Rule Based Classifiers

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Rule-Based Classifier

- Classify records by using a collection of "if...then..." rules
- Rule: $(Condition) \rightarrow y$
 - where
 - Condition is a conjunctions of attributes
 - y is the class label
 - LHS: rule antecedent or condition
 - RHS: rule consequent
 - Examples of classification rules:
 - (Blood Type=Warm) ∧ (Lay Eggs=Yes) → Birds
 - (Taxable Income < 50K) ∧ (Refund=Yes) → Evade=No

Rule-based Classifier (Example)

Name	Blood Type	Give Birth	Can Fly	Live in Water	Class
human	warm	yes	no	no	mammals
python	cold	no	no	no	reptiles
salmon	cold	no	no	yes	fishes
whale	warm	yes	no	yes	mammals
frog	cold	no	no	sometimes	amphibians
komodo	cold	no	no	no	reptiles
bat	warm	yes	yes	no	mammals
pigeon	warm	no	yes	no	birds
cat	warm	yes	no	no	mammals
leopard shark	cold	yes	no	yes	fishes
turtle	cold	no	no	sometimes	reptiles
penguin	warm	no	no	sometimes	birds
porcupine	warm	yes	no	no	mammals
eel	cold	no	no	yes	fishes
salamander	cold	no	no	sometimes	amphibians
gila monster	cold	no	no	no	reptiles
platypus	warm	no	no	no	mammals
owl	warm	no	yes	no	birds
dolphin	warm	yes	no	yes	mammals
eagle	warm	no	yes	no	birds

R1: (Give Birth = no) \land (Can Fly = yes) \rightarrow Birds

R2: (Give Birth = no) \land (Live in Water = yes) \rightarrow Fishes

R3: (Give Birth = yes) ∧ (Blood Type = warm) → Mammals

R4: (Give Birth = no) \land (Can Fly = no) \rightarrow Reptiles



Application of Rule-Based Classifier

 A rule r covers an instance x if the attributes of the instance satisfy the condition of the rule

R1: (Give Birth = no) \land (Can Fly = yes) \rightarrow Birds

R2: (Give Birth = no) \land (Live in Water = yes) \rightarrow Fishes

R3: (Give Birth = yes) \land (Blood Type = warm) \rightarrow Mammals

R4: (Give Birth = no) \land (Can Fly = no) \rightarrow Reptiles

R5: (Live in Water = sometimes) → Amphibians

Name	Blood Type	Give Birth	Can Fly	Live in Water	Class
hawk	warm	no	yes	no	?
grizzly bear	warm	yes	no	no	?

The rule R1 covers a hawk => Bird

The rule R3 covers the grizzly bear => Mammal

Rule Coverage and Accuracy

- Coverage of a rule:
 - Fraction of records that satisfy the antecedent of a rule
- Accuracy of a rule:
 - Fraction of records that satisfy both the antecedent and consequent of a rule

Tid	Refund	Marital Status	Taxable Income	Class
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

(Status=Single) → No Coverage = 40%, Accuracy = 50%

How does Rule-based Classifier Work?

R1: (Give Birth = no) \land (Can Fly = yes) \rightarrow Birds

R2: (Give Birth = no) \land (Live in Water = yes) \rightarrow Fishes

R3: (Give Birth = yes) \land (Blood Type = warm) \rightarrow Mammals

R4: (Give Birth = no) \land (Can Fly = no) \rightarrow Reptiles

R5: (Live in Water = sometimes) → Amphibians

Name	Blood Type	Give Birth	Can Fly	Live in Water	Class
lemur	warm	yes	no	no	?
turtle	cold	no	no	sometimes	?
dogfish shark	cold	yes	no	yes	?

A lemur triggers rule R3, so it is classified as a mammal

A turtle triggers both R4 and R5

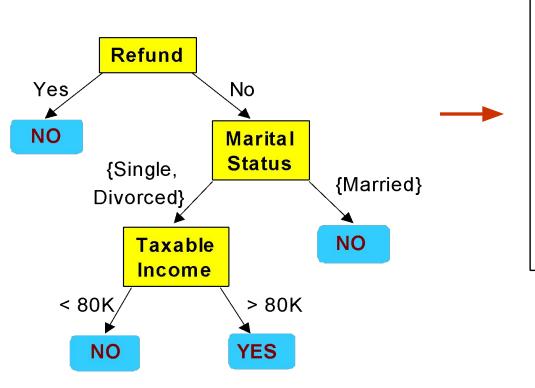
A dogfish shark triggers none of the rules

