

Outlier Detection and Explanation with Random Forests

Graph mining and outlier detection meets Logic proof tutoring

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Outline

- Resolution for theorem proving
- Graph data – student solutions
- New features - generalized subgraph patterns
- Class outlier detection
- Finding anomalous graphs
- Explanation of outliers

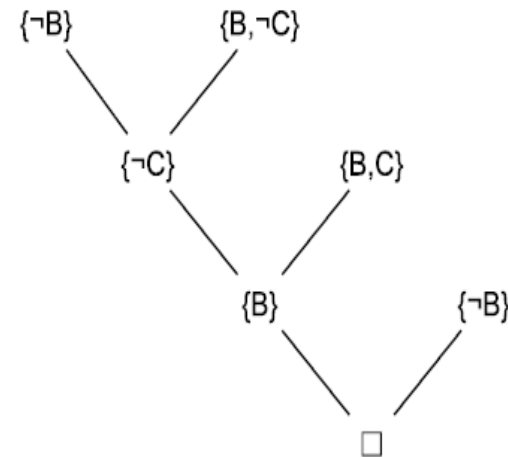
Introduction

Resolution in propositional logic

- Theorem-proving technique based on refutation
- *Resolution rule* produces a new clause implied by two clauses
- *Example*: Prove that the following set of clauses is contradictory

(B or \neg C) and \neg C and (B or C) and \neg B and
(\neg A,B) and (A or C)

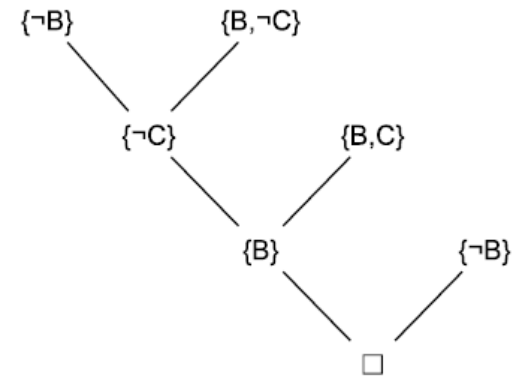
$\{\{B, \neg C\}, \{\neg C\}, \{B, C\}, \{\neg B\}, \{\neg A, B\}, \{A, C\}\}$



Method and goal

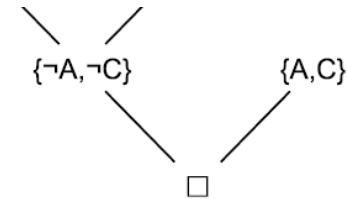
$\{\{B, \neg C\}, \{\neg C\}, \{B, C\}, \{\neg B\}, \{\neg A, B\}, \{A, C\}\}$

- graph mining, class outlier detection
- teaching enhancement by analysing students' solutions



Data

- 351 students solved resolution proofs via a web-based tool
- 873 resolution proofs classified into two classes
 - 772 correct
 - 101 incorrect



Incorrect ~ at least one error has been detected by an automatic evaluator

The most serious and common error: resolving on two literals at the same time

Načítať formulu

Pridať klauzulu

Vytvoriť čiaru

Odstrániť

Znovu vybrať typ rezolúcie a klauzúl

Vložiť spor

Vložiť nekonečno ∞

Rozšíriť klauzulu

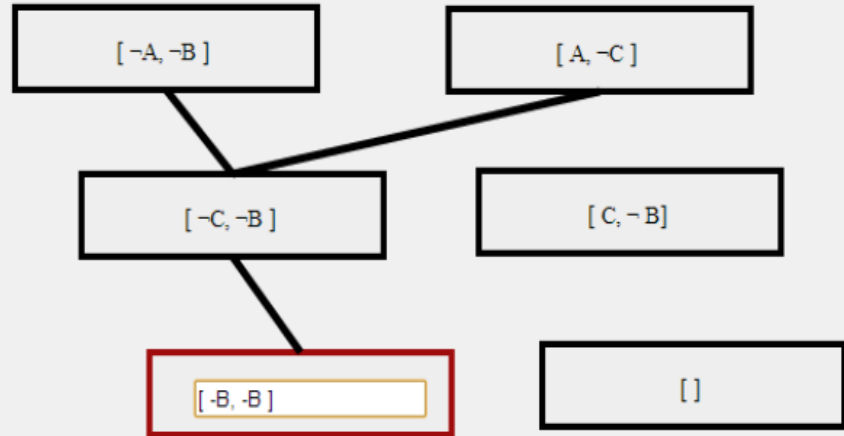
Uložiť a ukončiť

Help

Znak pre negáciu sa vkladá znakom "-"

Rozhodnite, či nasledujúca množina klauzúl je splniteľná prostredníctvom rezolúcie: $\{ [-A, -B], [A, -C], [B, -A], [C, -B] \}$ použite SLD rezolúciou (Selective Linear Definite)

Zvolil si: SLD rezolúcia (Selective Linear Definite Res.)



