to instances

Unknown instance is routed down the tree

Nominal and numeric attributes

Nominal:

- number of children usually equal to number values
- ⇒ attribute won't get tested more than once
- Other possibility: division into two subsets

Numeric:

- test whether value is greater or less than constant
- ⇒ attribute may get tested several times
- Other possibility: three-way split (or multi-way split)
  - Integer: *less than, equal to, greater than*
  - Real: *below, within, above*

Missing values

Does absence of value have some significance?

Yes ⇒ "missing" is a separate value

No ⇒ "missing" must be treated in a special way

- Solution A: assign instance to most popular branch
- Solution B: split instance into pieces
  - Pieces receive weight according to fraction of training instances that go down each branch
  - Classifications from leave nodes are combined using the weights that have percolated to them

Classification rules

Popular alternative to decision trees

Antecedent (pre-condition): a series of tests (just like the tests at the nodes of a decision tree)

Tests are usually logically ANDed together (but may also be general logical expressions)

Consequent (conclusion): classes, set of classes, or probability distribution assigned by rule

Individual rules are often logically ORed together

- Conflicts arise if different conclusions apply

From trees to rules

Easy: converting a tree into a set of rules

- One rule for each leaf:
  - Antecedent contains a condition for every node on the path from the root to the leaf
  - Consequent is class assigned by the leaf

Produces rules that are unambiguous

- Doesn't matter in which order they are executed

But: resulting rules are unnecessarily complex

- Pruning to remove redundant tests/rules

From rules to trees

More difficult: transforming a rule set into a tree

- Tree cannot easily express disjunction between rules

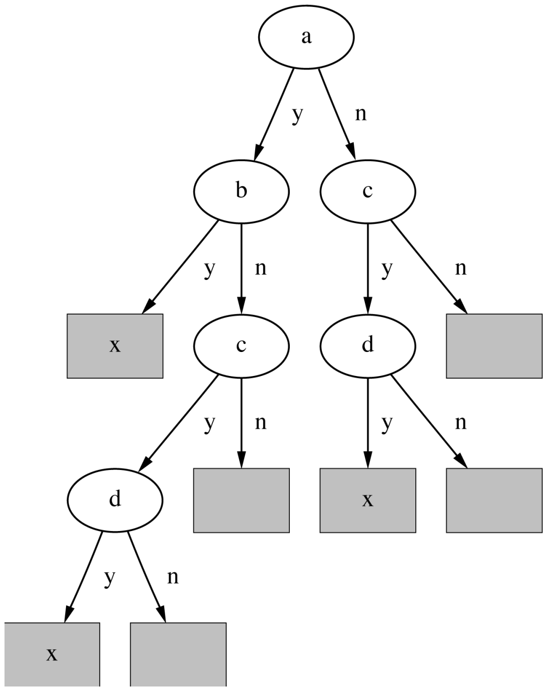
Example: rules which test different attributes

```
If a and b then x
If c and d then x
```

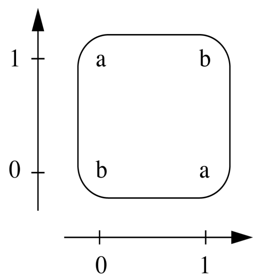
Symmetry needs to be broken

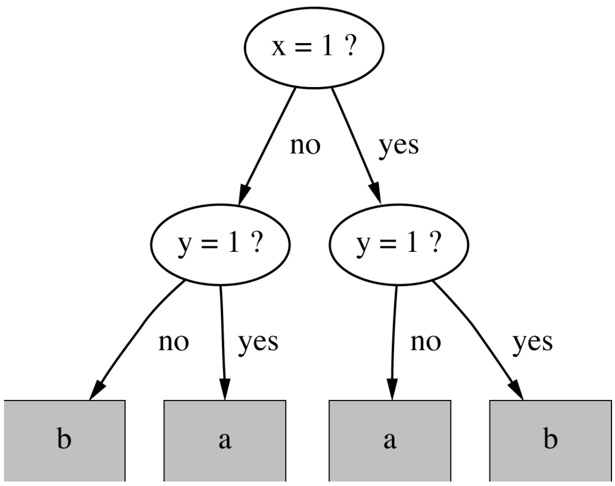
Corresponding tree contains identical subtrees (⇒ "replicated subtree problem")

