Lazy Rule Learning

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Introduction

Lazy Rule Learning Algorithm

Possible Improvements

Improved Lazy Rule Learning Algorithm

Implementation

Evaluation and Results

Rule Learning

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- Learns classifier once on the training data to classify test instances
- Classifier $\rightarrow$ Rule set
- Separate-and-conquer
  - add rules that cover many positive examples

Lazy Learning

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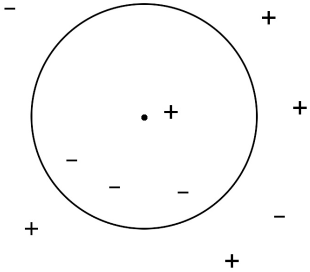
- Training data utilized by each query instance individually
- Classify instances simultaneously
- More time for classification

k-NN



$$w_i = \frac{1}{d(TestInstance, x_i)}$$

Lazy Rule Learning

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- Combine lazy learning and rule learning
  - produces many context-less rules
- Learn **one** rule
- Rule consists of conditions from test instance
- Rule should classify test instance correctly
- Example:
  - Test instance: <rainy, 68, 80, FALSE>
  - Rule: play = yes :- windy = FALSE.
- # rules = # instances to classify

LazyRule

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LazyRule (*Instance*, *Examples*)
InitialRule = $\emptyset$
BestRule = *InitialRule*
for *Class* $\in$ *Classes*
    Conditions $\leftarrow$ PossibleConditions(*Instance*)
    NewRule = RefineRule (*Instance*, *Conditions*, *InitialRule*, *Class*)
    if *NewRule* $>$ *BestRule*
        BestRule = *NewRule*
return *BestRule*

PossibleConditions

PossibleConditions (*Instance*)
Conditions $\leftarrow \emptyset$
for *Attribute* $\in$ *Attributes*
    Value = AttributeValue (*Attribute*, *Instance*)
    if *Value* $\neq \emptyset$
        Conditions = *Conditions* $\cup$ $\{$(*Attribute* = *Value*)$\}$
return *Conditions*

REFINERULE

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REFINERULE (*Instance*, *Conditions*, *Rule*, *Class*)
if *Conditions* $\neq \emptyset$
    BestRule = *Rule*
    BestCondtion = BESTCONDITION (*Rule*, *Conditions*)
    Refinement = *Rule* $\cup$ *BestCondtion*
    Evaluation = EVALUATERULE (*Refinement*)
    NewRule = $<$*Evaluation*, *Refinement*$>$
    if *NewRule* $>$ *BestRule*
        BestRule = *NewRule*
        REFINERULE (*Instance*, *Conditions* $\setminus$ *BestCondition*, *NewRule*, *Class*)
return *BestRule*

Numeric Attributes

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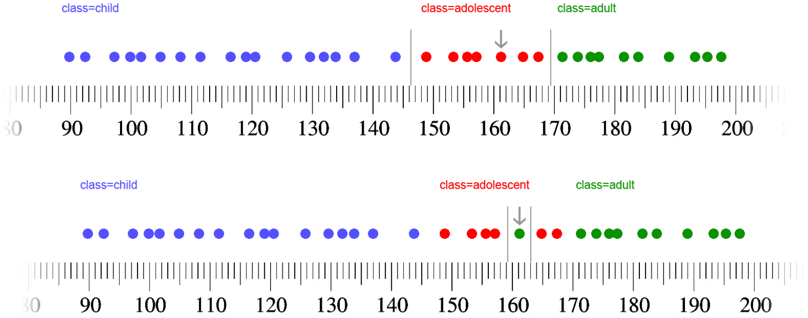
- Test instance:
  <sunny, 85 ,85, FALSE>

- Condition *outlook* = *sunny*
  $\rightarrow$ covers some training examples

- but condition *temperature* = 85
  $\rightarrow$ covers **no** training example

- Solution
  $\rightarrow$ infer two conditions, e.g. $temperature \geq 80 \wedge temperature < 90$

Numeric Attributes



Example of Learned Rules

play = yes :- humidity < 88, humidity >= 70, windy = FALSE.

play = yes :- temperature >= 72, temperature < 84.

play = yes :- outlook = overcast.

play = yes :- humidity >= 70, humidity < 82.5, windy = FALSE.

play = no :- outlook = sunny, temperature >= 70.5, temperature < 80.5.

