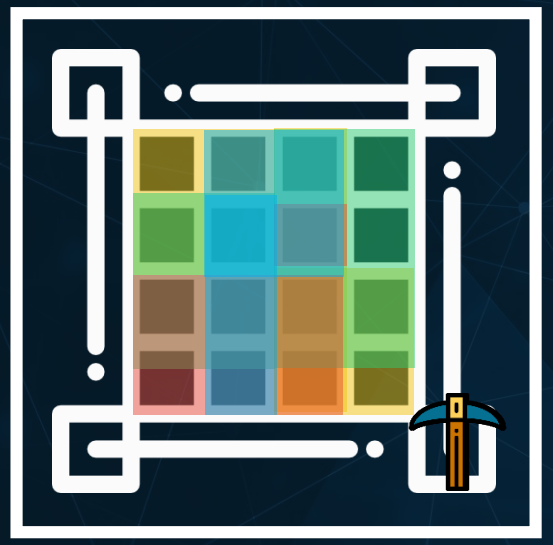
ECMLPKDD'18

September 13, 2018

ECML/PKDD 2018



REFINE&MINE:

ANYTIME SUBGROUP DISCOVERY IN NUMERICAL DOMAINS WITH GUARANTEES

AUTHORS.

Aimene BELFODIL Adnene BELFODIL

Mehdi KAYTOUE

\°/ All icons used are courtesy of flaticon.com

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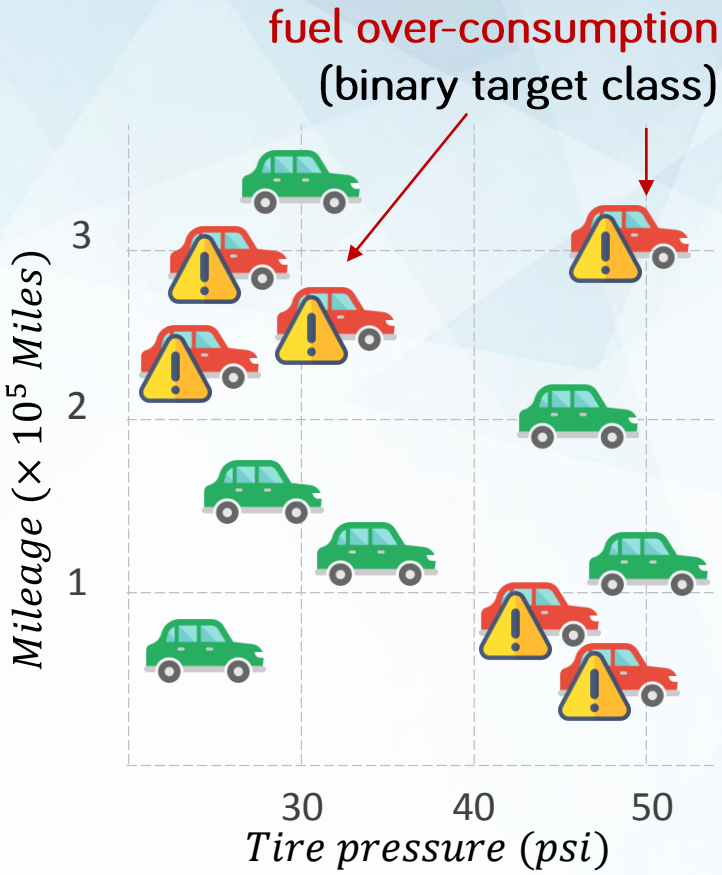
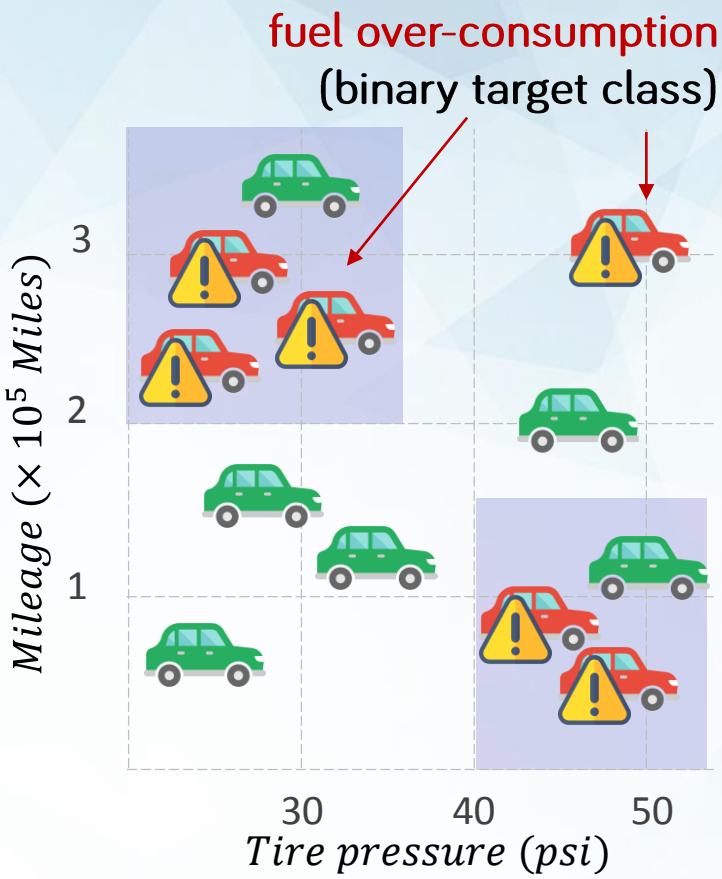
INTRODUCTION

PROBLEM DEFINITION

Subgroup Discovery



Subgroup Discovery



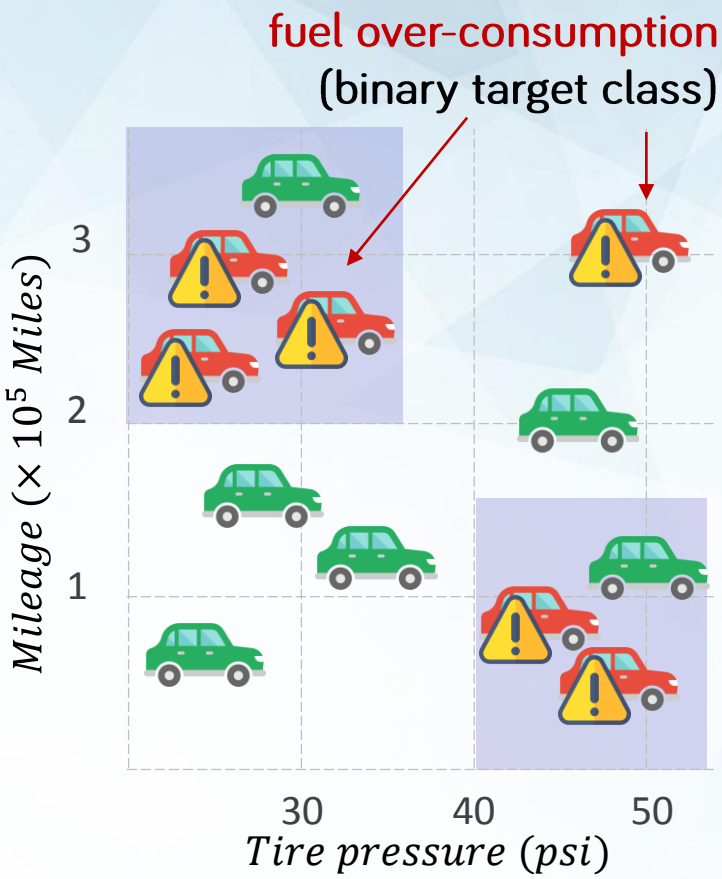
Hypothesis.

Fuel over-consumption is fostered when:

1. $Tire\ pressure \leq 35$ psi **and** $Milage \geq 2 \times 10^5\ miles$
2. $Tire\ pressure \geq 40$ psi **and** $Milage \leq 1.7 \times 10^5\ miles$

Subgroups - Discriminant Interval patterns

Subgroup Discovery



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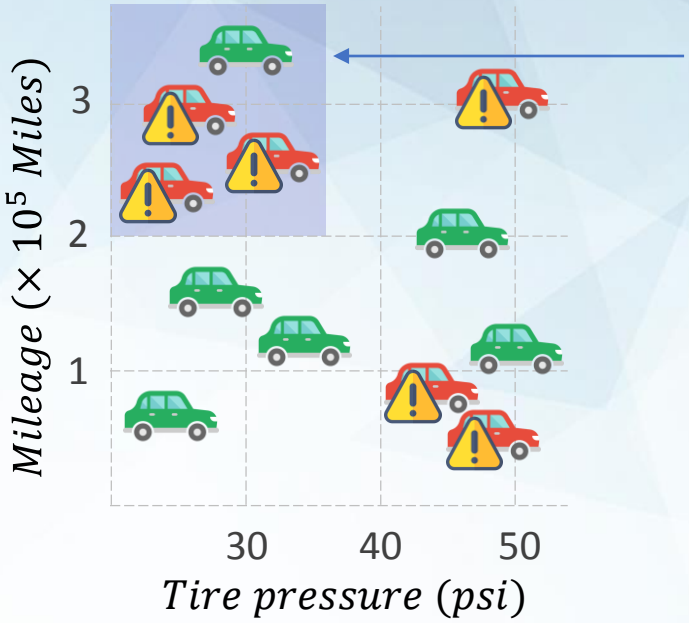
Subgroups - Discriminant Interval patterns

Subgroup discovery. The task of discovering patterns that accurately discriminate the target class from others.

*We are interested only in datasets where all the attributes are numerical.

Preliminary notions



Interval pattern intent. Conjunction of interval restrictions:

E.g. $x \in [0, 35]$ **and** $y \in [2, +\infty)$

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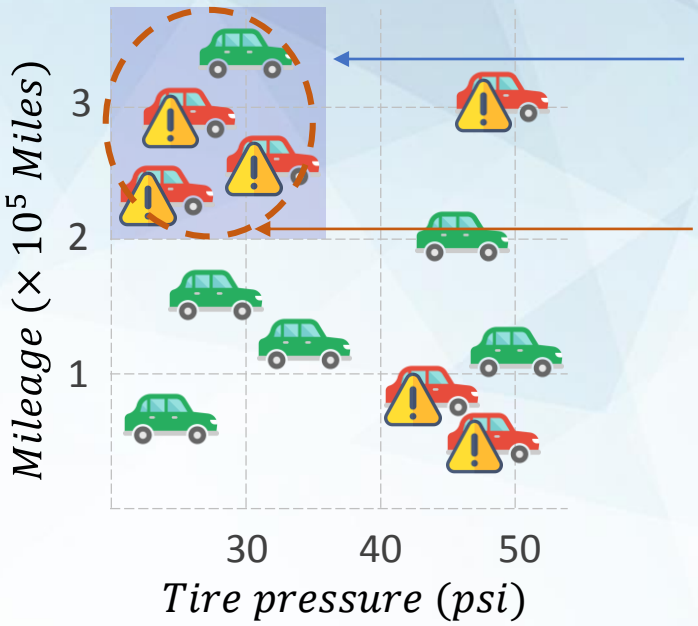

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Interval pattern extent. Set of instances for which the pattern hold.

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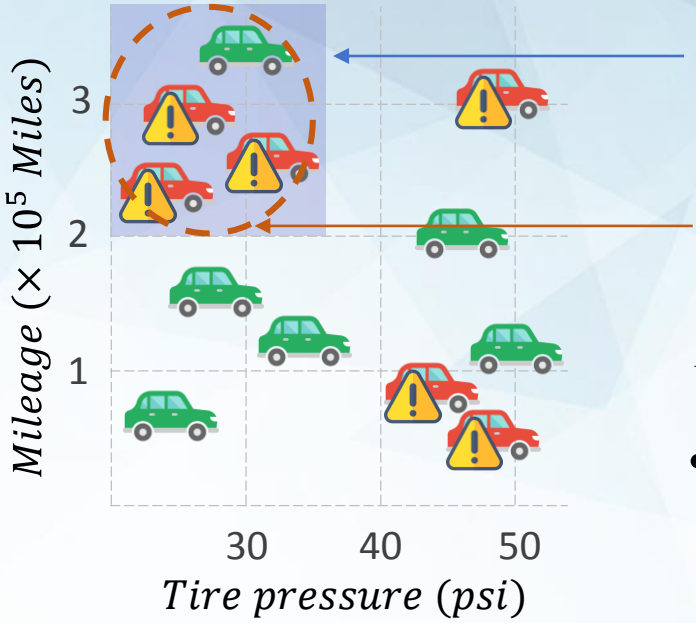

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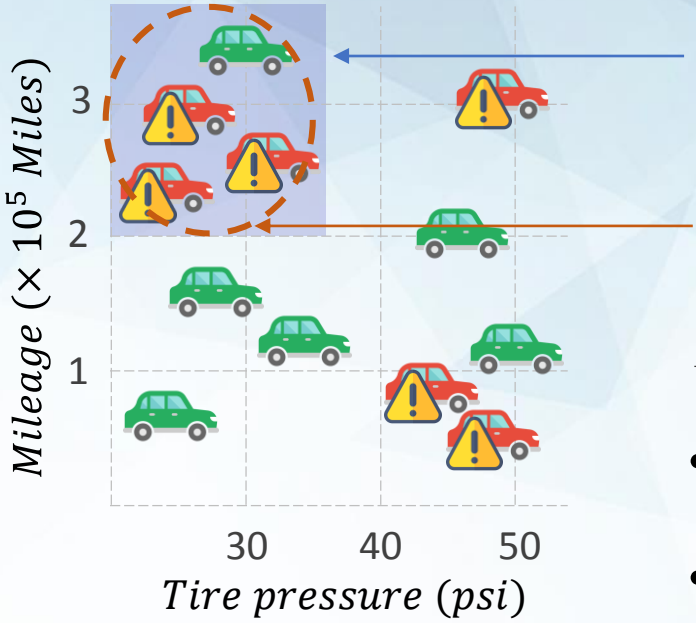