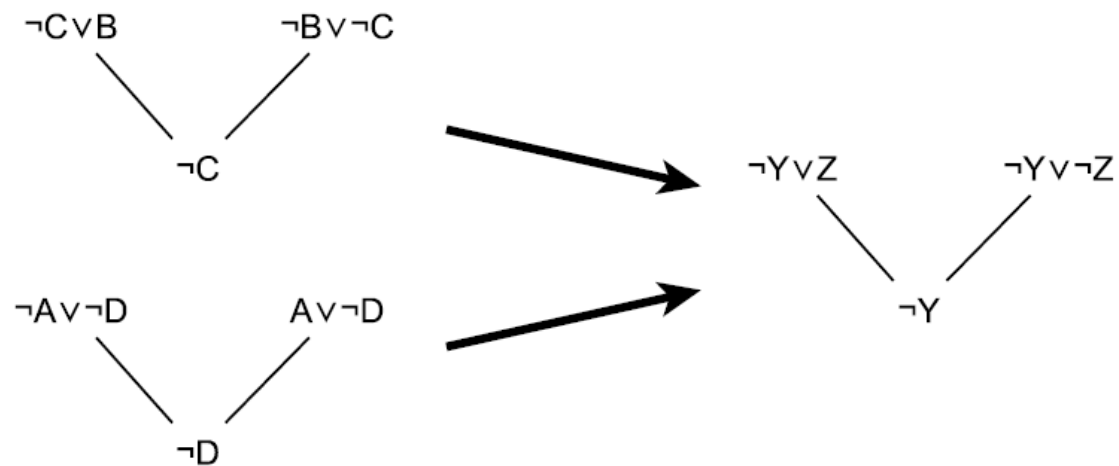
New features : subgraph patterns

- Representation of graphs by their substructures – patterns
 - $Pattern_i$ appeared in the graph -> true
 - $Pattern_i$ did not appear in the graph -> false

pattern₁	pattern₂	...	pattern_m	class
true	false	...	false	incorrect
...	
false	true	...	true	correct

Generalized Subgraph Patterns

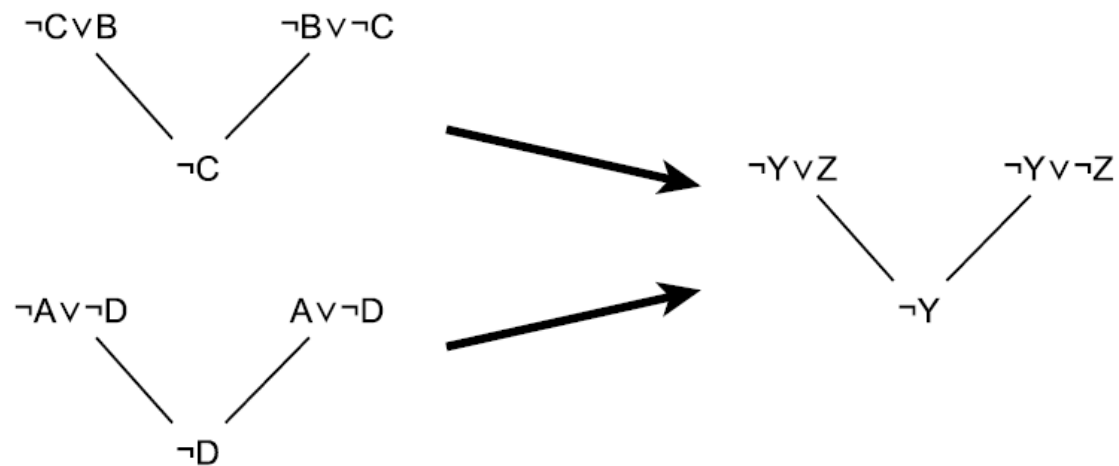
- Representation of graphs by their substructures (patterns)
- Simple subgraphs inappropriate
=> generalized subgraphs



Generalized Subgraph Patterns

Procedure:

1. Extract all 3-node subgraphs (parents with the resolvent)
2. Perform generalization on these subgraphs



Generalized Subgraph Patterns – Higher Level

- To increase performance of algorithms, we created a new, higher-level, generalization
- This method generalizes patterns created by previous gen. method
- It exploits domain knowledge about general resolution principle
- From 3-node generalized pattern it creates new pattern in following form:

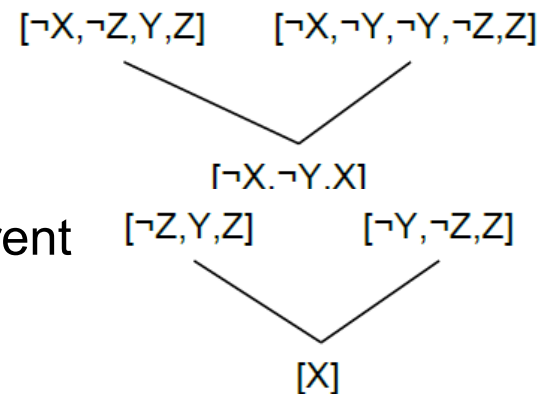
$$\begin{array}{cc} [L_{i_1}, L_{i_2}, \dots, L_{i_n}]; [L_{j_1}, L_{j_2}, \dots, L_{j_m}] \\ \text{(added)} \qquad \qquad \text{(dropped)} \end{array}$$

- *added*: literals which were added erroneously to the resolvent
- *dropped*: literals from parents which participated in the resolution process

Generalized Subgraph Patterns – Higher Level

Example:

- Go through literals in resolvent and delete those that occur in at least one parent



$added = [X]$, $dropped = [¬Z, Y, Z, ¬Y, ¬Z, Z]$

- Rename letters in lists *dropped* and *added*, and sort both lists to get the final pattern

$[Z]; [¬X, ¬X, ¬Y, X, X, Y]$

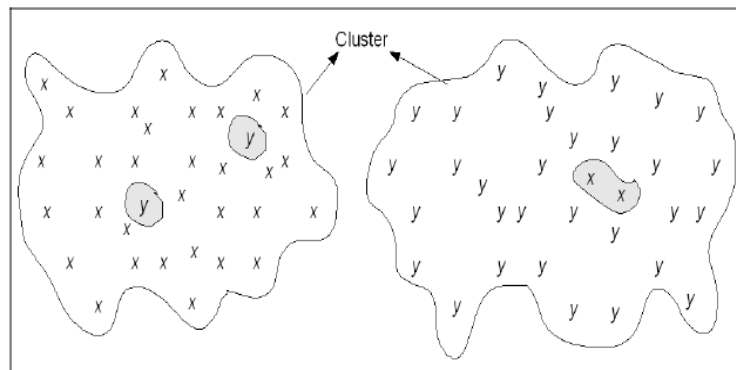
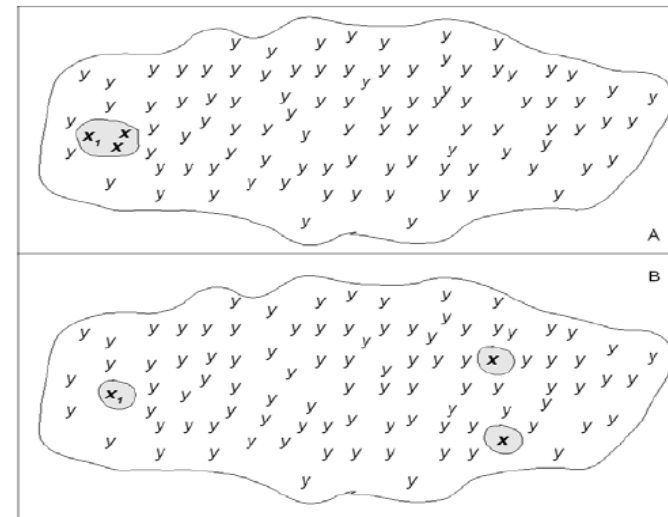
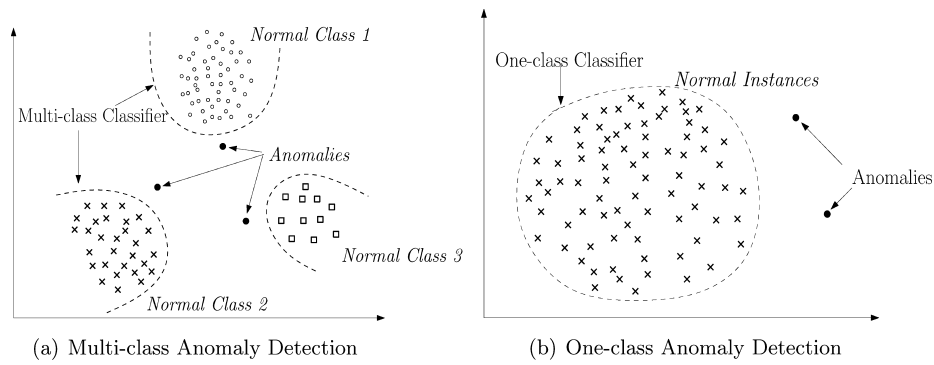
Detection of anomalous solutions

