RULES-6: a simple rule induction algorithm for handling large data sets

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RULe Extraction System

Version 6

RULES algorithm family

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Deveoped over 20 years by D.T. Pham et al.

1:	Pham and Aksoy	(93)
2:	Pham and Aksoy	(95)
3:	Pham and Aksoy	(95)
3+	Pham and Dimov	(97)
4:	Pham and Dimov	(97)
5:	Pham, Bigot and Dimov	(03)
F:	Pham, Bigot and Dimov	(06)
6:	Pham and Afify	(05)
7:	Pham and Shehzad	(10)
8:	Pham and Pham	(12)

RULES-3 Plus - Problems

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Complete and consistent on training data

- Overfitting
- Noise

H measure is complex and not accurate enough

Equal-width discretisation is inefficient

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Inductive seperate and conquer rule set learning

```
RuleSet = ∅
While any example in TrainingSet is not covered
    s = any uncovered example (seed)
    InduceRule(s, TrainingSet, BeamWidth)
    Mark examples covered by Rule as covered
    RuleSet = RuleSet ∪ {Rule}
Return RuleSet
```

InduceOneRule(s, TrainingSet, BeamWidth: w)

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pruned general to specific beam search

PartialRules = NewPartialRules = $\varnothing$
BestRule = most general rule (no conditions)
PartialRules = PartialRules $\cup$ {BestRule}
While (PartialRules $\neq \varnothing$)
    $\forall Rule \in PartialRules$:
        Specialise(Rule, s) $\Rightarrow$ NewPartialRules, BestRule
    Prune rules that cannot improve from NewPartialRules
    $\forall Rule \in NewPartialRules$:
        Rule.ValidValues -= Parent(Rule).InvalidValues
    PartialRules = w best Rules from NewPartialRules (no duplicates)
Return BestRule

BeamSearch

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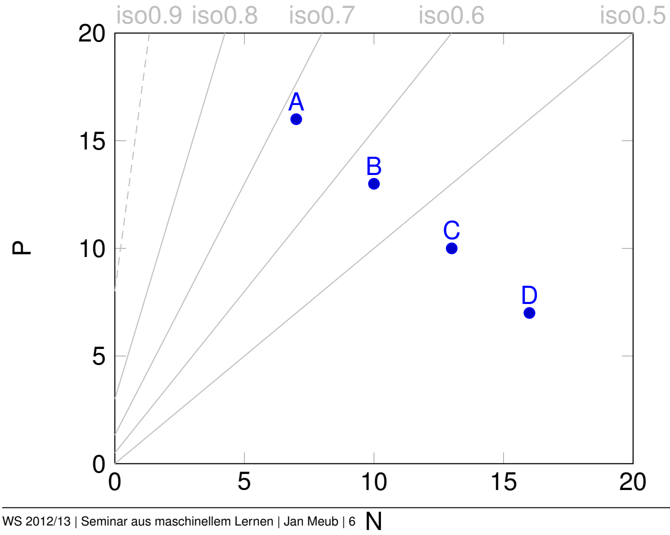
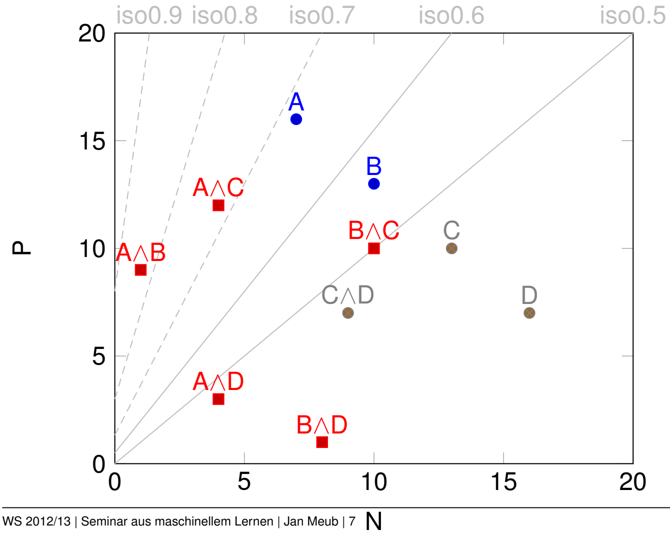


BeamSearch



iso0.9
iso0.8
iso0.7
iso0.6
iso0.5
A
B
A∧C
B∧C
C
A∧B
C∧D
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A∧D
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0
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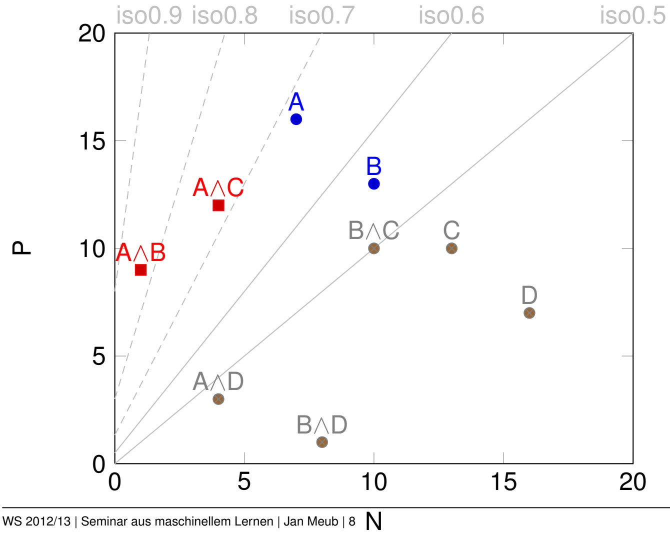
20