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* *True Positive Rate* * *False Positive Rate*

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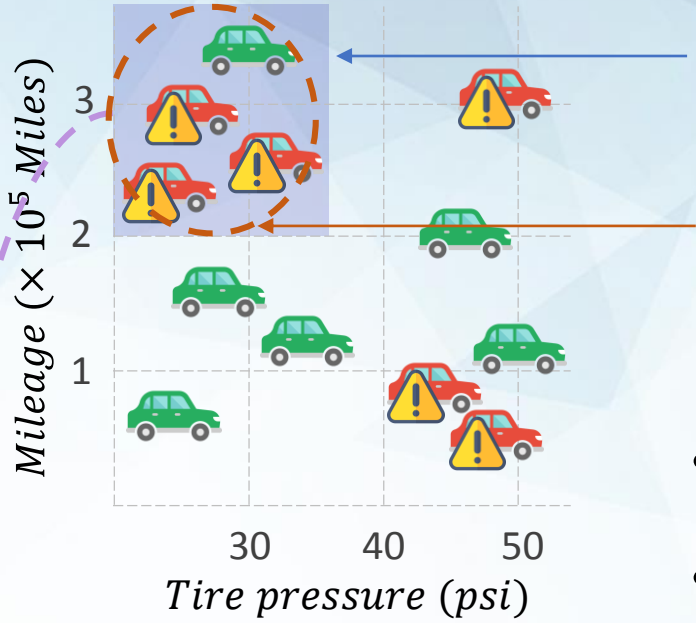

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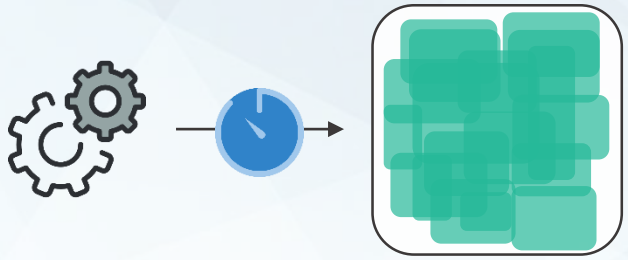
* *True Positive Rate* * *False Positive Rate*

$$\phi(p) = \frac{3}{6} - \frac{1}{6} = 0.33$$

$$\phi(pattern) = tpr(pattern) - fpr(pattern)$$

*Informedness is order-equivalent to the well-known WRAcc measure.

State-of-the-art (a small one)



Exhaustive Search

Generally unfeasible.

e.g. A 200 × 3 dataset has up to 8 Billions Interval Patterns.

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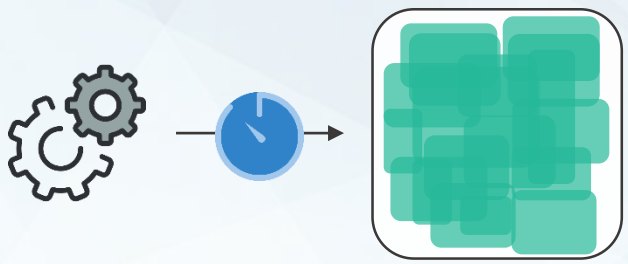

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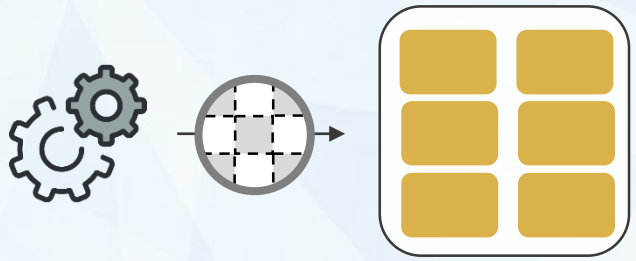

Prior Discretization

Loss of information.

e.g. overlapping intervals are ignored. Look for [1,2] and [2,3] patterns but ignore [1,3].

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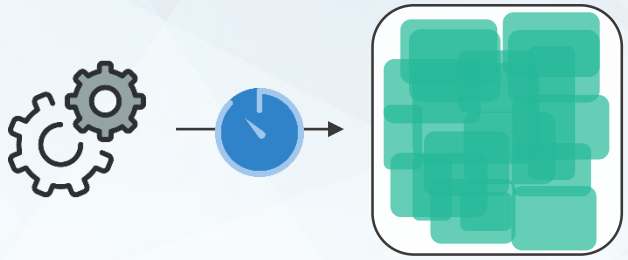

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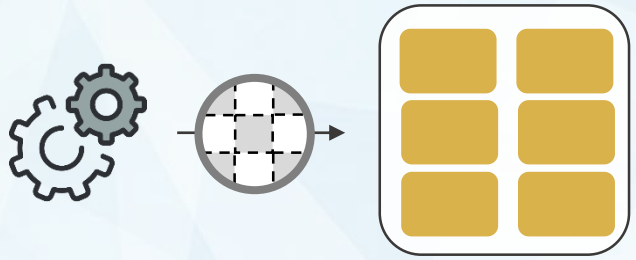

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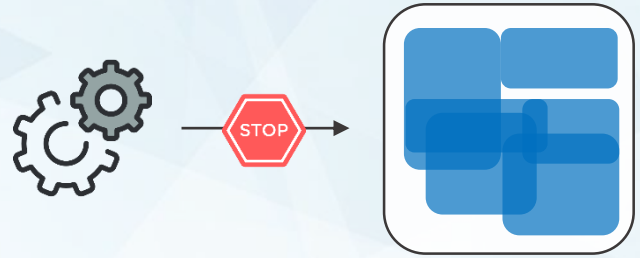

Heuristics and sampling

No guarantee on the outputted patterns at the end or upon interruption

G. Bosc, J.F. Boulicaut, C. Raïssi, M. Kaytoue. Anytime discovery of a diverse set of patterns with MCTS. In DMKD 2018.

Problem Statement

Algorithm searching for discriminant interval patterns ...

Few patterns
after 5”

More patterns
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Many patterns after 20’

Some or All patterns after the End

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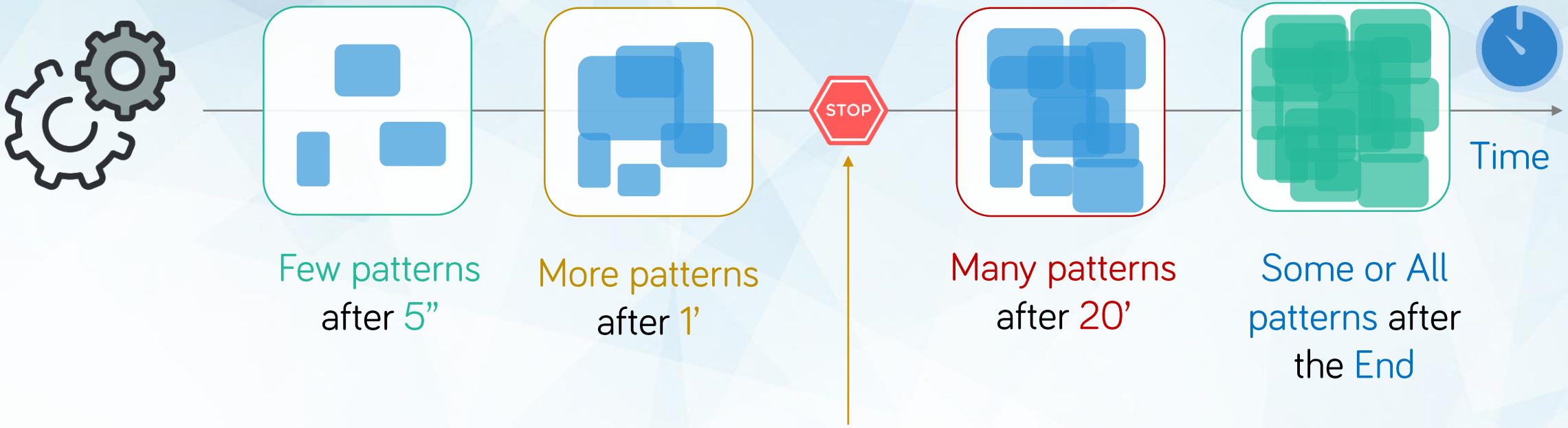

Few patterns after 5”

More patterns after 1’

Many patterns after 20’

Some or All patterns after the End

All state-of-the-art subgroup discovery algorithms provide no guarantees on the outputted discriminant interval patterns when interrupted during execution

Contributions (1)

Propose the new algorithm

Refine&Mine

Anytime Algorithm

Provide patterns anytime

with two guarantees on them

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Guarantee 1: Accuracy

Bound the quality difference between the best possible pattern and the best already found pattern

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Propose the new algorithm

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Anytime Algorithm

Provide patterns anytime with two guarantees on them

* The more time it is given, the lower are the bounds.

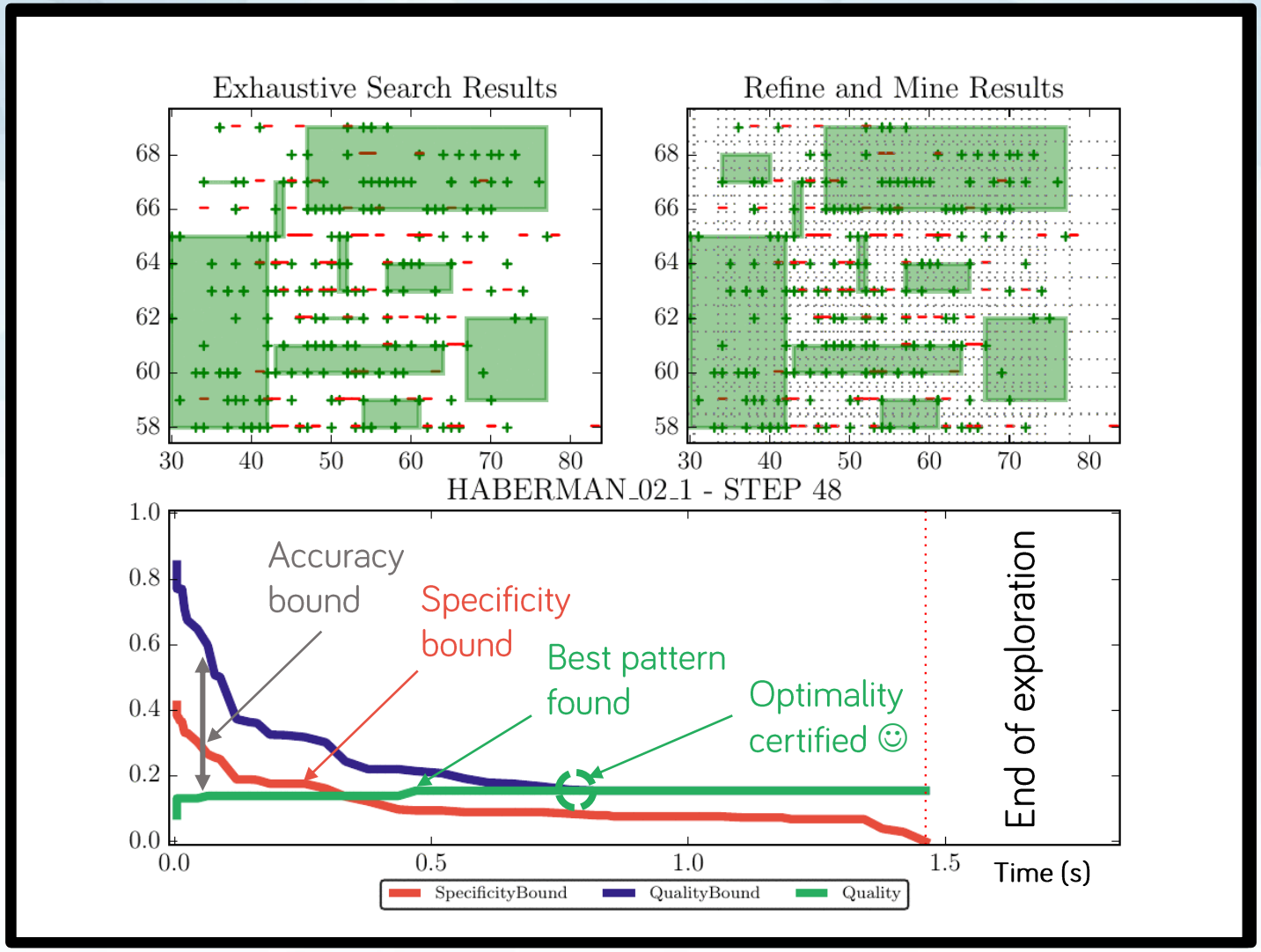
Guarantee 1: Accuracy

Bound the quality difference between the best possible pattern and the best already found pattern

Guarantee 2: Specificity

Bound the distance of found patterns to ground truth patterns to ensure diversity of found patterns.

Contributions (2)



OUTLINE

- Overview and Contributions
- Refine&Mine in a nutshell
- Guarantees computation
- Building blocks of Refine&Mine
- Wrap-up and concluding remarks

REFINE&MINE

REFINE&MINE: In a Nutshell (1)

Refine&Mine

Sequence of discretization refinements and mining patterns within the discretization.