- (1a) Learn a **classifier** that would discriminate between correct and incorrect solutions, and
Detect **rare cases** that are incorrectly classified – outliers
- (1b) Clustering and observing **class** distribution in clusters
- (2) **BETTER:** Directly detect outliers without learning a classifier.

Data have been classified => common outlier detection does not help

=> **Class-based outlier detection**

Class outliers



Class Outlier Detection

CODB (Hewahi and Saad 2007) – distance and density based

- weka-peka (Pekarčíková 2013)
 - Based on Random Forests
 - Analysis of proximity matrix

Class Outlier Detection via Random Forest

weka-peka (Pekarčíková 2013)

- Learn Random Forest
- After each tree is built, all of the data are run down the tree, and **proximities** are computed for each pair of cases:
If two cases occupy the same terminal node, their proximity is increased by one.
- At the end of the run, the proximities are normalized by dividing by the number of trees.

Class Outlier Detection via Random Forest

weka-peka (Pekarčíková 2013)

$$FO(p) = FO1(p) + FO2(p) + cFO3(p)$$

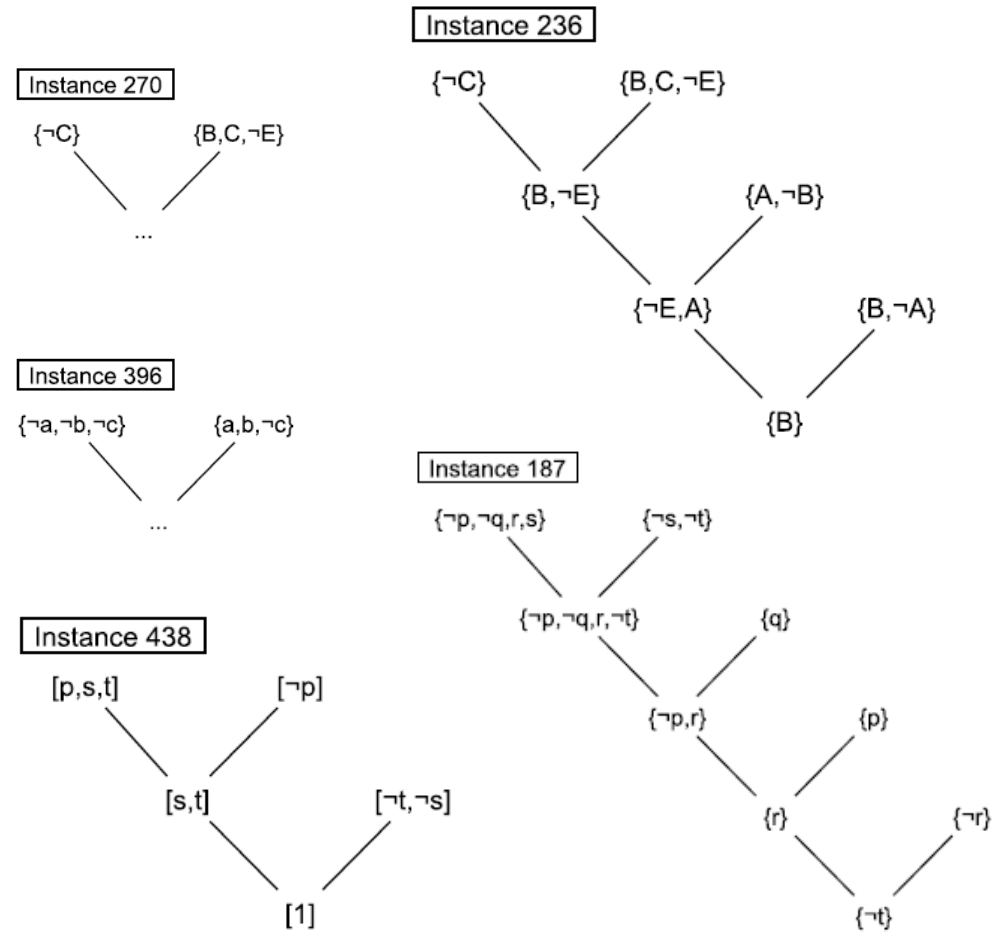
- $1/FO1(p)$... proximity of p to elements from the same class
- $FO2(p)$ frequency of incorrect classification of p
- $FO3(p)$ proximity p to all elements, i.e. when ignoring the class attribute

