Rule-Based Classification

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Local vs. Global Rule learning

Local Rule Discovery

  - Find a rule that allows to make predictions for some examples
- Techniques:
  - Association Rule Discovery
  - Subgroup Discovery
  - ...

Global Rule Learning

  - Find a rule set with which we can make a prediction for all examples
- Techniques:
  - Decision Tree Learning / Divide-And-Conquer
  - Covering / Separate-And-Conquer
  - Weighted Covering
  - Classification by Association Rule Discovery
  - Statistical Rule Learning
  - ...

Local Patterns and Covering

- Covering is a simple, proto-typical strategy for constructing a global theory out of local patterns

```
function COVERING(Examples)

# initialize the classifier
GlobalClassifier ← ∅

# loop until all examples are covered
while Examples ≠ ∅

    # find the best local pattern
    LocalPattern ← FINDBESTLOCALPATTERN(Examples)

    # add the local pattern to the classifier
    GlobalClassifier ← GlobalClassifier ∪ LocalPattern

    # remove the covered examples
    Examples ← Examples \ COVERED(LocalPattern,Examples)

return GlobalClassifier
```

Key Problem:
- What is the best local pattern?

What is the Best Local Pattern?

- We have a global requirement...
  - We want a rule set that is as accurate as possible
- ... that needs to be translated into local constraints.

→ What local properties are good for achieving the global requirement?

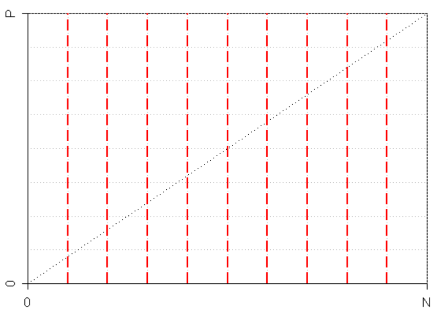
- class probability close to 1?
- class probability different from prior probability?
- coverage of the pattern?
- size of the pattern?
- ...

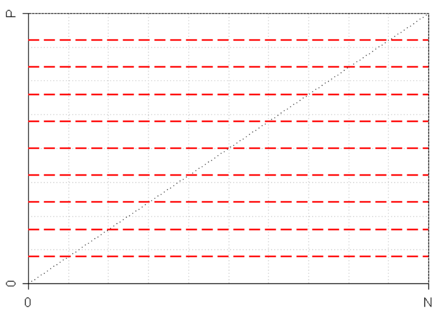
- Typically decided by a single rule learning heuristic / rule evaluation metric

What is measured by a Rule Learning Heuristic?

- Rule learning heuristics focus on good discrimination between positive and negative examples
  - Consistency:
    - cover few negative examples

Coverage:
cover many positive examples





- **Commonly used heuristics**
  - information gain, m-Estimate, weighted relative accuracy / Klösgen measures, correlation, ...
  - Study of trade-off between consistency and coverage in many popular rule learning heuristics (Janssen & Fürnkranz, submitted to MLJ-08)

What should be measured by a Rule Learning Heuristics?

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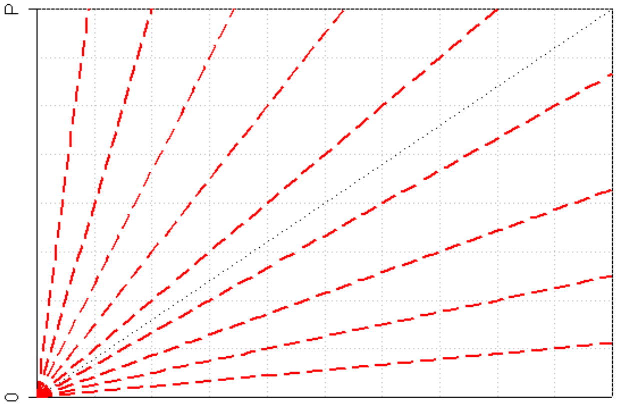
- Discrimination
  - How good are the positive examples separated from the negative examples?
- Completeness
  - How many positive examples are covered?
- Gain
  - How good is the rule in comparison to other rules (e.g., default rule, predecessor rules)?
- Novelty
  - How different is the rule from known or previously found rules?
- Utility
  - How good / useful will be the local pattern in a team with other patterns?
- Bias
  - How will the quality estimate change on new examples?
- Potential
  - How close is the rule to a good rule?

Discrimination

- How good are the positive examples separated from the negative examples?

- Typically ensured ensured by some sort of purity measure
  - e.g., precision $h_{Prec} = \frac{p}{p+n}$



- Most other measures try to achieve different goals at the same time!
  - e.g., Laplace / m-Estimate
    → bias correction and coverage

Completeness

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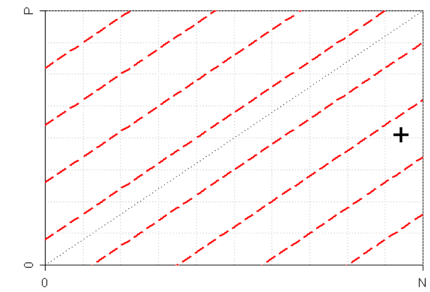
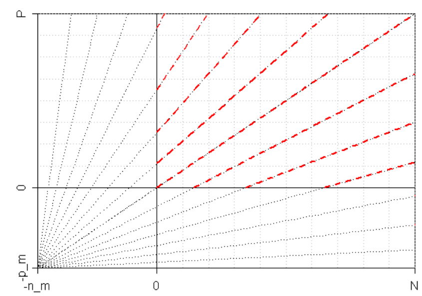
- How many positive examples are covered?