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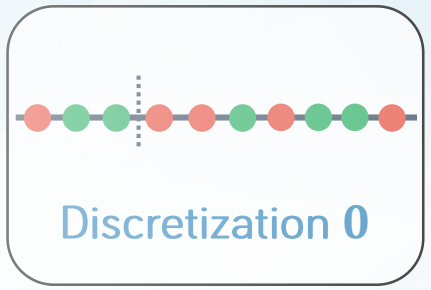

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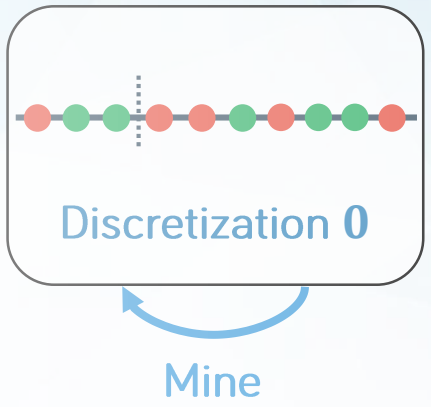

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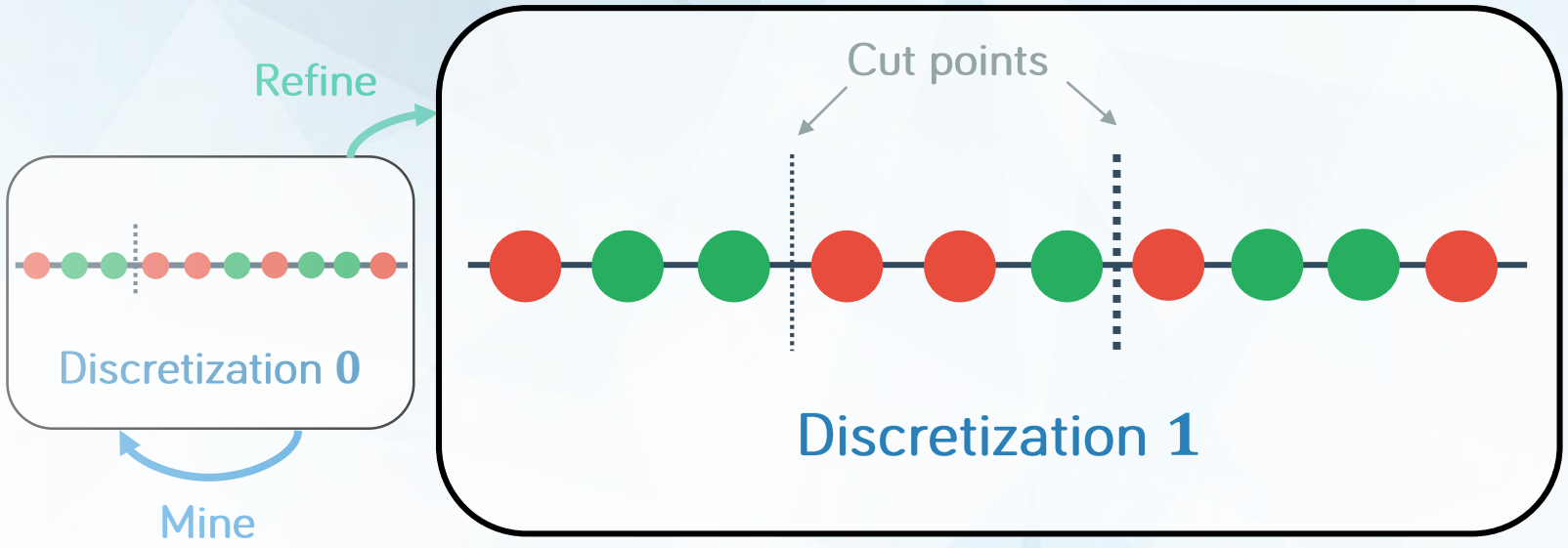

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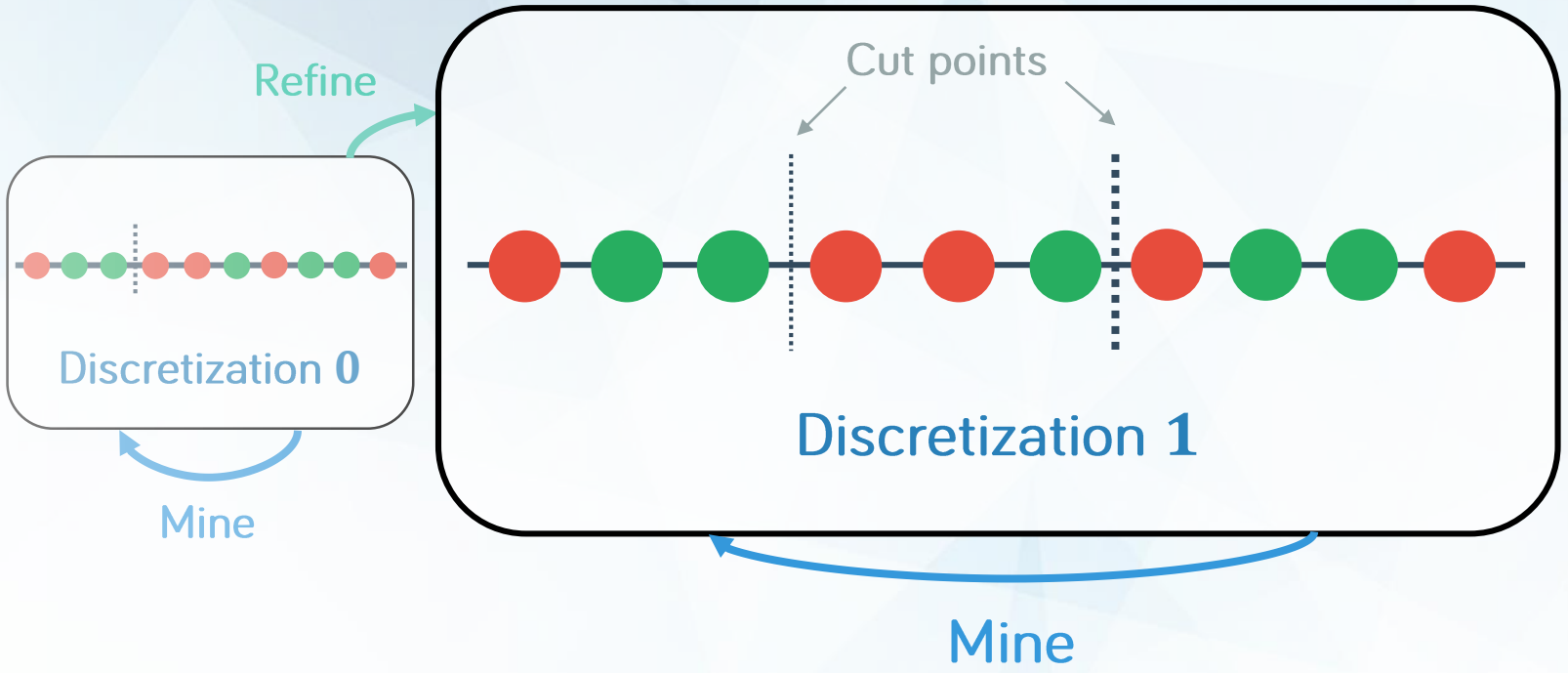

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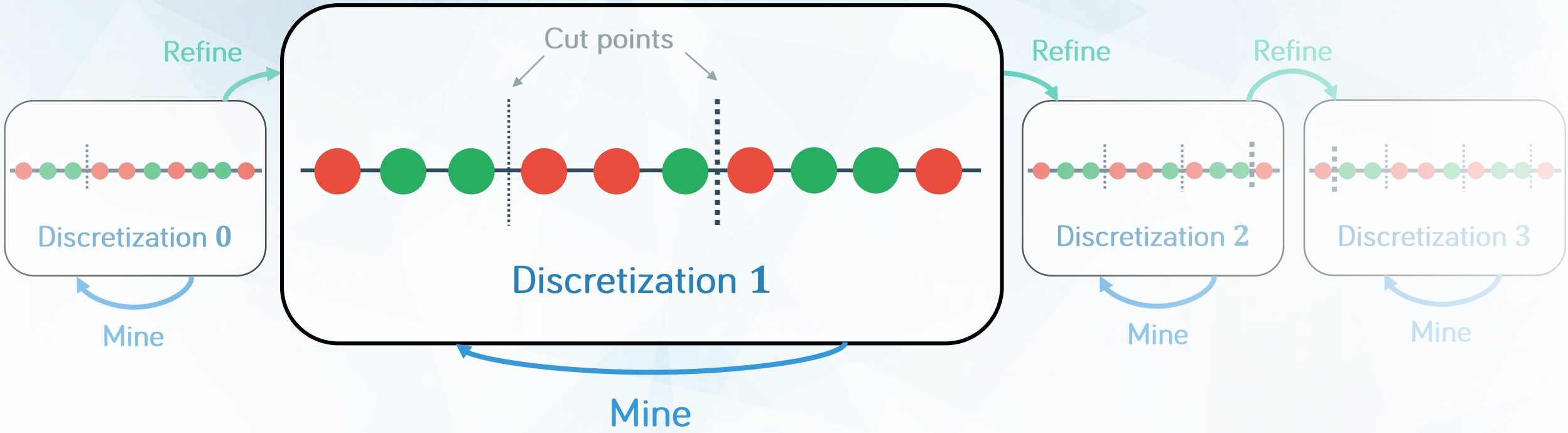

Refine&Mine

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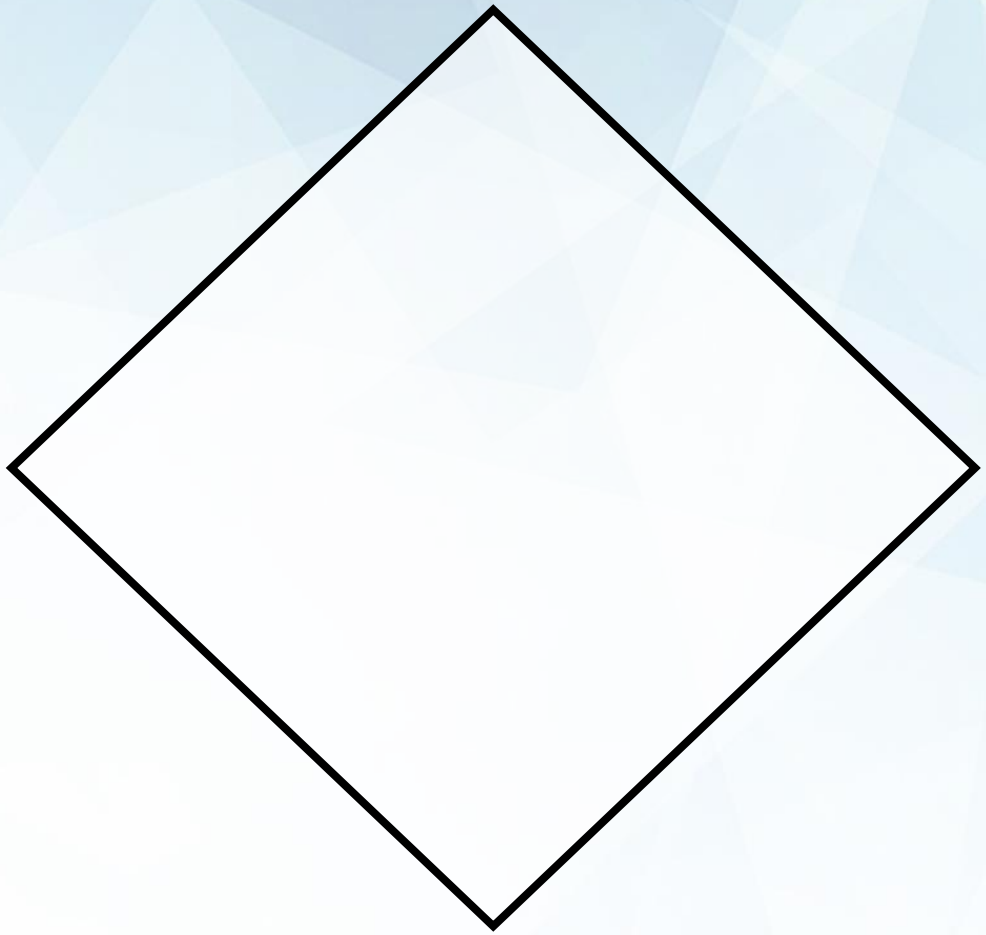
REFINE&MINE: In a Nutshell (2)

Refine

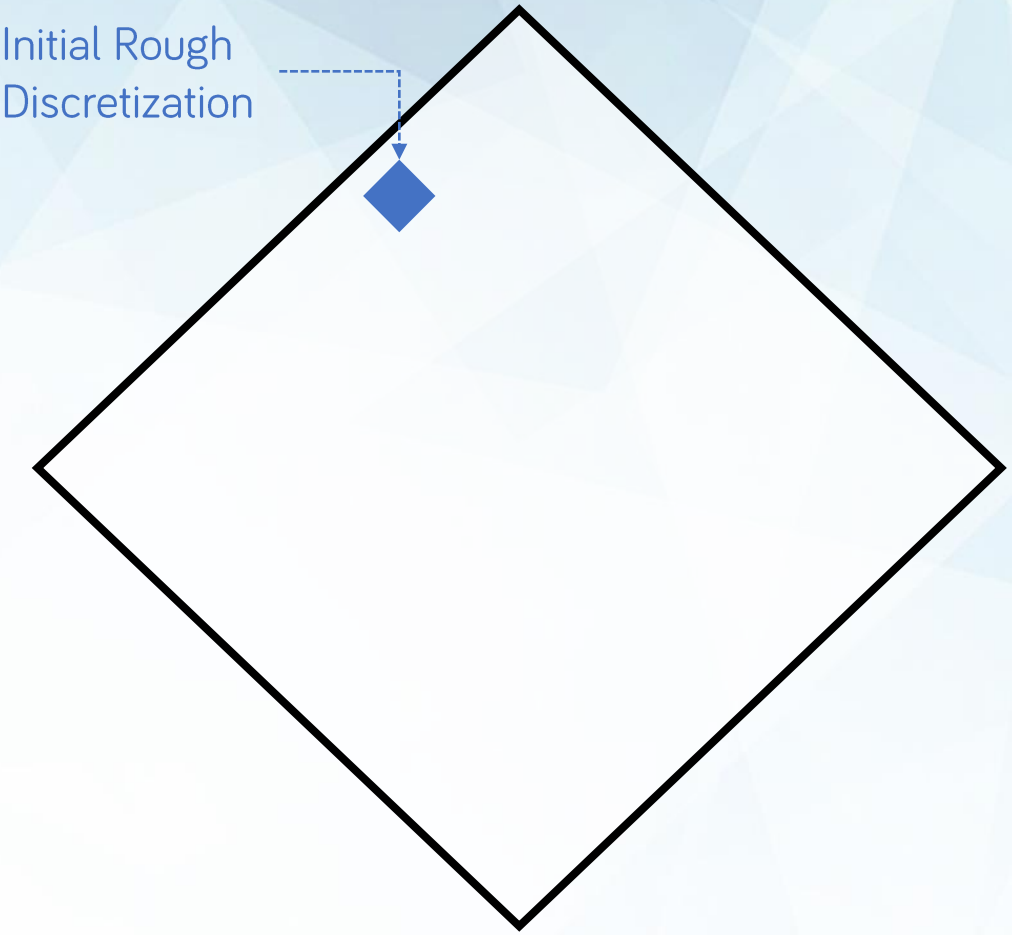


Mine

REFINE&MINE: In a Nutshell (2)