Outlier detection by weka-peka

Instance	Error E3	Outlier score
270	no	131.96
396	no	131.96
236	no	73.17
187	no	61.03
438	yes	54.43
389	yes	52.50
74	yes	15.91
718	yes	15.91

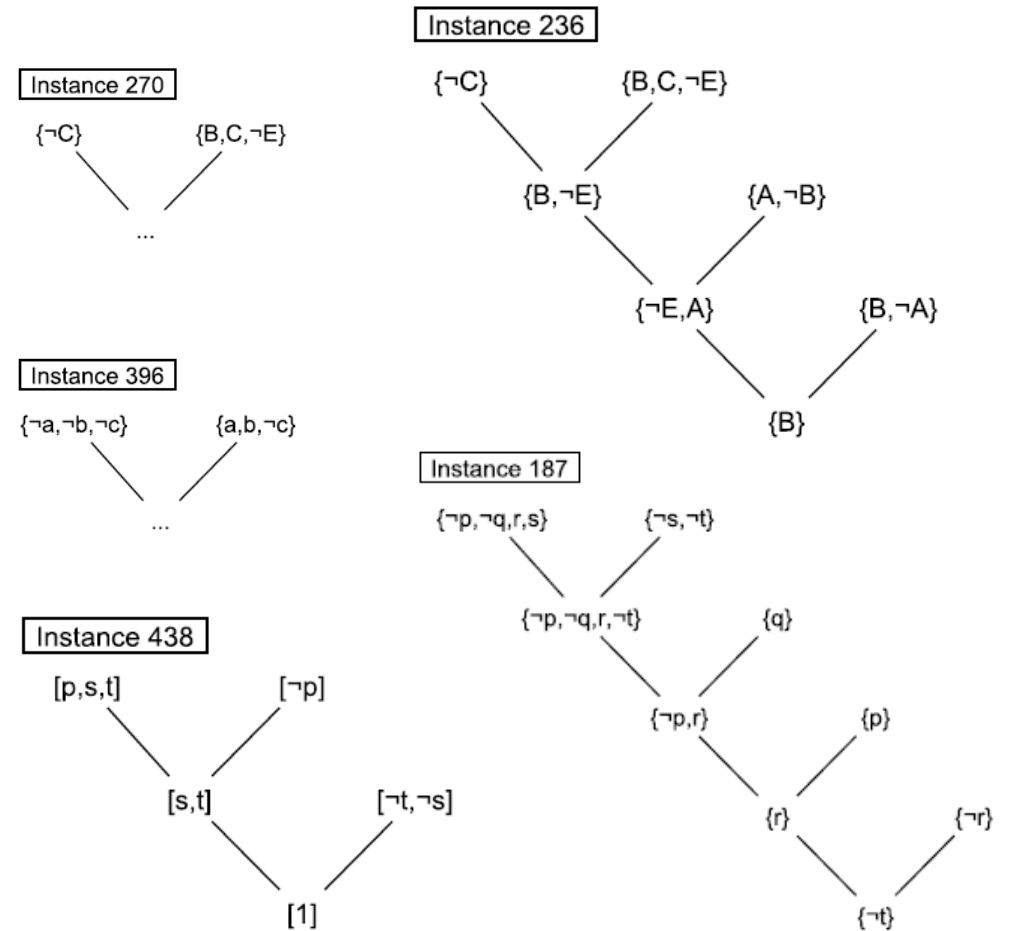
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Goal now: to explain/interpret outliers

References

VACULÍK, Karel, NEZVALOVÁ, Leona a Lubomír POPELÍNSKÝ. Graph Mining and Outlier Detection Meet Logic Proof Tutoring. Proc. of EDM 2014 Ws Graph-based Educational Data Mining

VACULÍK, Karel, Leona NEZVALOVÁ a Lubomír POPELÍNSKÝ. Educational data mining for analysis of students' solutions. 16th International Conference, AIMS 2014. London: Springer, 2014.

CODB:

Hewahi N.M. and Saad M.K. *Class Outliers Mining: Distance-Based Approach*. International Journal of Intelligent Systems and Technologies, Vol. 2, No. 1, pp 55-68, 2007.