- Can be maximized in different ways
  - directly
    - include an explicit term that captures coverage
      - weighted relative accuracy $$h_{WRA} = \frac{p+n}{P+N}\left(\frac{p}{p+n} - \frac{P}{P+N}\right)$$
      - information gain $$h_{foil} = -p\left(\log_2 c - \log_2 \frac{p}{p+n}\right)$$





  - indirectly
    - implicit biases towards coverage
    - e.g.. Laplace or m-Estimate $$h_{Lap} = \frac{p+1}{p+n+2}$$
  - algorithmically
    - the covering loop makes sure that successive rules cover at least one new examples
    - can also be found, e.g., in many classification by association algorithms

Gain

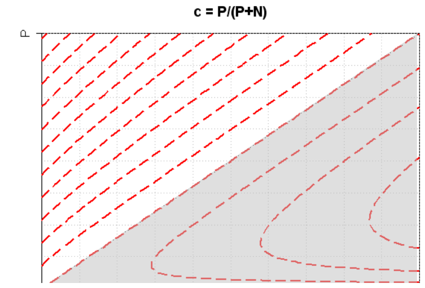
- How good is the rule in comparison to other rules?

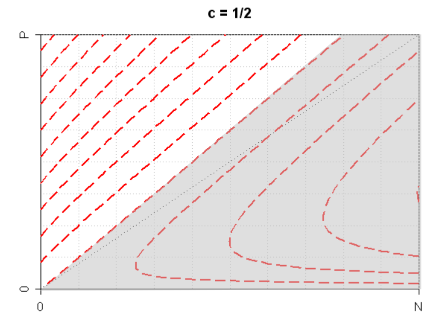
- Can be found in various heuristics
  - information gain compares to predecessor rule

$$h_{foil} = -p\left(\log_2 \frac{p'}{p'+n'} - \log_2 \frac{p}{p+n}\right)$$

  - weighted relative accuracy compares to default rule

$$h_{WRA} = \frac{p+n}{P+N}\left(\frac{p}{p+n} - \frac{P}{P+N}\right)$$





  - Lift / Leverage compare to a rule with empty body

$$h_{lift} = \frac{confidence(A \rightarrow B)}{confidence(\rightarrow B)} \qquad h_{levarage} = confidence(\rightarrow B) - confidence(A \rightarrow B)$$

  - Various concepts in association rule discovery
    - e.g., prune a condition if it doing so does not change the support
    - e.g., closed itemsets / rules

Novelty

- How different is the rule from known or previously found rules?

- Novelty is an important criterion for local pattern discovery by itself
  - part of the classifical definition of Knowledge Discovery by Fayyad et al.
  - however, difficult to formalize what is known

- In the context of global pattern discovery, the covering loop can be used to ensure that new patterns are found
  - the knowledge of the past is implicitly handled by removing the examples that are covered by known rules
- trade-off between novelty and other criteria can be realized by weighted covering
  - instead of entirely removing covered examples, only reduce their weight
  - has also been used for local pattern discovery (e.g., Lavrac et al.)

(Global) Utility

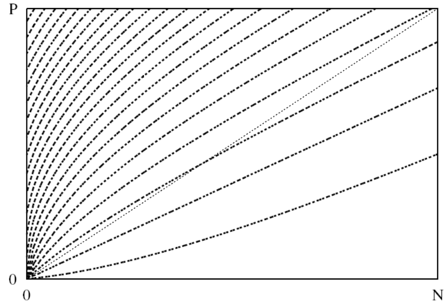
- How good / useful will be the local pattern in a team with other patterns?

- The covering loop only takes care of the past (novelty)
  - We also should consider how well the remaining examples will be covered by future rules
- The future is tried to be captured by some heuristics, in particular in decision trees
  - rule learning heuristics typically only consider the examples covered by the current rule
  - decision tree heuristics try to optimize all branches / rules simultaneously
  - Foil's information gain heuristic vs. C4.5's information gain
- Ripper's optimization loop
  - repeatedly try to re-learn a rule in the context of all other rules
- Pattern team selection heuristics
  - (Knobbe et al., Bringmann & Zimmermann, Rückert)

Bias

- How will the quality estimate change on new examples?

- Various works on estimating the out-of-sample precision/confidence/etc. of a local pattern
  - statistical
    - modeling the distribution of local patterns (Scheffer, IDAJ 05)
    - correct optimistic evaluations (Mozina et al. ECML-06)
  - meta-learning
    - trying to predict the performance of a rule on an independent test set (Janssen & Fürnkranz, ICDM-07)



  - pruning / evaluation on a separate pruning set
    - I-REP (Fürnkranz & Widmer 1994), Ripper (Cohen 1995) for classification rules
    - recently also proposed for local pattern evaluation (Webb, MLJ 2008)

Potential

- How close is the rule to a good rule?

- If exhaustive search is not feasible, heuristic search might be an option
  - Typically, heuristic search algorithms evaluate candidate patterns by their quality according to some rule learning heuristic
- We need a clear formulation as a search problem
  - do not evaluate the quality of the rule
  - but how close it gets us to the goal (a high-quality rule)
- Approaches
  - use bounds to bound the quality function
    - optimistic pruning (Webb, Zimmermann et al.)
      - assume that the best refinement of the rule will cover all positives and no negatives
      - if not better → prune
  - reinforcement learning to learn a function for the search problem
    - preliminary (bad) results

Conclusion

- Inducing good Rule-Based Classifiers is still a not very well understood problem
  - despite decades of research
- Various algorithms are known to perform well
  - but their solutions are ad hoc and not very principled
- Typical rule learning heuristics address (too) many problems at once
  - maybe trying to understand each of them separately is a first step for understanding their interplay
- Rule-Based Classification is not an old hat!