A tree for a simple disjunction



The exclusive-or problem

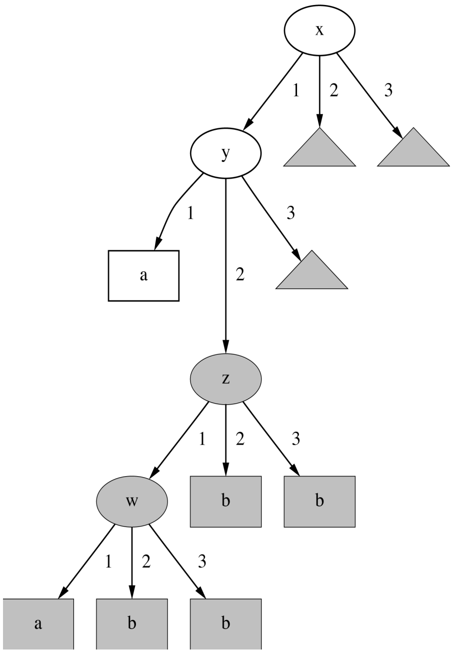





```
If x = 1 and y = 0
   then class = a
If x = 0 and y = 1
   then class = a
If x = 0 and y = 0
   then class = b
If x = 1 and y = 1
   then class = b
```

A tree with a replicated subtree

```
If x = 1 and y = 1
   then class = a
If z = 1 and w = 1
   then class = a
Otherwise class = b
```



"Nuggets" of knowledge

Are rules independent pieces of knowledge? (It seems easy to add a rule to an existing rule base.)

Problem: ignores how rules are executed

Two ways of executing a rule set:

- Ordered set of rules ("decision list")
  - Order is important for interpretation
- Unordered set of rules
  - Rules may overlap and lead to different conclusions for the same instance

Interpreting rules

What if two or more rules conflict?

- Give no conclusion at all?
- Go with rule that is most popular on training data?
- …

What if no rule applies to a test instance?

- Give no conclusion at all?
- Go with class that is most frequent in training data?
- …

Special case: boolean class

Assumption: if instance does not belong to class "yes", it belongs to class "no"

Trick: only learn rules for class "yes" and use default rule for "no"

```
If x = 1 and y = 1 then class = a
If z = 1 and w = 1 then class = a
Otherwise class = b
```

Order of rules is not important. No conflicts!

Rule can be written in *disjunctive normal form*

Association rules

Association rules…

… can predict any attribute and combinations of attributes

… are not intended to be used together as a set

Problem: immense number of possible associations

Output needs to be restricted to show only the most predictive associations ⇒ only those with high *support* and high *confidence*

Support and confidence of a rule

Support: number of instances predicted correctly

Confidence: number of correct predictions, as proportion of all instances that rule applies to

Example: 4 cool days with normal humidity

```
If temperature = cool then humidity = normal
```

Support = 4, confidence = 100%

Normally: minimum support and confidence pre-specified (e.g. 58 rules with support ≥ 2 and confidence ≥ 95% for weather data)

Interpreting association rules

Interpretation is not obvious:

```
If windy = false and play = no then outlook = sunny
                                and humidity = high
```

is *not* the same as

```
If windy = false and play = no then outlook = sunny
If windy = false and play = no then humidity = high
```

It means that the following also holds:

```
If humidity = high and windy = false and play = no
    then outlook = sunny
```


Rules with exceptions

Idea: allow rules to have *exceptions*

Example: rule for iris data

```
If petal-length ≥ 2.45 and petal-length < 4.45 then Iris-versicolor
```

New instance:

Sepal length	Sepal width	Petal length	Petal width	Type
5.1	3.5	2.6	0.2	Iris-setosa

Modified rule:

```
If petal-length ≥ 2.45 and petal-length < 4.45 then Iris-versicolor
  EXCEPT if petal-width < 1.0 then Iris-setosa
```