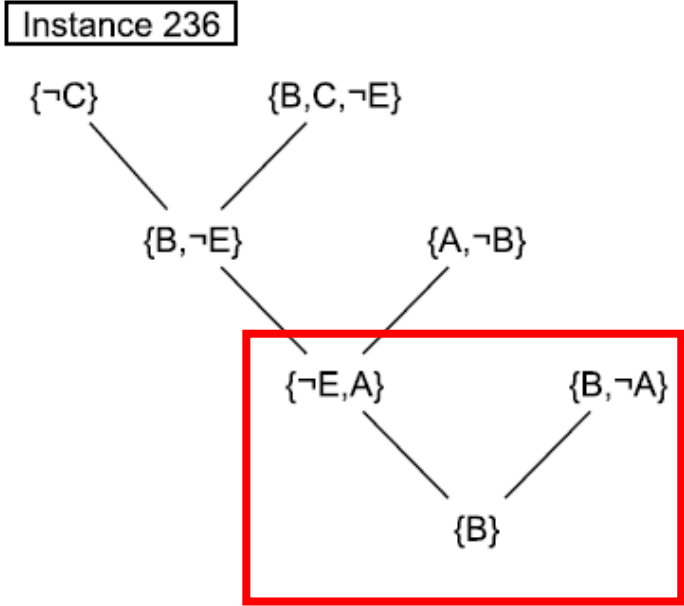
pattern	text
1 $\{\}$; $\{\text{neg } Z, Z\}$	
2 $\{\}$; $\{\}$	
3 $\{\}$; $\{\text{neg } Z\}$	
4 $\dots(\text{cykli})$; $\dots(\text{cykli})$	
5 $\{\text{neg } Z\}$; $\{\text{neg } Y, Y\}$	
6 $\{\text{neg } Y, Z\}$; $\{\text{neg } X, X\}$	
7 $\{\}$; $\{Z\}$	
8 $\{\}$; $\{\text{neg } Y, \text{neg } Z, Y, Z\}$	
9 $\{Y\}$; $\{\text{neg } Y, \text{neg } Z, Z\}$	
10 $\{\}$; $\{Z, Z\}$	
11 $\{\text{neg } Y\}$; $\{\text{neg } Z, Y, Z\}$	
12 $\{\}$; $\{\text{neg } Z, \text{neg } Z\}$	
13 $\{Z\}$; $\{\text{neg } Y, Y\}$	
14 $\{\}$; $\{\text{neg } Y, \text{neg } Z, Y\}$	
15 $\{\}$; $\{\text{neg } Y, Y, Z, Z\}$	
16 $\{Z\}$; $\{\text{neg } X, \text{neg } Y, X, Y\}$	
17 $\{\text{neg } Z\}$; $\{\text{neg } X, \text{neg } Y, X, Y\}$	
18 $\{\}$; $\{\text{neg } X, \text{neg } Y, \text{neg } Z, X, Y, Z\}$	
19 $\{Y\}$; $\{\text{neg } X, X, Z\}$	
20 $\{\}$; $\{\text{neg } Y, Z\}$	

AScore

- Let P be a pattern and suppose its value is *true* for the outlier
- Compute AScore of P as the fraction of remaining instances from the same class as the outlier whose value of P is equal to *false*
- Similarly for P equal to *false*, but AScore ranges from 0 to -1

Outlier Explanation

Instance	Error E3	Outlier score	Significant patterns* [(AScore) added; dropped]	Significant missing patterns* [(AScore) added; dropped]
270	no	131.96	(0.96) <i>looping</i>	(-0.99) {};{¬Z,Z}
396	no	131.96	(0.96) <i>looping</i>	(-0.99) {};{¬Z,Z}
236	no	73.17	(0.99) {};{¬Y, ¬Z,Y}	
187	no	61.03	(0.99) {¬Z};{¬Y,Y} (0.99) {};{¬Y, ¬Z,Y}	
438	yes	54.43	(1.00) {Z};{¬X, ¬Y,X,Y}	(-0.94) {};{¬Y, ¬Z,Y,Z}
389	yes	52.50	(1.00) {};{¬Y, ¬Z,Y}	(-0.94) {};{¬Y, ¬Z,Y,Z} (-0.81) {};{¬Z,Z}
74	yes	15.91	(0.98) {¬Z};{¬X, ¬Y,X,Y} (0.98) {};{¬X, ¬Y, ¬Z,X,Y,Z}	(-0.94) {};{¬Y, ¬Z,Y,Z}
718	yes	15.91	(0.98) {¬Z};{¬X, ¬Y,X,Y} (0.98) {};{¬X, ¬Y, ¬Z,X,Y,Z}	(-0.94) {};{¬Y, ¬Z,Y,Z}