Refine

Initial Rough Discretization



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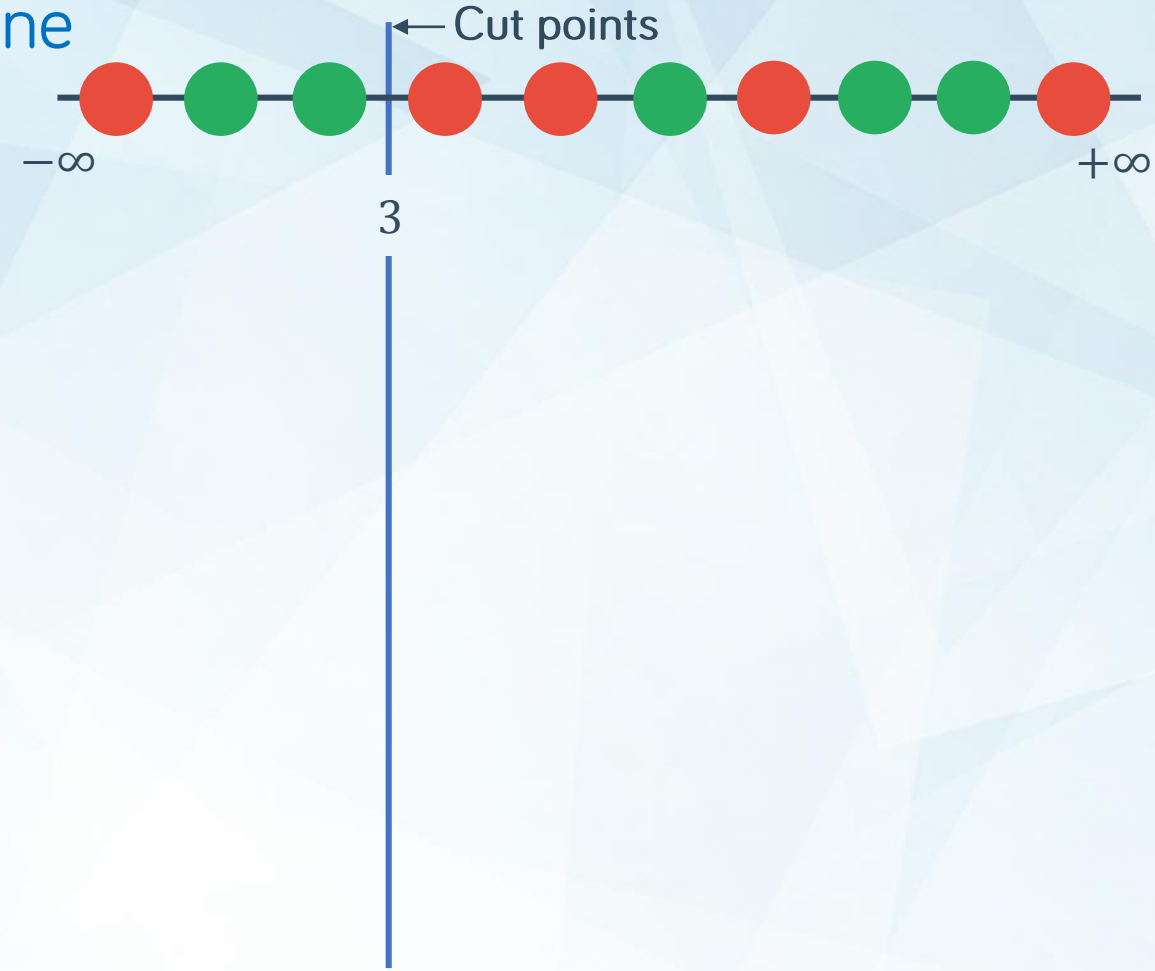

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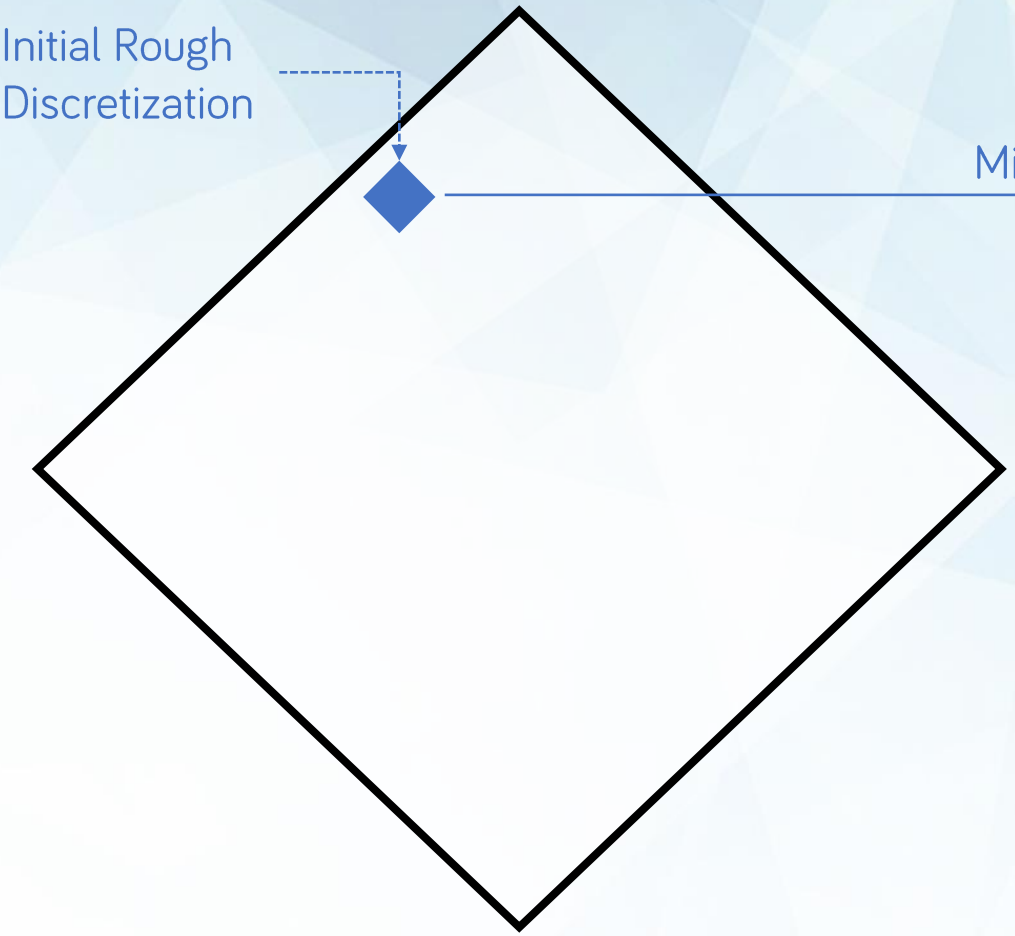

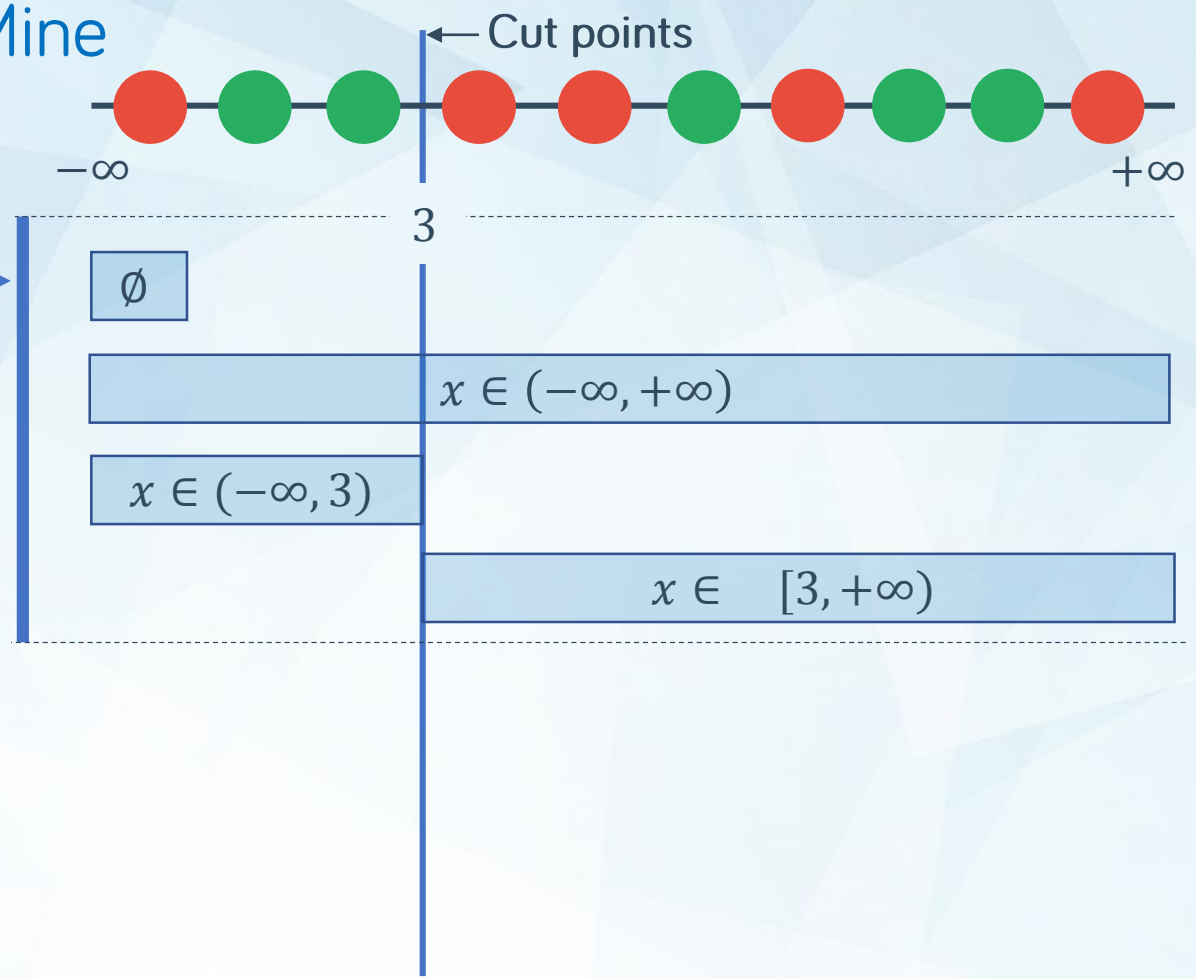

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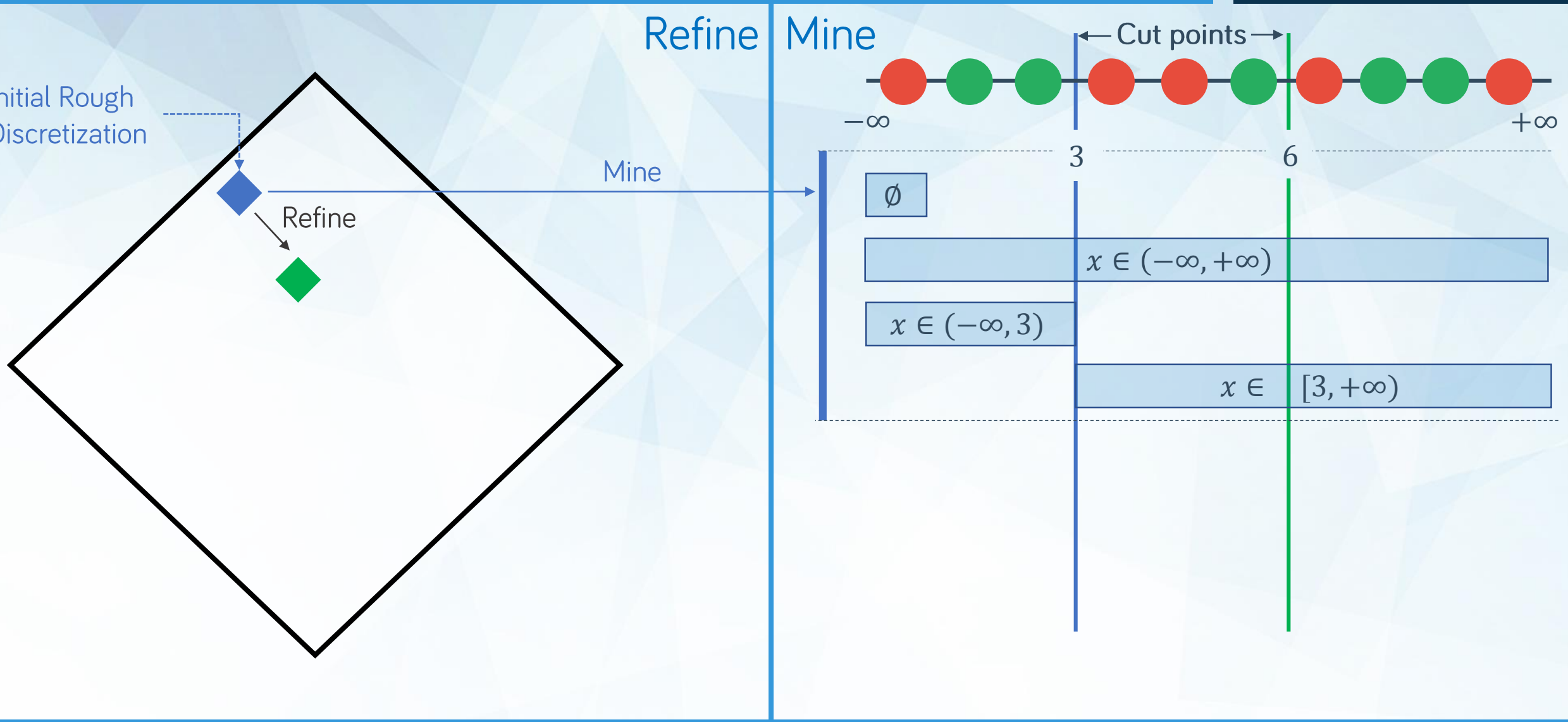