BeamSearch



Specialise (Rule, s)

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For each nominal attribute A_i that does not appear in Rule
  If $v_{is} \in$ Rule.ValidValues (v_{is} value of A_i in s) **Then**
    NewRule = Rule $\wedge$ (A_i = v_{is})
    If NewRule.Score > BestRule.Score **Then**
      BestRule = NewRule
    If stopSpecialisation
      Then Parent(NewRule).InvalidValues += v_{is}
      Else NewPartialRules += NewRule

stopSpecialisation
Pruning conditions 1-3

CoveredPositives(NewRule) $\leq$ MinPositives
Or
CoveredNegatives(Rule) - CoveredNegatives(NewRule) $\leq$ MinNegatives
Or
Consistency(NewRule) = 100%

MinPositives and MinNegatives:
- Empirical evidence suggest values between 1 and 5
- Smaller values if noise is low

CovP(NewRule) $\leq$ MinP
Pruning 1

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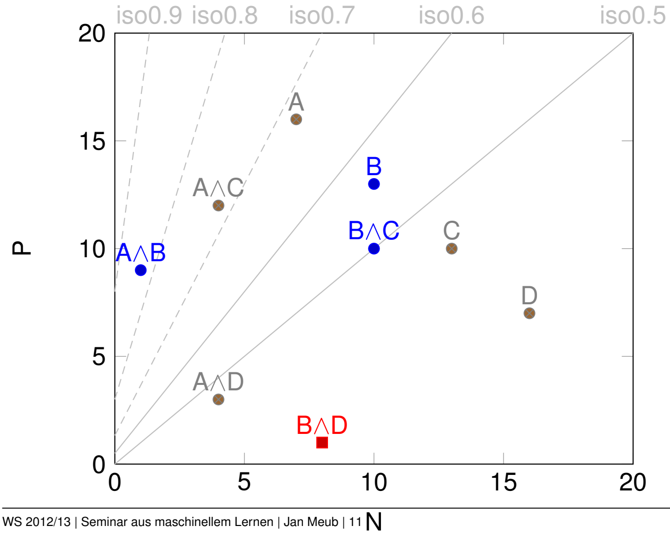

CovN(Rule) - CovN(NewRule) $\leq$ MinN
Pruning 2

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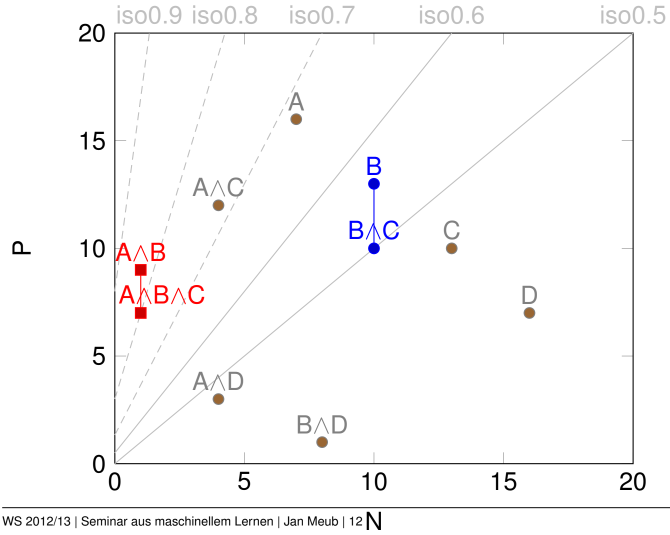

Consistency(NewRule) = 100%
Pruning 3

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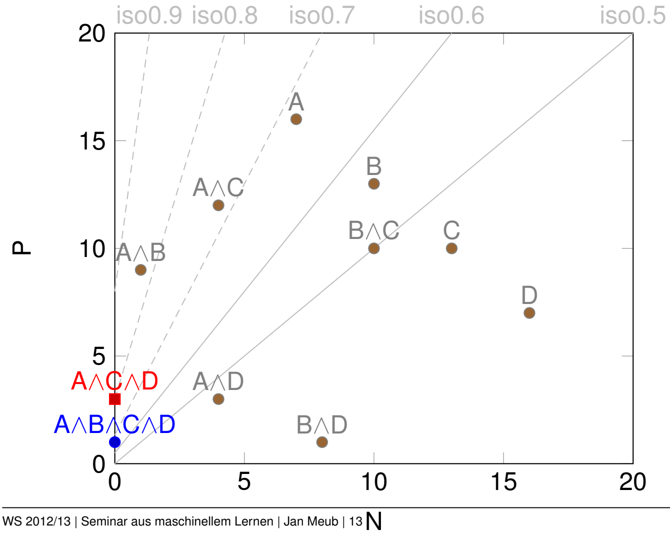