Characteristics of Rule-Based Classifier

- Mutually exclusive rules
 - Classifier contains mutually exclusive rules if the rules are independent of each other
 - Every record is covered by at most one rule

- Exhaustive rules
 - Classifier has exhaustive coverage if it accounts for every possible combination of attribute values
 - Each record is covered by at least one rule

From Decision Trees To Rules



Classification Rules

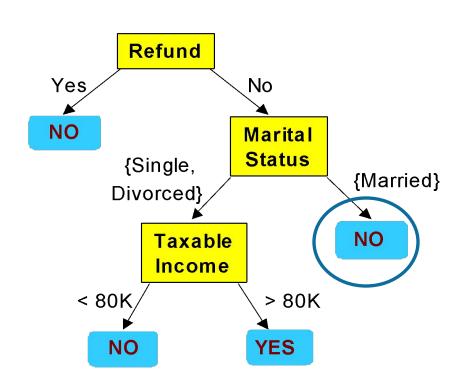
(Refund=Yes) ==> No

(Refund=No, Marital Status={Single,Divorced}, Taxable Income<80K) ==> No

(Refund=No, Marital Status={Single,Divorced}, Taxable Income>80K) ==> Yes

(Refund=No, Marital Status={Married}) ==> No

Rules Can Be Simplified



Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Initial Rule: (Refund=No) ∧ (Status=Married) → No

Simplified Rule: (Status=Married) → No



Ordered Rule Set

- Rules are rank ordered according to their priority
 - An ordered rule set is known as a decision list
- When a test record is presented to the classifier
 - It is assigned to the class label of the highest ranked rule it has triggered
 - If none of the rules fired, it is assigned to the default class.

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R1: (Give Birth = no) \land (Can Fly = yes) \rightarrow Birds
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R2: (Give Birth = no) \land (Live in Water = yes) \rightarrow Fishes

R3: (Give Birth = yes) ∧ (Blood Type = warm) → Mammals

R4: (Give Birth = no) \land (Can Fly = no) \rightarrow Reptiles

R5: (Live in Water = sometimes) → Amphibians

Name	Blood Type	Give Birth	Can Fly	Live in Water	Class
turtle	cold	no	no	sometimes	?

Rule Ordering Schemes

- Size based ordering
 - High priority to the rules with toughest requirement
 - Toughness is measured by the size of antecedent
- Rule-based ordering
 - Individual rules are ranked based on their quality, i.e., accuracy, coverage, size and advice from the domain experts.
- Class-based ordering
 - Priority to the rules with most prevalent classes or most rare classes

Building Classification Rules

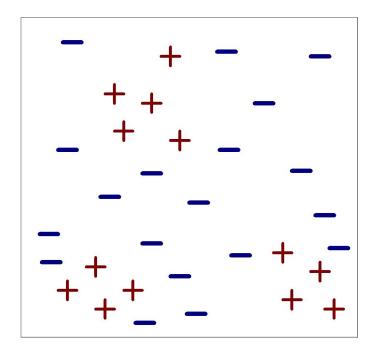
- Direct Method:
 - Extract rules directly from data
 - e.g.: RIPPER, CN2, Holte's 1R

- Indirect Method:
 - Extract rules from other classification models (e.g. decision trees, neural networks, etc).
 - e.g: C4.5rules

Direct Method: Sequential Covering

- Start from an empty rule
- Grow a rule using the Learn-One-Rule function
- 3. Remove training records covered by the rule
- Repeat Step (2) and (3) until stopping criterion is met