A more complex example

Exceptions to exceptions to exceptions …

```
default: Iris-setosa
except if petal-length ≥ 2.45 and petal-length < 5.355
          and petal-width < 1.75
       then Iris-versicolor
            except if petal-length ≥ 4.95 and petal-width < 1.55
                   then Iris-virginica
                   else if sepal-length < 4.95 and sepal-width ≥ 2.45
                        then Iris-virginica
       else if petal-length ≥ 3.35
            then Iris-virginica
                 except if petal-length < 4.85 and sepal-length < 5.95
                        then Iris-versicolor
```


Advantages of using exceptions

- Rules can be updated incrementally
  - Easy to incorporate new data
  - Easy to incorporate domain knowledge
- People often think in terms of exceptions
- Each conclusion can be considered just in the context of rules and exceptions that lead to it
  - Locality property is important for understanding large rule sets
  - "Normal" rule sets don't offer this advantage

More on exceptions

`Default...except if...then...`

is logically equivalent to

`if...then...else`

(where the else specifies what the default did)

But: exceptions offer a psychological advantage

- Assumption: defaults and tests early on apply more widely than exceptions further down
- Exceptions reflect special cases

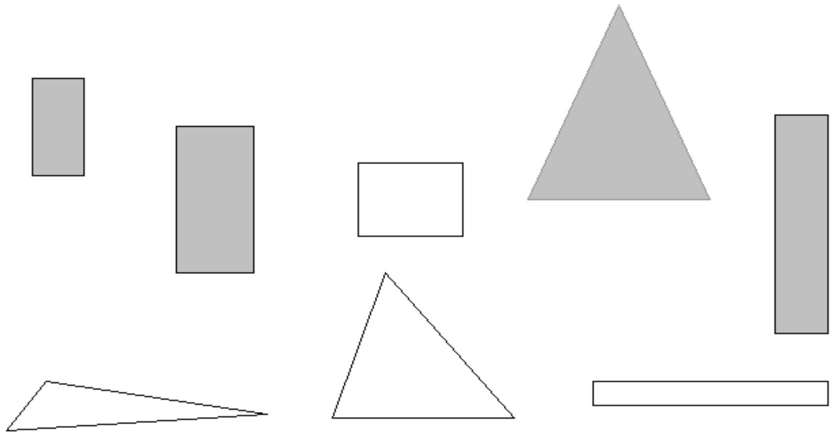
Rules involving relations

- So far: all rules involved comparing an attribute-value to a constant (e.g. temperature < 45)
- These rules are called "propositional" because they have the same expressive power as propositional logic
- What if problem involves relationships between examples (e.g. family tree problem from above)?
  - Can't be expressed with propositional rules
  - More expressive representation required

The shapes problem

Target concept: *standing up*

Shaded: *standing*
Unshaded: *lying*



A propositional solution

Width	Height	Sides	Class
2	4	4	Standing
3	6	4	Standing
4	3	4	Lying
7	8	3	Standing
7	6	3	Lying
2	9	4	Standing
9	1	4	Lying
10	2	3	Lying

```
If width ≥ 3.5 and height < 7.0
   then lying
If height ≥ 3.5 then standing
```

A relational solution

Comparing attributes with each other

```
If width > height then lying
If height > width then standing
```

Generalizes better to new data

Standard relations: =, <, >

But: learning relational rules is costly

Simple solution: add extra attributes
(e.g. a binary attribute *is width < height?*)

Rules with variables

Using variables and multiple relations:

```
If height_and_width_of(x,h,w) and h > w
   then standing(x)
```

The top of a tower of blocks is standing:

```
If height_and_width_of(x,h,w) and h > w
     and is_top_of(y,x)
   then standing(x)
```

The whole tower is standing:

```
If is_top_of(x,z) and
   height_and_width_of(z,h,w) and h > w
   and is_rest_of(x,y)and standing(y)
   then standing(x)
If empty(x) then standing(x)
```

Recursive definition!