Heuristics

- LazyRule evaluated with heuristics available in SeCo
- Laplace significantly better on most datasets
- Results:
  - Laplace 76.17
  - Linear Regression 72.44
  - *F*-Measure 70.62
  - Linear Cost 69.17
  - *m*-Estimate 68.81
  - Foil Gain 65.99
  - ...

Complexity

- # rules to check for one test instance: $O(c \cdot a^2)$
- # rules all instances: $O(c \cdot a^2 \cdot d)$
- # instances to check on first call RefineRule: $c \cdot a \cdot t$
- Decrease a or t

c : # classes
a : # attributes
d : # instances to classify
t : # training instances

Possible Improvements

- Increase accuracy
  - Beam search
- Reduce execution time
  - Consider less data $\rightarrow$ random subset of training data
  - Preselect attributes
- Increase accuracy and decrease execution time
  - Learn rules on k-nearest neighbors

LazyRuleNN

- Learn rule on *k*-nearest neighbors
- Less training data to learn rule on
  $\rightarrow$ faster
- Consider only useful instances to learn rule on
  $\rightarrow$ higher accuracy

Computation Time

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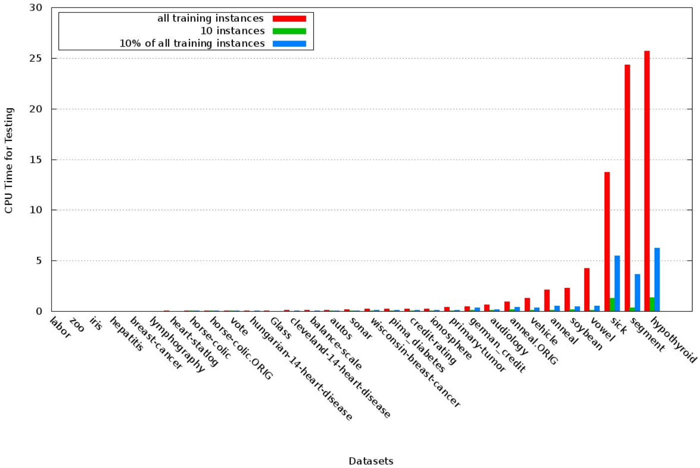

Accuracy

Dataset	LazyRule	LazyRuleNN, $k = 5$
iris	94.27	95.40
labor	85.67	88.20
balance-scale	85.44	86.16
heart-statlog	70.63	79.33 ∘
zoo	77.10	96.35 ∘
hepatitis	79.70	84.91
Glass	61.10	66.77
wisconsin-breast-cancer	91.47	96.81 ∘
lymphography	76.16	84.11
breast-cancer	72.15	73.37
autos	65.45	68.81
hungarian-14-heart-disease	80.41	82.52
primary-tumor	41.18	43.45
credit-rating	84.55	86.17
cleveland-14-heart-disease	75.59	83.08 ∘
pima-diabetes	69.91	73.84
vote	94.05	93.38
horse-colic.ORIG	71.92	63.02 •
audiology	48.30	66.02 ∘
vehicle	52.74	70.56 ∘
horse-colic	81.79	82.15
ionosphere	91.91	85.36 •
anneal.ORIG	89.21	94.42 ∘
vowel	29.42	93.67 ∘
sonar	64.14	82.42 ∘
anneal	90.75	98.24 ∘
german-credit	70.84	73.11
soybean	80.08	91.07 ∘
sick	93.88	96.28 ∘
segment	73.89	95.68 ∘
hypothyroid	92.86	93.43
Average	75.37	82.84

significance level: 0.01

improvement

degradation

Learned Rules

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- Shorter rules for small *k*
- More empty rules