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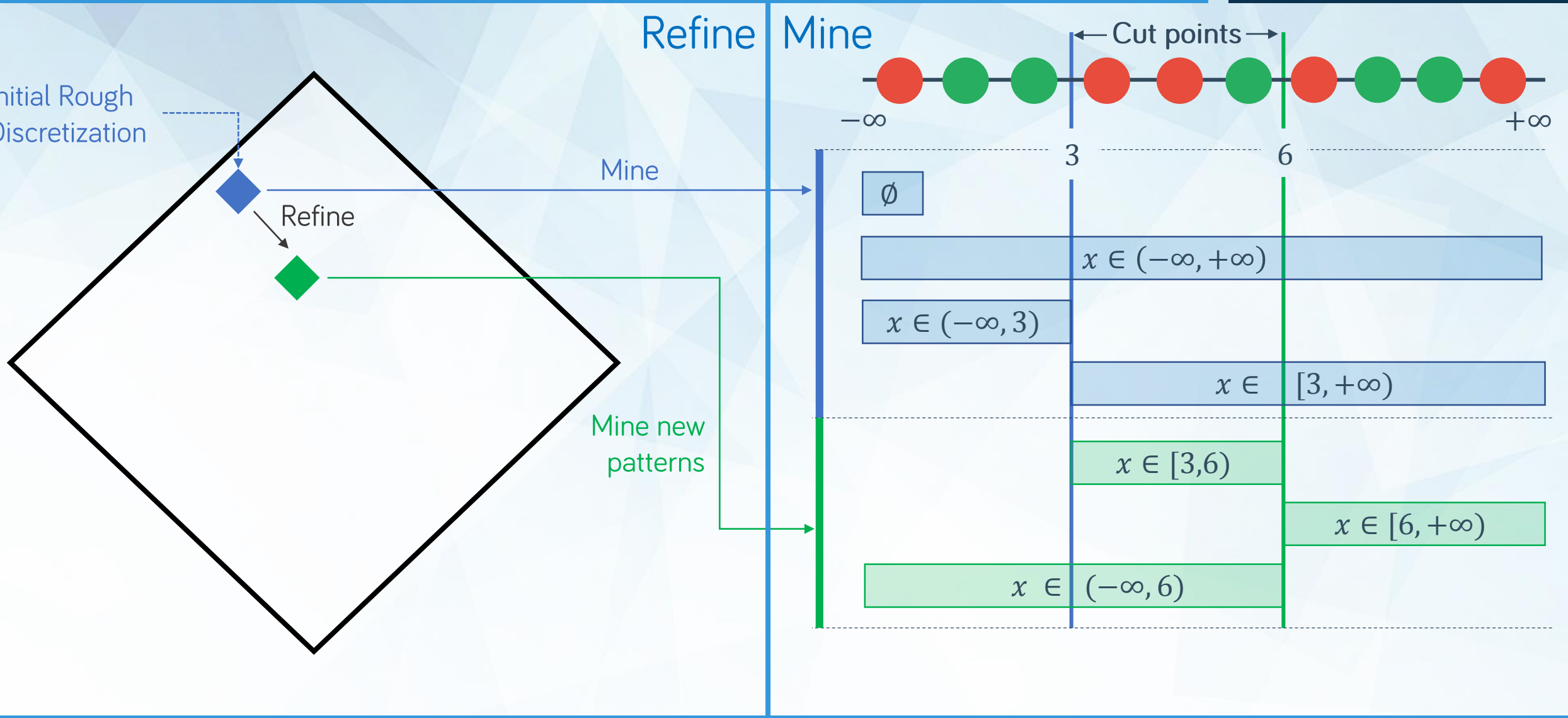

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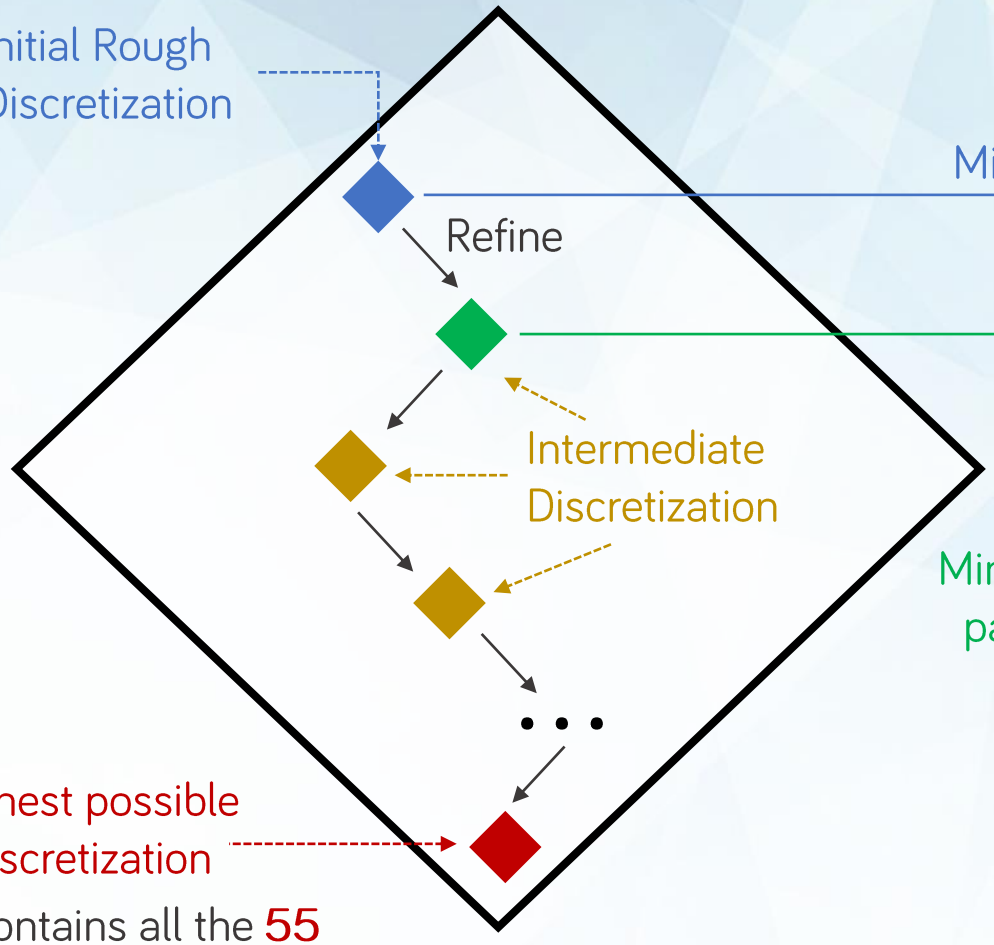
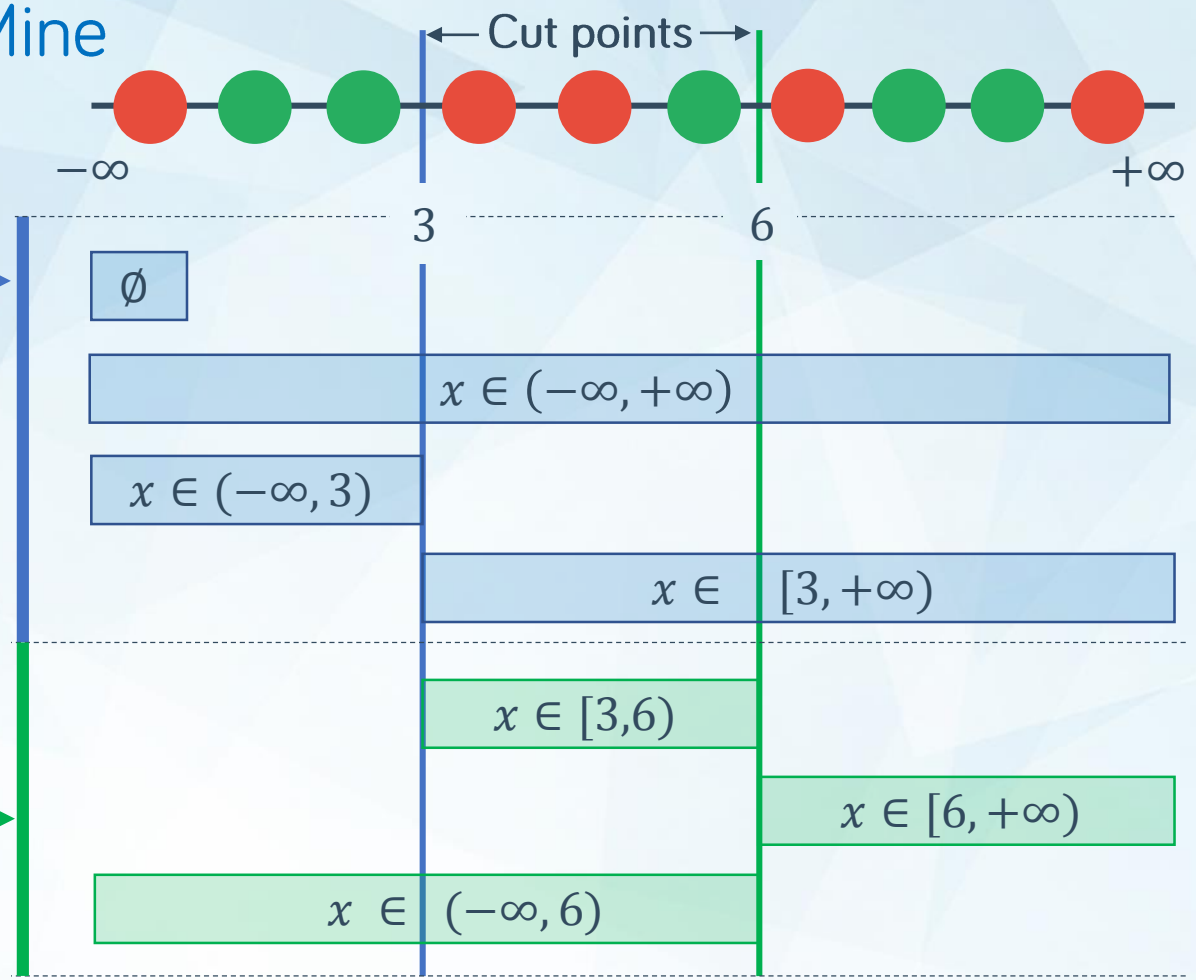