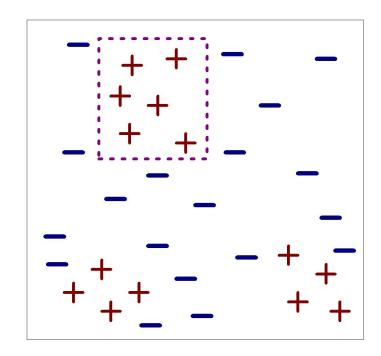
Example of Sequential Covering



(i) Original Data

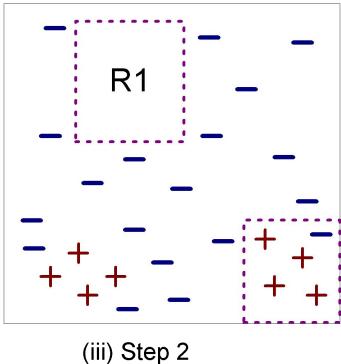
Example of Sequential Covering

(i) Original Data

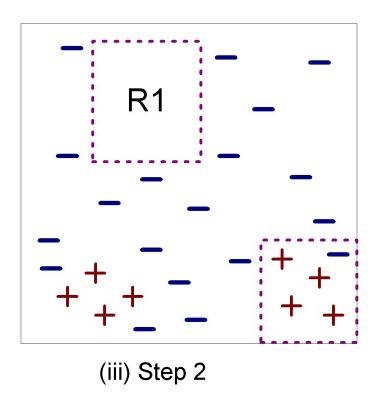


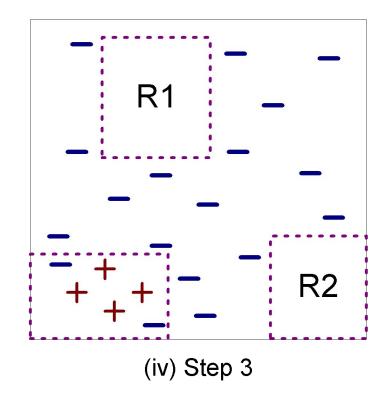
(ii) Step 1

Example of Sequential Covering...



Example of Sequential Covering...





Aspects of Sequential Covering

Rule Growing

Instance Elimination

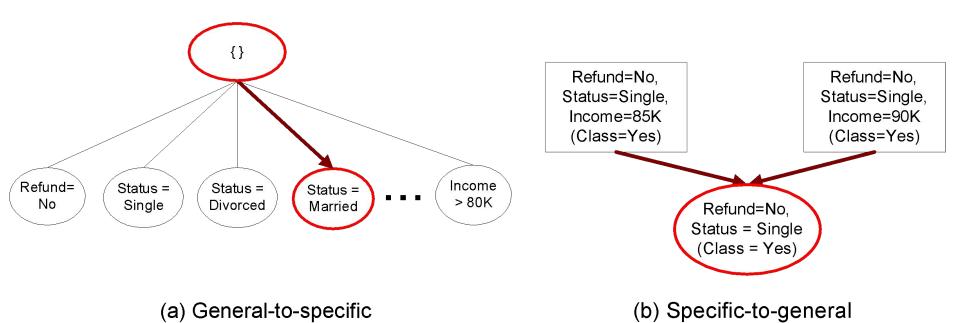
Rule Evaluation

Stopping Criterion

Rule Pruning

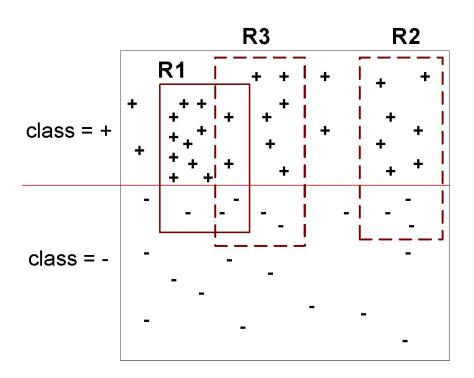
Rule Growing

Two common strategies



Instance Elimination

- Why do we need to eliminate instances?
 - Otherwise, the next rule is identical to previous rule
- Why do we remove positive instances?
 - Ensure that the next rule is different
- Why do we remove negative instances?
 - Prevent underestimating accuracy of rule
 - Compare rules R2 and R3 in the diagram



Rule Evaluation

Metrics:

- Accuracy =
$$\frac{n_c}{n}$$

- Laplace =
$$\frac{n_c + 1}{n + k}$$

n : Number of instances covered by rule

 n_c : Number of instances correctly covered by rule

k: Number of classes

p : Prior probability

Stopping Criterion and Rule Pruning

- Stopping criterion
 - Compute the gain
 - If gain is not significant, discard the new rule
- Rule Pruning
 - Similar to post-pruning of decision trees
 - Reduced Error Pruning:
 - Remove one of the conjuncts in the rule
 - Compare error rate on validation set before and after pruning
 - If error improves, prune the conjunct

Summary of Direct Method

- Grow a single rule
- Remove Instances from rule

- Prune the rule (if necessary)
- Add rule to Current Rule Set

Repeat