	LazyRule	LazyRuleNN $>$, k = 5	LazyRuleNN $\geq$, k = 5
Accuracy (%)	75.41	82.86	82.86
Average Rule Length	2.88	0.89	19.56
Empty Rules (%)	0.01	54.41	1.78

Implementation

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- Based on SECo-framework
  - Rules
  - Heuristics
- Weka:
  - Evaluation
  - Interface
  - kNN

Weka Interface

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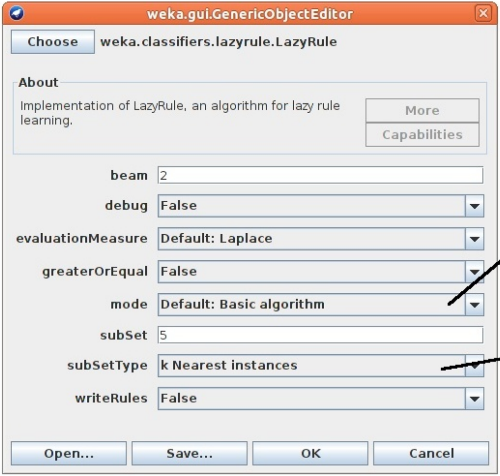

- hillclimbing
- beam
- all

- k nearest neighbors
- % nearest neighbors
- k random instances
- % random instances

Evaluation

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- 37 datasets
- Evaluating possible improvements:
  - Weka: ten-fold CV
  - Corrected paired Student's t-Test
  - Leave-one-out cross-validation
- Comparing algorithms:
  - Weka: ten-fold CV
  - Friedmann test with post-hoc Nemenyi test

LazyRuleNN and other algorithms

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Compared to:

- Decision tree algorithm J48 (C4.5)
- Separate-and-conquer rule learning algorithm JRip (RIPPER)
- k-nearest neighbor
- Weighted k-nearest neighbor
- $k = 1, 2, 3, 5, 10, 15, 25$

Results

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- Average accuracy

	$k = 1$	$k = 2$	$k = 3$	$k = 5$	$k = 10$	$k = 15$	$k = 25$
LazyRuleNN	83.31	83.02	84.00	83.90	82.94	82.47	82.09
kNN	83.35	82.75	83.73	83.47	81.73	80.23	78.18
kNN, weighted	83.35	83.29	84.16	84.27	83.69	83.29	82.14
JRip	83.09						
J48	83.37						

Results

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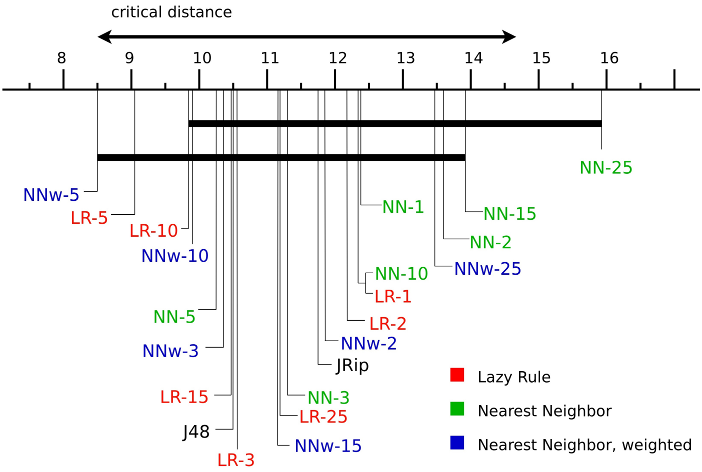

Summary

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- Combines lazy learning and rule learning
- Improved lazy rule learning algorithm uses kNN
- Not significantly worse than considered learning algorithms
- Learns many context-free rules (one for each instance)
- May be useful for other projects (e.g. Learn-a-LOD)