Contains all the 55 interval patterns

Refine | Mine

Mine

Mine new patterns



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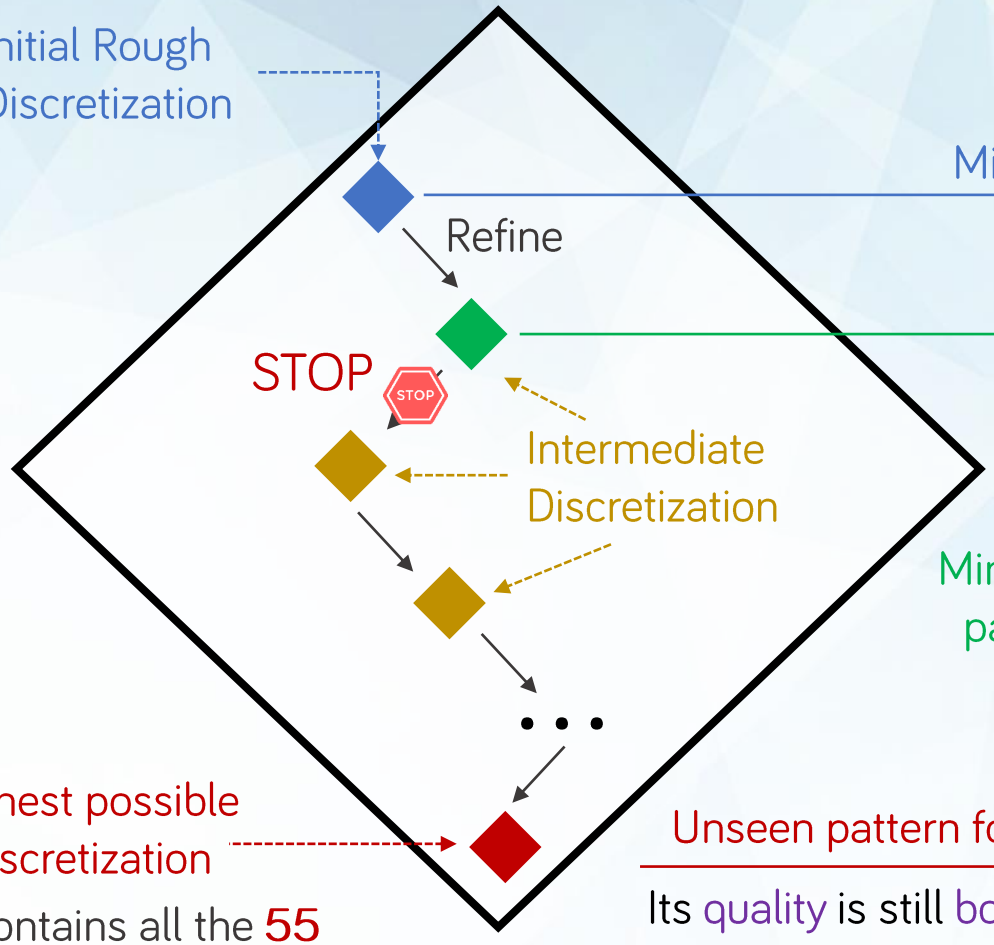
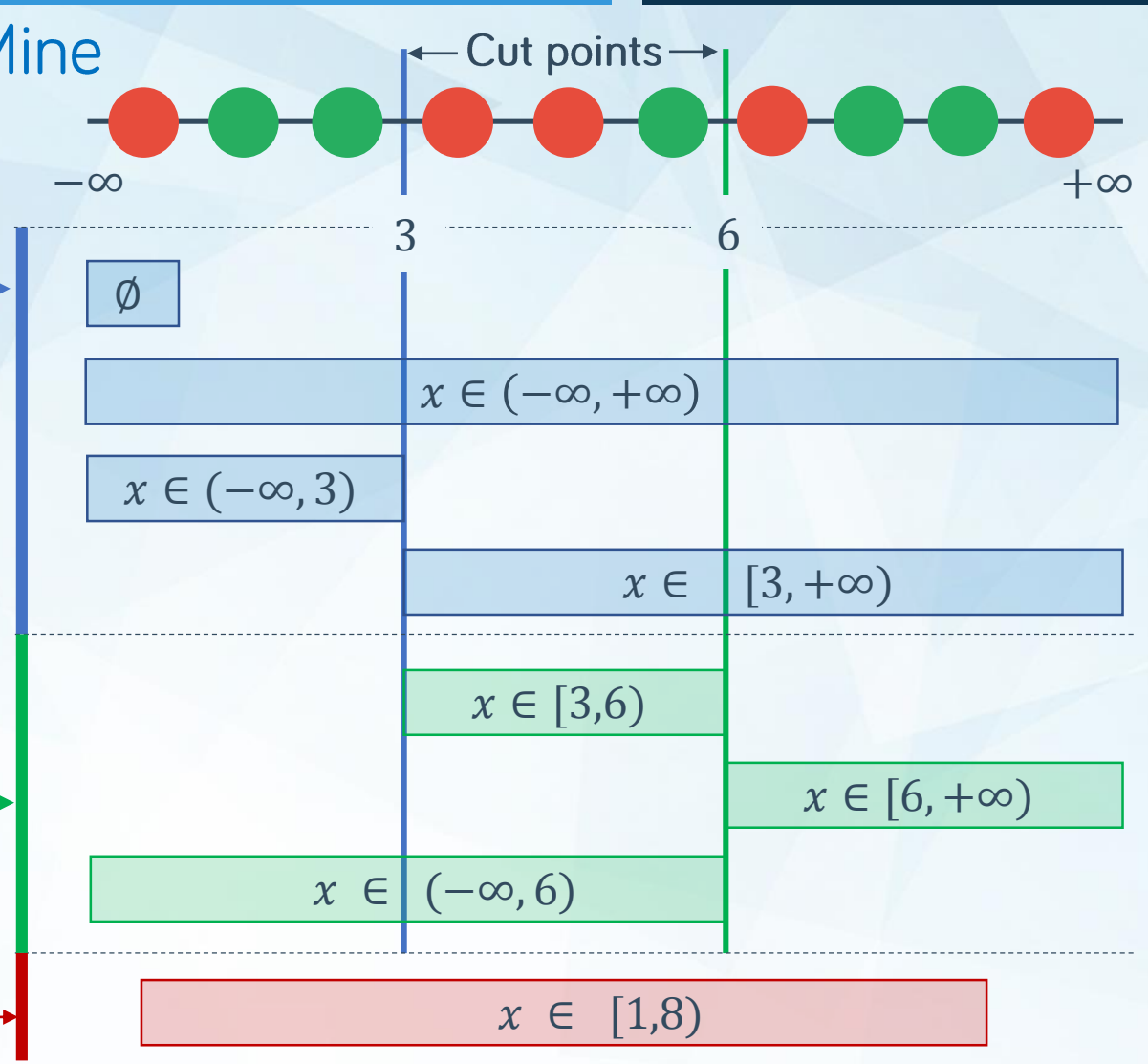


Mine

Mine new patterns

Unseen pattern for now

Its quality is still bounded by a guarantee.



Guarantees provided by Refine&Mine

Accuracy Guarantee

e.g. Informedness

$$\text{Accuracy} = \phi(\text{best pattern in the dataset}) - \phi(\text{best found pattern})$$

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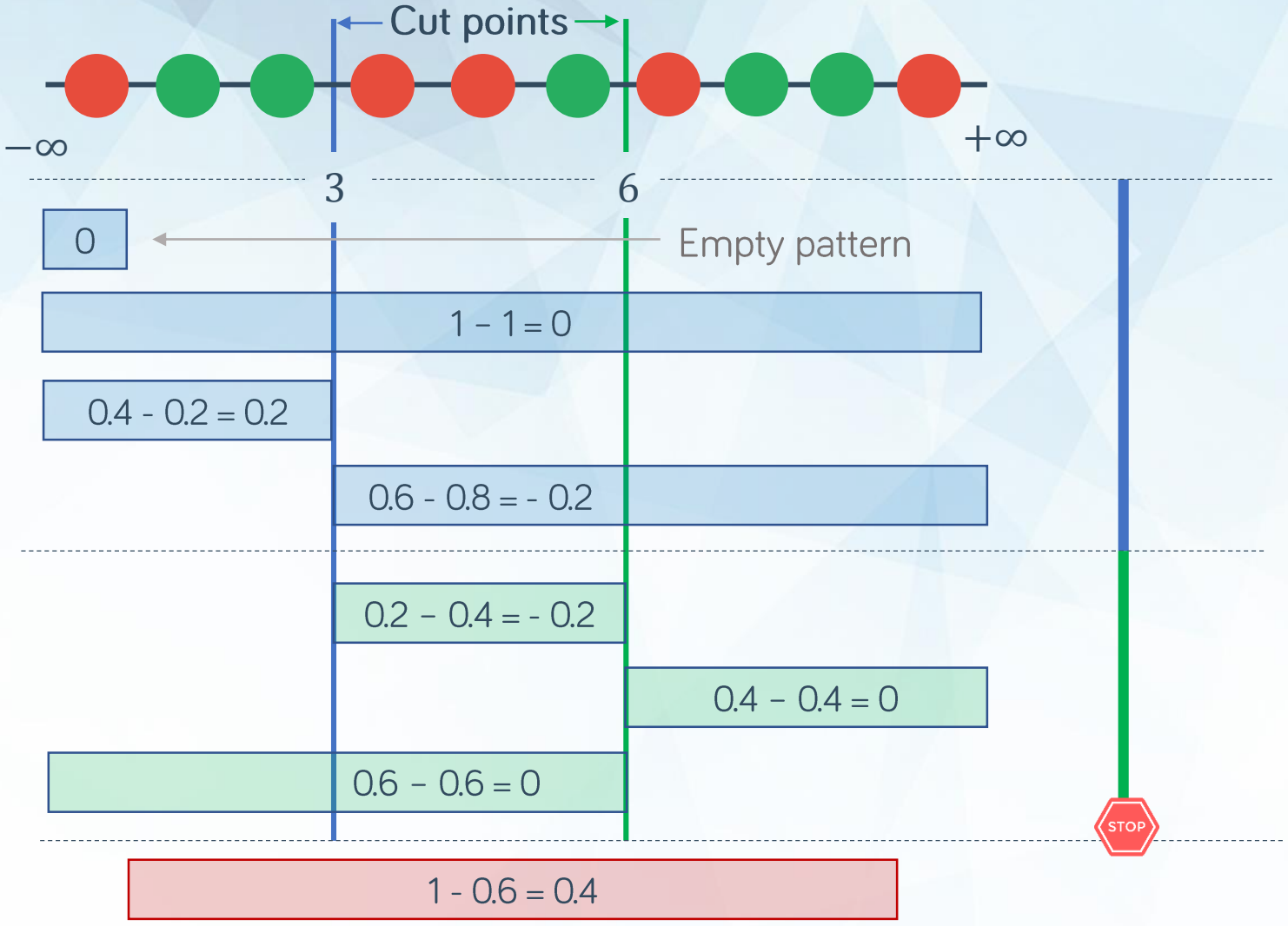
$$\text{Accuracy} = \phi(\text{best pattern in the dataset}) - \phi(\text{best found pattern})$$

$$\text{Accuracy} \leq \text{Accuracy bound}$$

Refine&Mine computes this bound using only already found patterns.

Accuracy Guarantee – Introduction



$$tpr(pattern) - fpr(pattern) = Informedness(pattern)$$

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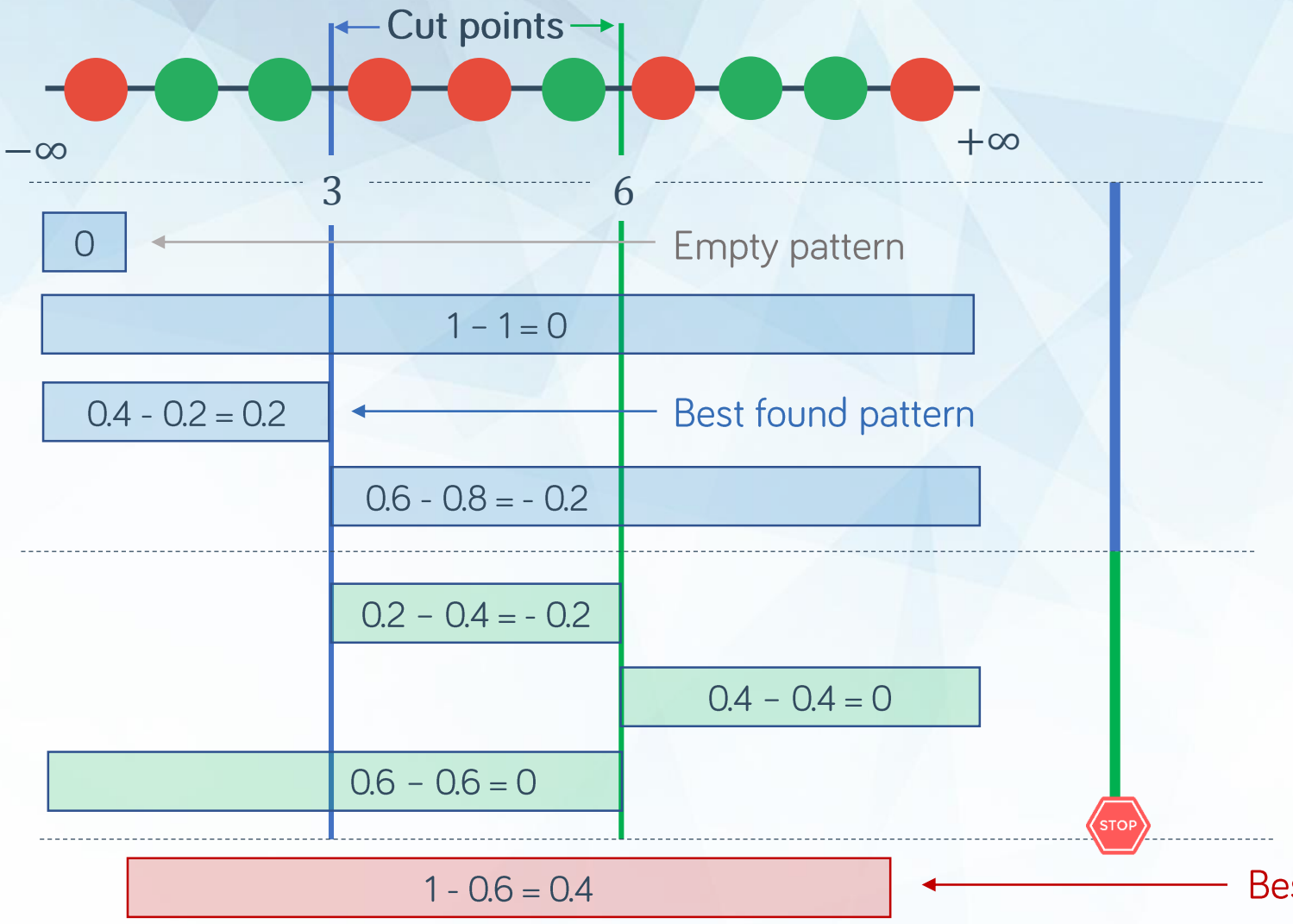