Prune rules that cannot improve
Pruning 4

For each Rule $\in$ NewPartialRules
  If Rule.OptimisticScore < BestRule.Score **Then**
    NewPartialRules -= Rule
    Parent(NewRule).InvalidValues += v_{is}

OptimisticScore: Assume CoveredNegatives = 0
$\Rightarrow$ max score any specialisation of Rule can get

Prune rules that cannot improve
Pruning 4

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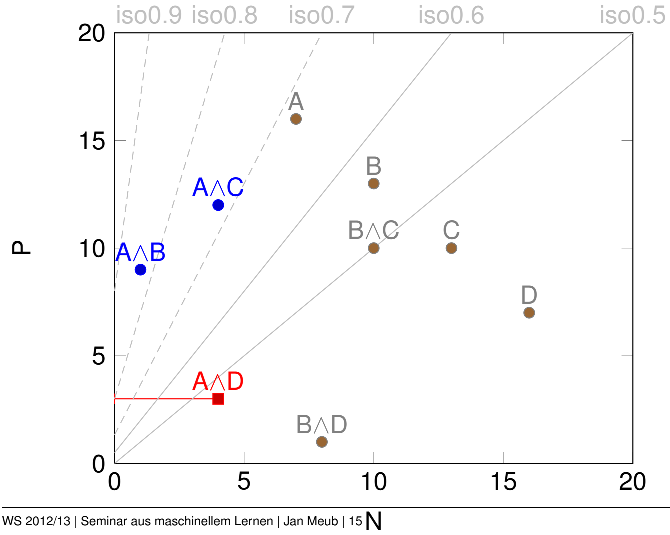

Rule.Score
Metric: m-probability-estimate

Rule.Score = $\frac{n_{class}+mP_0(C_t)}{n_{covered}+m}$

n_{class} = | positive examples covered |
$n_{covered}$ = | total examples covered |
$P_0(C_t)$ = a priori probability of class C_t
m = domain dependant parameter, increase with noise

For m = k = |classes| and P_0 = uniform = $\frac{1}{k}$
$\rightarrow$ Laplace estimate ($\frac{n_{class}+1}{n_{covered}+k}$)

In RULES-6:
m = k, $P_0(C_t) = \frac{N_{C_t}}{N}$

Evaluation of the search-space pruning rules

Evaluation on 40 data sets from the University of California at Irvine (UCI) repository of machine learning databases.

Total reduction of search space: 80% (up to 99.4%)

Total increase in accuracy: 8.3%

All four pruning methods can decrease accuracy.

MinNegatives seems to have the highest impact

Comparison with RULES-3 Plus

- Number of Rules: -88.5%
- Number of Conditions: -95.7%
- Number of Evaluations: -94.8%
- Execution Time: -97.6%

- Slight increase in accuracy (inc: 25 | dec:11)

Comparison with C5.0

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- Almost identical performance in accuracy and number of rules
- Fewer rules in 30 datasets for C5.0

Evaluation of different descretisation methods

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Afify, A. A. Design and analysis of scalable rule induction systems.
PhD Thesis, University of Wales Cardiff, School of Engineering,
Systems Engineering Division, Cardiff, UK, 2004.

“showed that the performance of the RULES-6 algorithm significantly improved when continuous valued attributes were discretized using”

Fayyad, U. M. and Irani, K. B. Multi-interval discretization of continuous-valued attributes for classification.
In Proceedings of the 13th International Joint Conference on Artificial intelligence, Chambery, France, 1993, pp. 1022-1027.

Future Work

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- Additional prepruning
- Use of postpruning
- Integrated discretization

Future Work
RULES-7

Khurram Shehzad
New Rule Induction Algorithm with improved Noise Tolerance and Scalability.
Ph.D. thesis, University of Wales Cardiff. 2010

Khurram Shehzad
EDISC: A Class-Tailored Discretization Technique for Rule-Based Classification
IEEE Transactions on Knowledge and Data Engineering,
vol. 24, no. 8, pp. 1435-1447. 2012

Khurram Shehzad
Simple Hybrid and Incremental Postpruning Techniques for Rule Induction
IEEE Transactions on Knowledge and Data Engineering,
vol. 25, no. 2, pp. 476-480, Feb. 2013

Future Work
RULES-8

Dinh Trung Pham
A Novel Rule Induction Algorithm with Improved Handling of Continuous Valued Attributes
Ph.D. thesis, University of Wales Cardiff. 2012

Sources

D.T. Pham and A.A. Afify, 2005
RULES-6: A Simple Rule Induction Algorithm for Supporting Decision Making
Proc. 31st Ann. Conf. IEEE Industrial Electronics Soc. (IECON), pp. 2184-2189

Questions?

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