Inductive logic programming

Recursive definition can be seen as logic program

Techniques for learning logic programs stem from the area of "inductive logic programming" (ILP)

But: recursive definitions are hard to learn

- Also: few practical problems require recursion
- Thus: many ILP techniques are restricted to non-recursive definitions to make learning easier

Trees for numeric prediction

Regression: the process of computing an expression that predicts a numeric quantity

Regression tree: "decision tree" where each leaf predicts a numeric quantity

- Predicted value is average value of training instances that reach the leaf

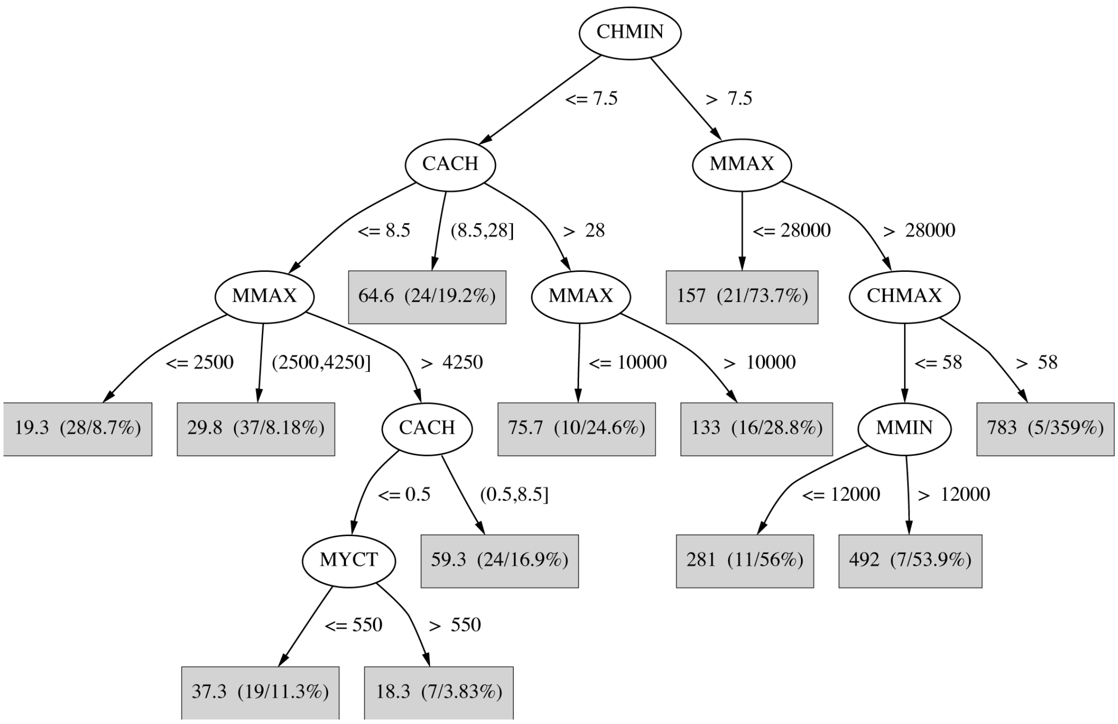
Model tree: "regression tree" with linear regression models at the leaf nodes

- Linear patches approximate continuous function

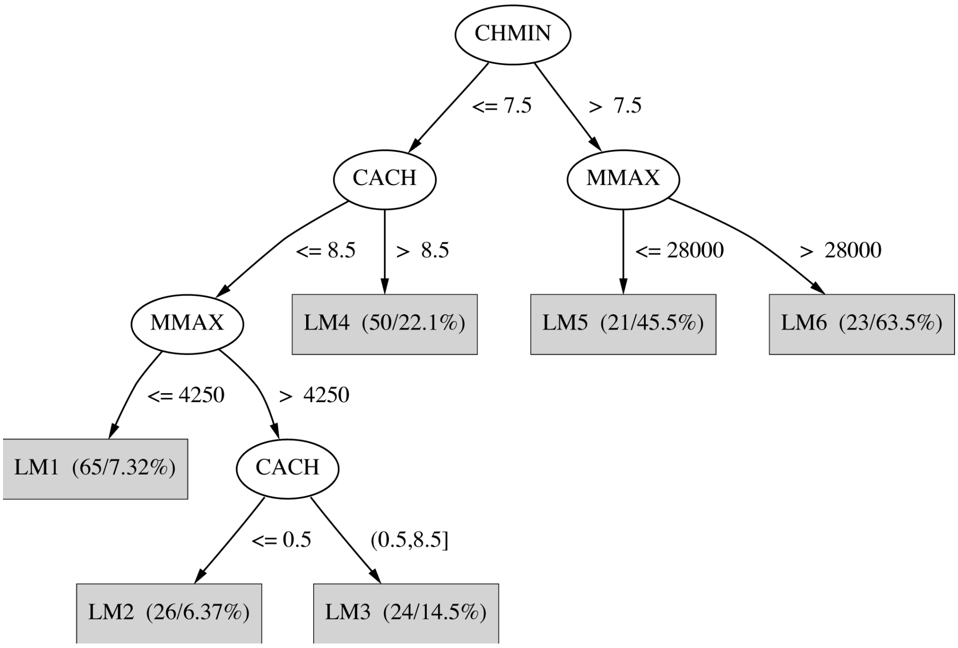
Linear regression for the CPU data

```
PRP =
   - 56.1
    + 0.049 MYCT
    + 0.015 MMIN
    + 0.006 MMAX
    + 0.630 CACH
    - 0.270 CHMIN
    + 1.46  CHMAX
```