$$tpr(pattern) - fpr(pattern) = Informedness(pattern)$$

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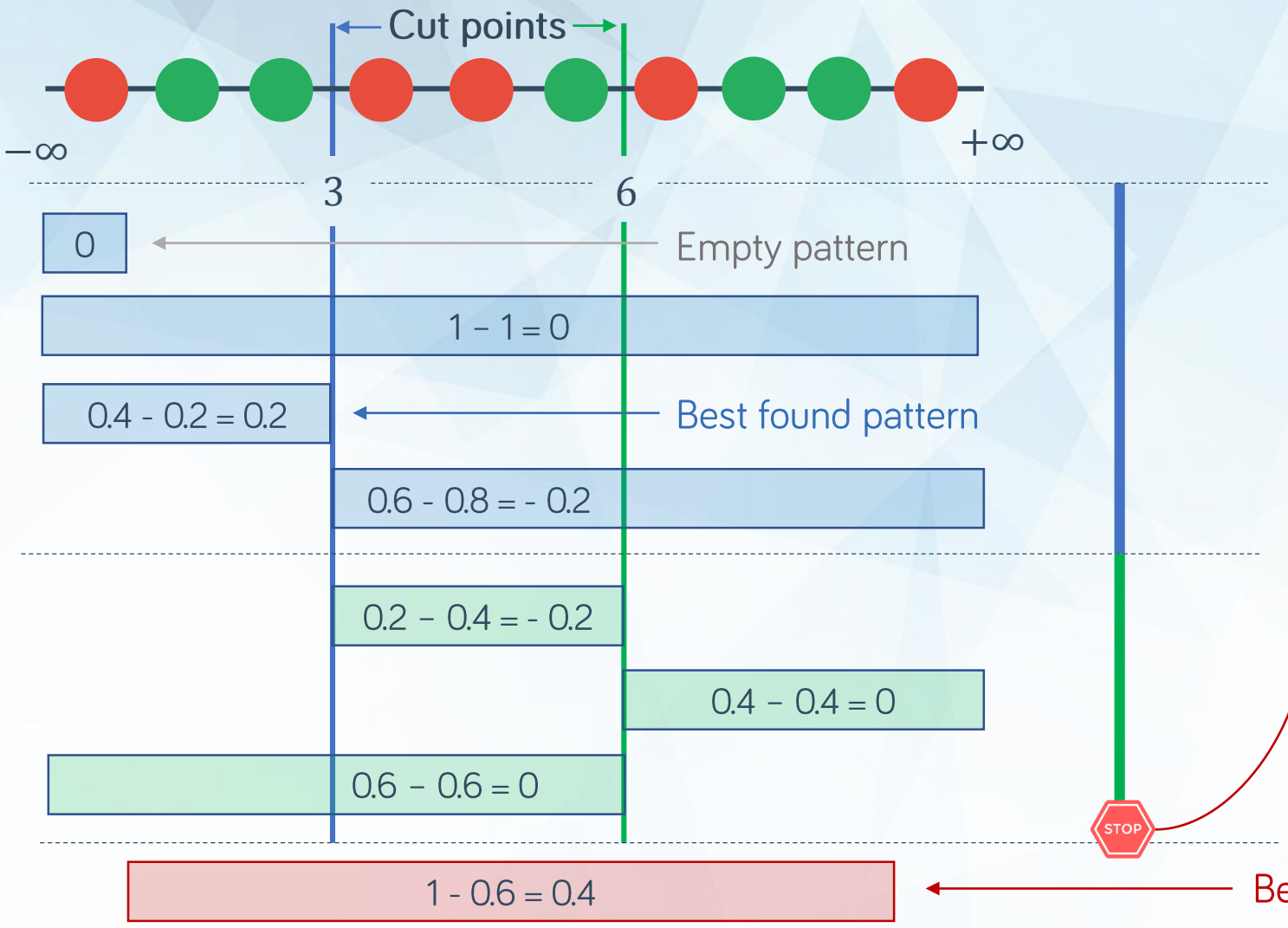

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Refine&Mine gives a bound of

0.6 on Informedness

when interrupted.

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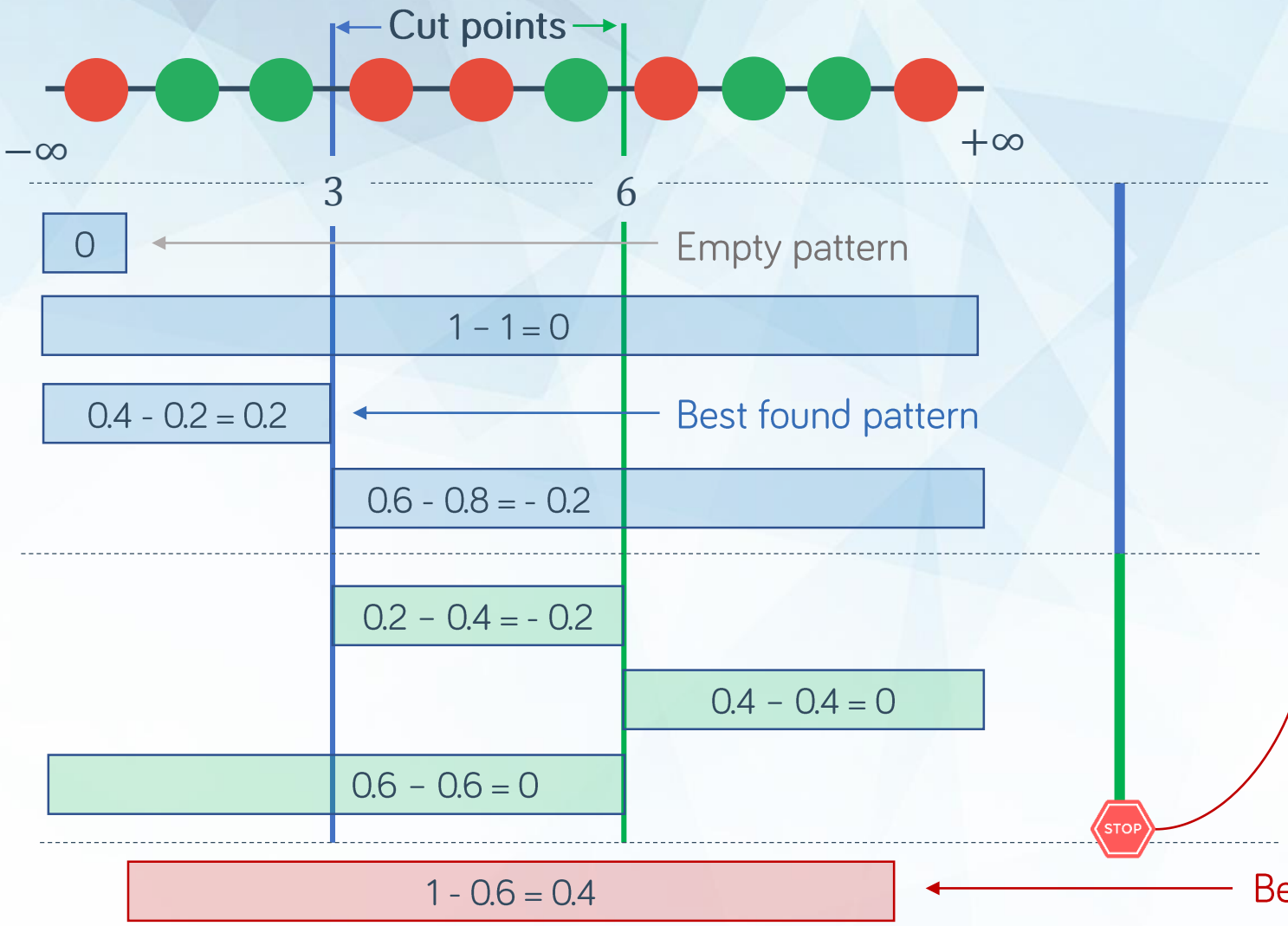

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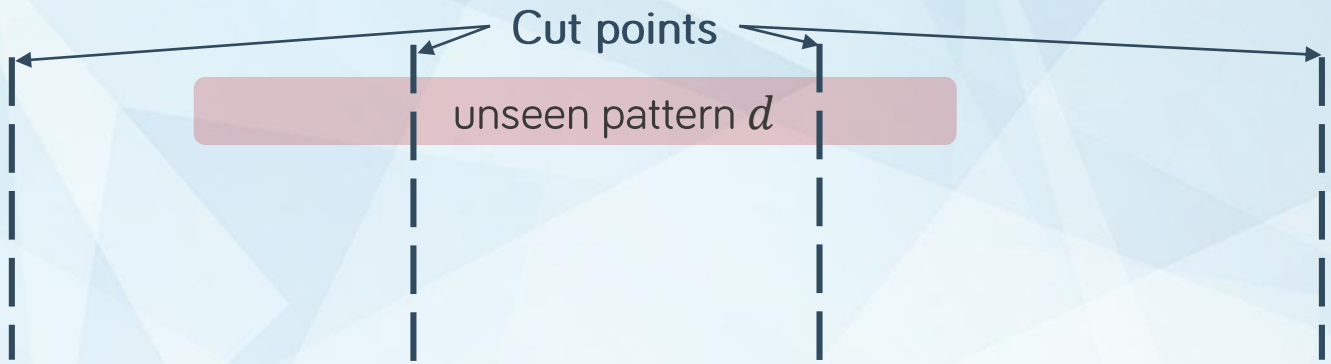
? How?

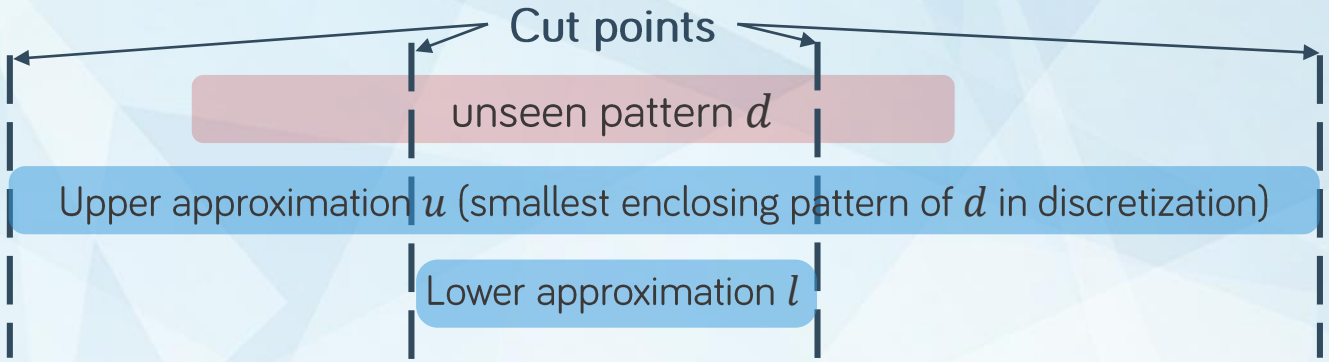
Accuracy Guarantee – Upper and lower approximations



Z. Pawlak. Rough sets. In International Journal of Parallel Programming 1982.
A. Tarski. A lattice-theoretical fixpoint theorem and its applications. In Pacific journal of Mathematics 1955.

Accuracy Guarantee – Upper and lower approximations

Any unseen interval pattern can be encapsulated between two found patterns.



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Accuracy Guarantee – Upper and lower approximations

I

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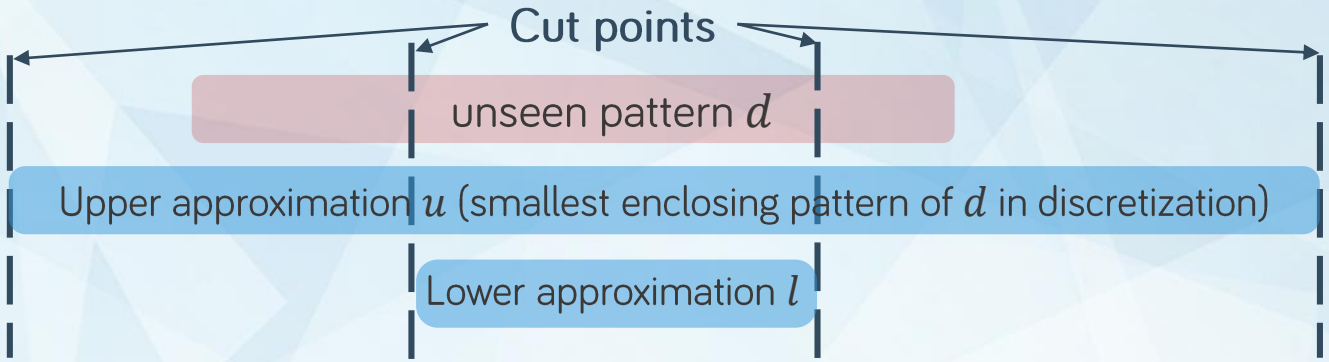

II

tpr and fpr measures are monotonous.

- $\text{tpr}(d) \leq \text{tpr}(u)$
- $\text{fpr}(d) \geq \text{fpr}(l)$

$\Rightarrow informedness(d) \leq \text{tpr}(u) - \text{fpr}(l)$

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Accuracy Guarantee – Upper and lower approximations

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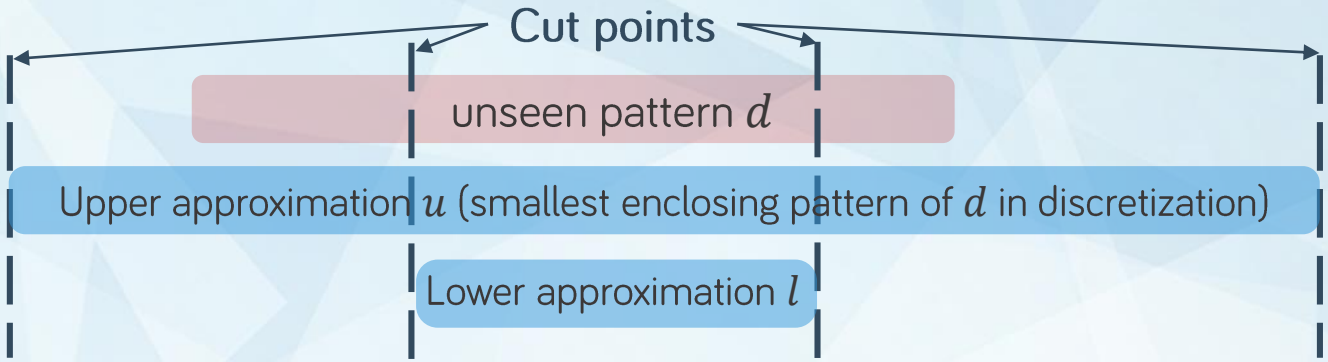

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Now, we gave a bound on the quality of an unseen pattern using its two already found patterns.