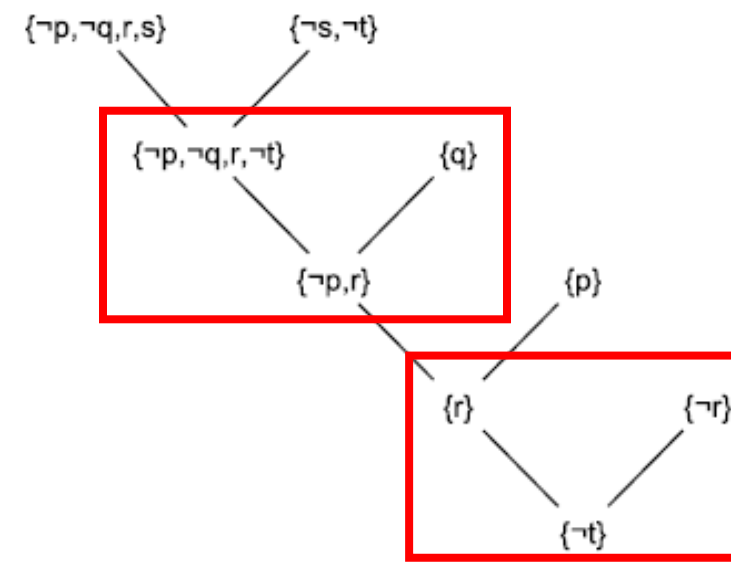


*Only patterns with |AScore| > 0.8 are displayed

Outlier Explanation

Instance	Error E3	Outlier score	Significant patterns* [(AScore) added; dropped]	Significant missing patterns* [(AScore) added; dropped]
270	no	131.96	(0.96) <i>looping</i>	(-0.99) {};{-Z,Z}
396	no	131.96	(0.96) <i>looping</i>	(-0.99) {};{-Z,Z}
236	no	73.17	(0.99) {};{-Y, -Z,Y}	
187	no	61.03	(0.99) {-Z};{-Y,Y} (0.99) {};{-Y, -Z,Y}	
438	yes	54.43	(1.00) {Z};{-X, -Y,X,Y}	(-0.94) {};{-Y, -Z,Y,Z}
389	yes	52.50	(1.00) {};{-Y, -Z,Y}	(-0.94) {};{-Y, -Z,Y,Z} (-0.81) {};{-Z,Z}
74	yes	15.91	(0.98) {-Z};{-X, -Y,X,Y} (0.98) {};{-X, -Y, -Z,X,Y,Z}	(-0.94) {};{-Y, -Z,Y,Z}
718	yes	15.91	(0.98) {-Z};{-X, -Y,X,Y} (0.98) {};{-X, -Y, -Z,X,Y,Z}	(-0.94) {};{-Y, -Z,Y,Z}