Regression tree for the CPU data



Model tree for the CPU data



Instance-based representation

- Simplest form of learning: *rote learning*
  - Training instances are searched for instance that most closely resembles new instance
  - The instances themselves represent the knowledge
  - Also called *instance-based* learning
- Similarity function defines what's "learned"
- Instance-based learning is *lazy* learning
- Methods: *nearest-neighbor, k-nearest-neighbor, …*

The distance function

Simplest case: one numeric attribute

- Distance is the difference between the two attribute values involved (or a function thereof)

Several numeric attributes: normally, Euclidean distance is used and attributes are normalized

Nominal attributes: distance is set to 1 if values are different, 0 if they are equal

Are all attributes equally important?

- Weighting the attributes might be necessary

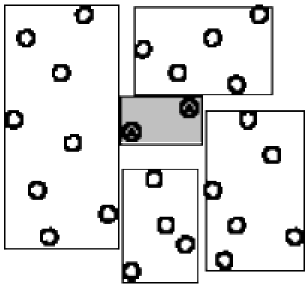
Learning prototypes

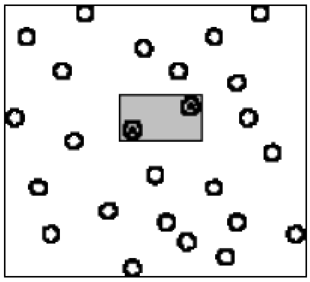
Only those instances involved in a decision need to be stored

Noisy instances should be filtered out

Idea: only use *prototypical* examples

Rectangular generalizations





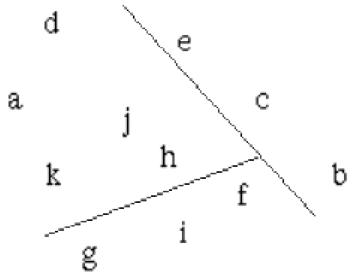
Nearest-neighbor rule is used outside rectangles

Rectangles are rules! (But they can be more conservative than “normal” rules.)

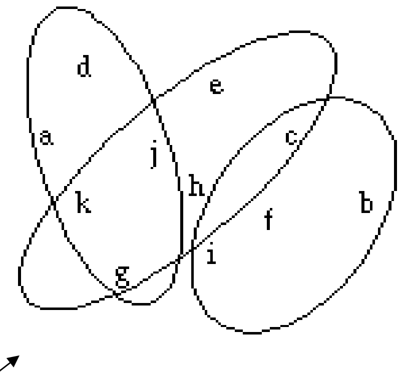
Nested rectangles are rules with exceptions

Representing clusters I

Simple 2-D representation



Venn diagram



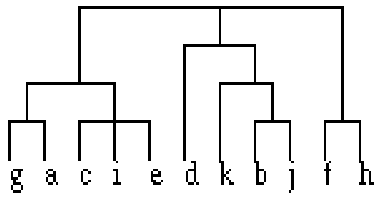
Overlapping clusters

Representing clusters II

Probabilistic assignment

	1	2	3
a	0.4	0.1	0.5
b	0.1	0.8	0.1
c	0.3	0.3	0.4
d	0.1	0.1	0.8
e	0.4	0.2	0.4
f	0.1	0.4	0.5
g	0.7	0.2	0.1
h	0.5	0.4	0.1
…			

Dendrogram



NB: dendron is the Greek word for tree