Instance 187

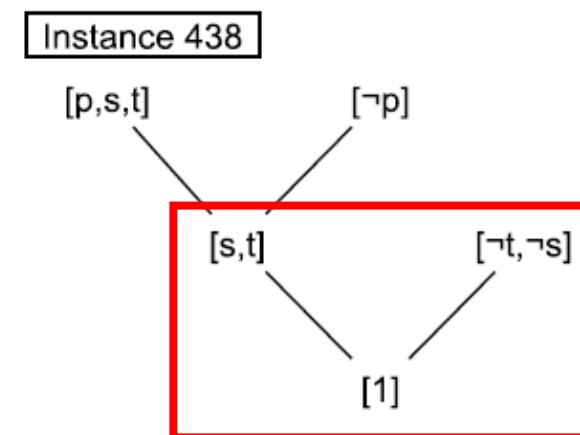


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Outlier Explanation

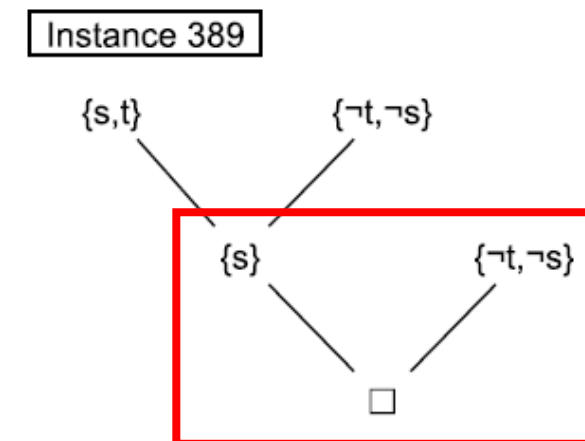
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396	no	131.96	(0.96) <i>looping</i>	(-0.99) {};{¬Z,Z}
236	no	73.17	(0.99) {};{¬Y, ¬Z,Y}	
187	no	61.03	(0.99) {¬Z};{¬Y,Y} (0.99) {};{¬Y, ¬Z,Y}	
438	yes	54.43	(1.00) {Z};{¬X, ¬Y,X,Y}	(-0.94) {};{¬Y, ¬Z,Y,Z}
389	yes	52.50	(1.00) {};{¬Y, ¬Z,Y}	(-0.94) {};{¬Y, ¬Z,Y,Z} (-0.81) {};{¬Z,Z}
74	yes	15.91	(0.98) {¬Z};{¬X, ¬Y,X,Y} (0.98) {};{¬X, ¬Y, ¬Z,X,Y,Z}	(-0.94) {};{¬Y, ¬Z,Y,Z}
718	yes	15.91	(0.98) {¬Z};{¬X, ¬Y,X,Y} (0.98) {};{¬X, ¬Y, ¬Z,X,Y,Z}	(-0.94) {};{¬Y, ¬Z,Y,Z}

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Outlier Explanation

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396	no	131.96	(0.96) <i>looping</i>	(-0.99) {};{¬Z,Z}
236	no	73.17	(0.99) {};{¬Y, ¬Z,Y}	
187	no	61.03	(0.99) {¬Z};{¬Y,Y} (0.99) {};{¬Y, ¬Z,Y}	
438	yes	54.43	(1.00) {Z};{¬X, ¬Y,X,Y}	(-0.94) {};{¬Y, ¬Z,Y,Z}
389	yes	52.50	(1.00) {};{¬Y, ¬Z,Y}	(-0.94) {};{¬Y, ¬Z,Y,Z} (-0.81) {};{¬Z,Z}
74	yes	15.91	(0.98) {¬Z};{¬X, ¬Y,X,Y} (0.98) {};{¬X, ¬Y, ¬Z,X,Y,Z}	(-0.94) {};{¬Y, ¬Z,Y,Z}
718	yes	15.91	(0.98) {¬Z};{¬X, ¬Y,X,Y} (0.98) {};{¬X, ¬Y, ¬Z,X,Y,Z}	(-0.94) {};{¬Y, ¬Z,Y,Z}



*Only patterns with |AScore| > 0.8 are displayed

Sapling Random Forest (LOF)

- Train trees (sapling) to distinguish normal instances from outliers
- Only subset of normal instances are used (k-nearest neighbours vs. random)
- Find explanation in resulting paths
- Knowledge about classes not taken into account

Tree Reduction

- Original classes replaced with two new classes
 - **Normal class** – includes labeled class of given instance
 - **Outlier class** – includes others original classes
- Analysis of the trees that classify instance to Outlier class
- Change attribute values on the path in given tree for given instance and check if **resulting class change** → **attribute is part of explanation**
- Find explanation in resulting paths and calculate support

Results

Instance	Error E3	Outlier score	AScore	Sapling Random Forest (LOF)	Tree Reduction
270	no	131.96	pattern_1 (-0.99) pattern_4 (0.96)	pattern_1=0 (1)	pattern_1=0 (0.81)
396	no	131.96	pattern_1 (-0.99) pattern_4 (0.96)	pattern_1=0 (1)	pattern_1=0 (0.81)
236	no	73.17	pattern_14 (0.99)	pattern_2=0 (0.8)	pattern_14=1 (0.46) pattern_14=1 && pattern_5=0 (0.22)
187	no	61.03	pattern_14 (0.99) pattern_5 (0.99)	pattern_2=0 (0.95)	pattern_14=1 (0.76)
438	yes	54.43	pattern_16 (1.00) pattern_8 (-0.94)	pattern_2=0 (0.75)	pattern_1=1 && pattern_8=0 && pattern_17=0 (0.23) pattern_8=0 && pattern_17=0 (0.20)
389	yes	52.50	pattern_14 (1.00) pattern_8 (-0.94) pattern_1 (-0.81)	pattern_1=0 (1)	pattern_8=0 (0.26) pattern_8=0 && pattern_16=0 && pattern_17=0 (0.21) pattern_8=0 && pattern_16=0 && pattern_18=0 (0.21)
74	yes	15.91	pattern_17 (0.98) pattern_18 (0.98) pattern_8 (-0.94)	pattern_2=0 (0.7)	pattern_8=0 && pattern_16=0 (0.29) pattern_1=1 && pattern_8=0 && pattern_16=0 (0.26)