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Accuracy Guarantee – Core notion

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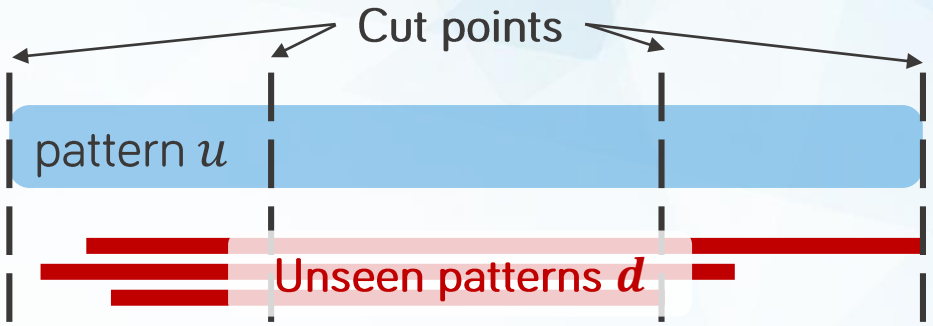

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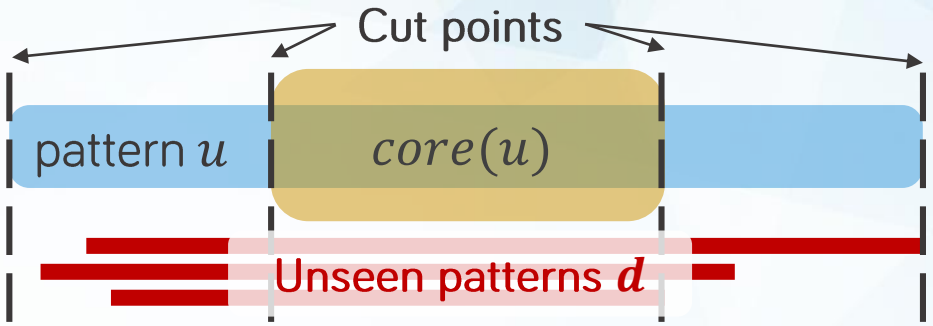

- Take all unseen patterns which upper approximation is u.
- The **core** of a found pattern u the largest possible lower approximation of all these unseen patterns.

Upper approximation

Core(found pattern) ⊆ some unseen patterns ⊆ found pattern

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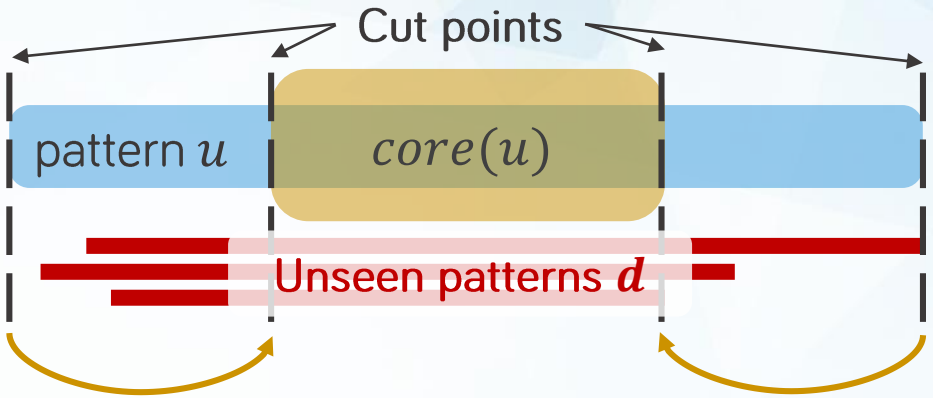

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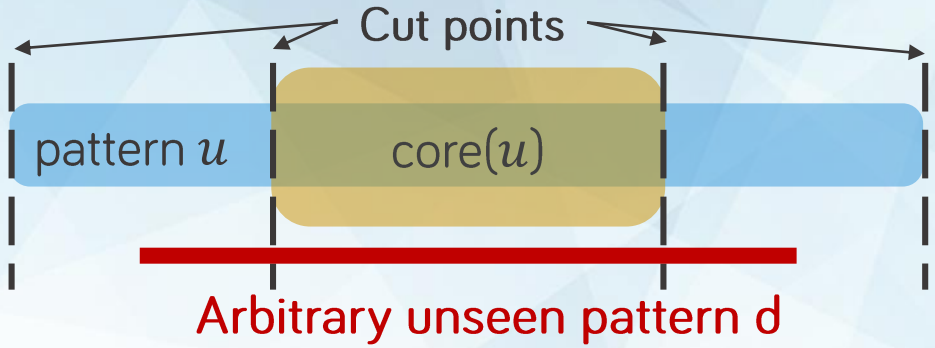
The core computation complexity is $O(d)$ with d is the number of dimensions.

Accuracy Guarantee – Computation

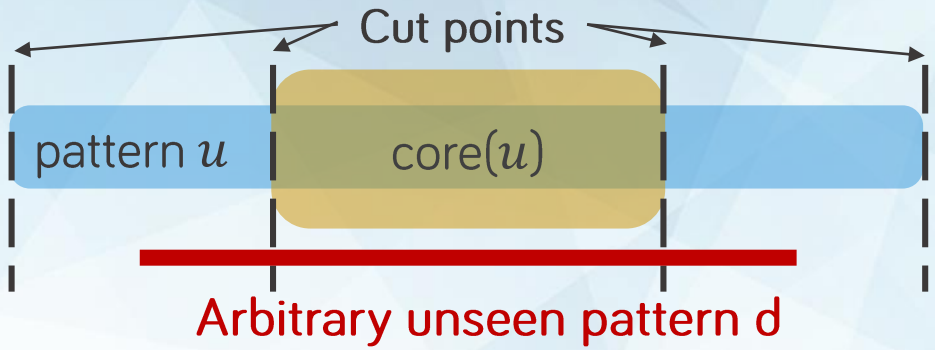


- Core(found pattern) ⊆ some unseen patterns ⊆ found pattern

Upper approximation

$$\text{Accuracy} = \sup_{d \in all} \phi(d) - \sup_{u \in found} \phi(u)$$

Accuracy Guarantee – Computation



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Upper approximation

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$$\downarrow \leq$$

$$\text{Accuracy} \leq \sup_{u \in found} \phi\left(tpr(u), fpr\left(core(u)\right)\right) - \sup_{u \in found} \phi(u)$$

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$$\text{Specificity} \leq \text{Specificity bound}$$

Same aforementioned notions are used to define the bound on specificity

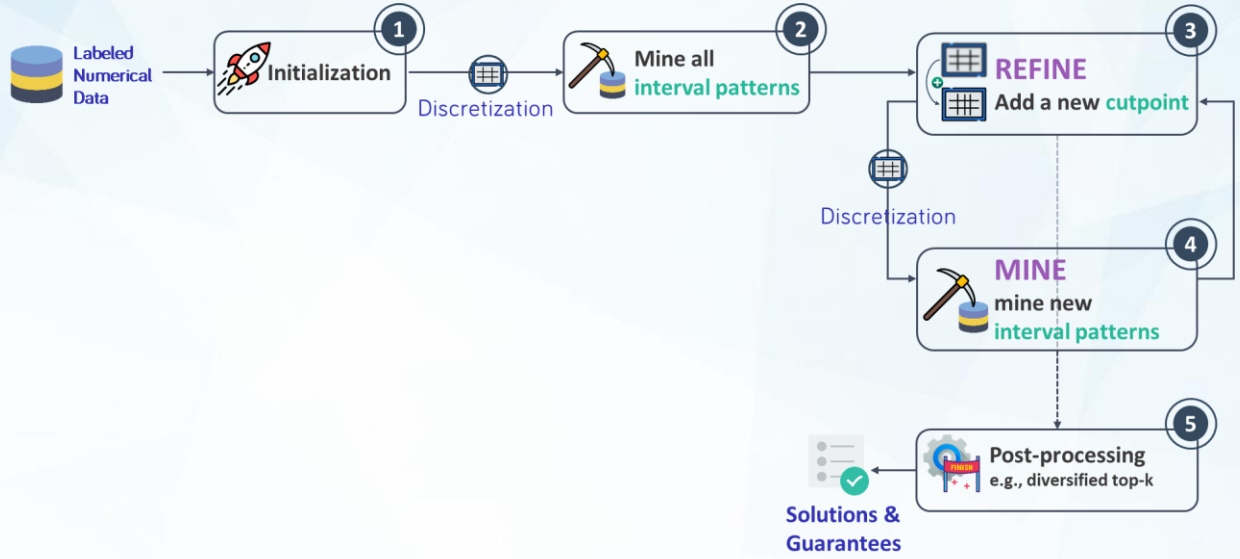
Refine&Mine computes this bound using only already found patterns.

OUTLINE

- Overview and Contributions
- Refine&Mine in a nutshell
- Guarantees computation
- Building blocks of Refine&Mine
- Wrap-up and concluding remarks

Refine&Mine

Step-by-step



REFINE&MINE: Step-by-step

Labeled
Numerical
Data

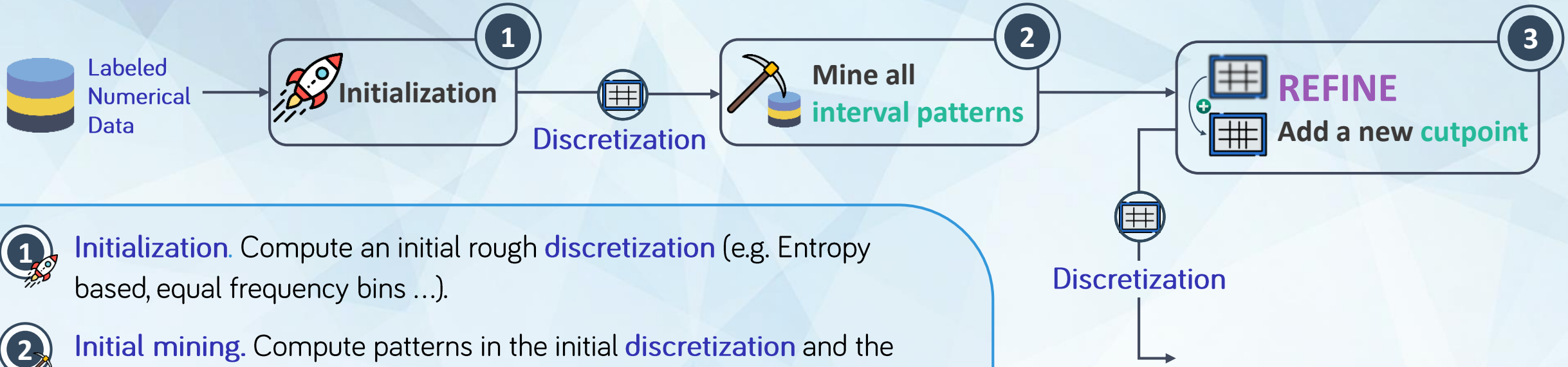
REFINE&MINE: Step-by-step

1 **Initialization.** Compute an initial rough **discretization** (e.g. Entropy based, equal frequency bins ...).

REFINE&MINE: Step-by-step

1. Initialization. Compute an initial rough discretization (e.g. Entropy based, equal frequency bins ...).
2. Initial mining. Compute patterns in the initial discretization and the first guarantees (e.g. use optimizations like closure operator) .

REFINE&MINE: Step-by-step



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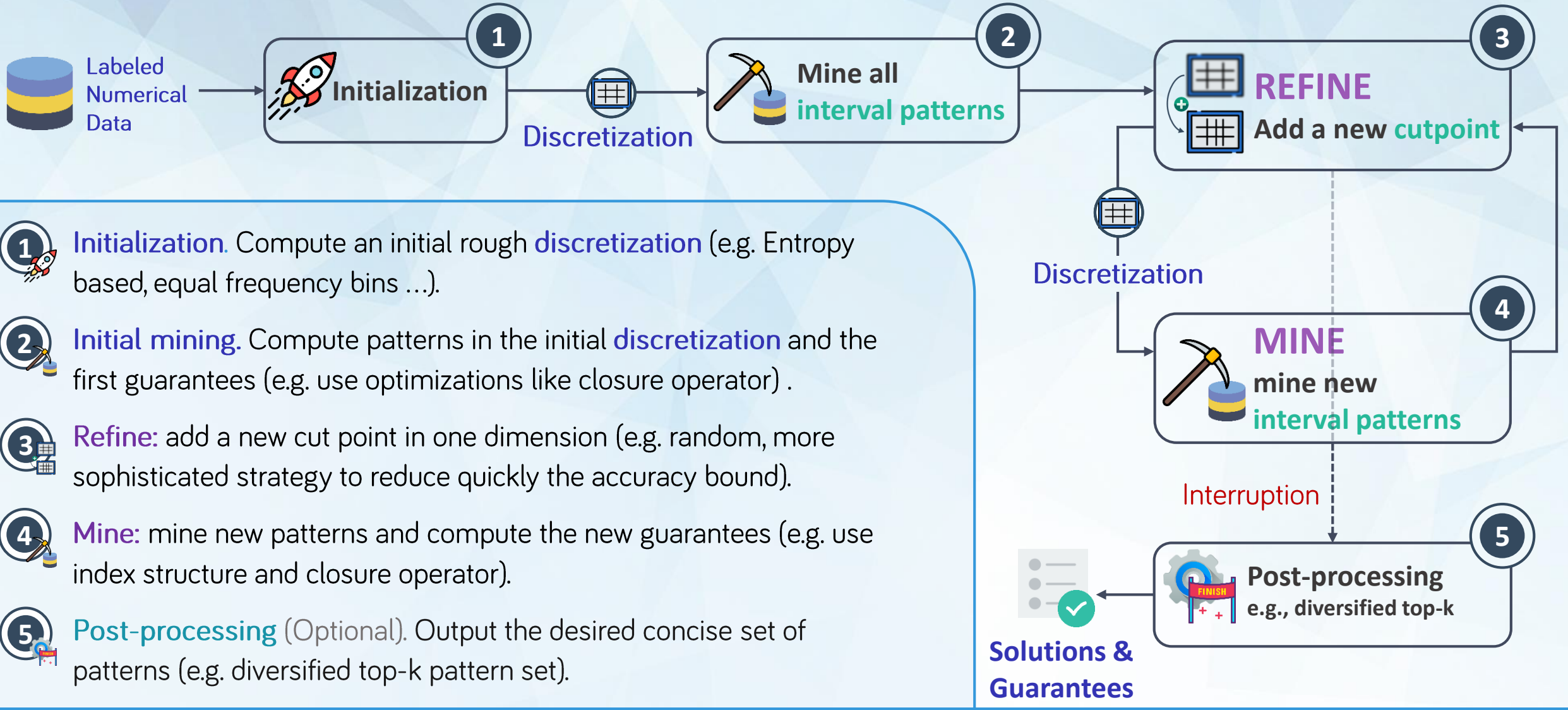

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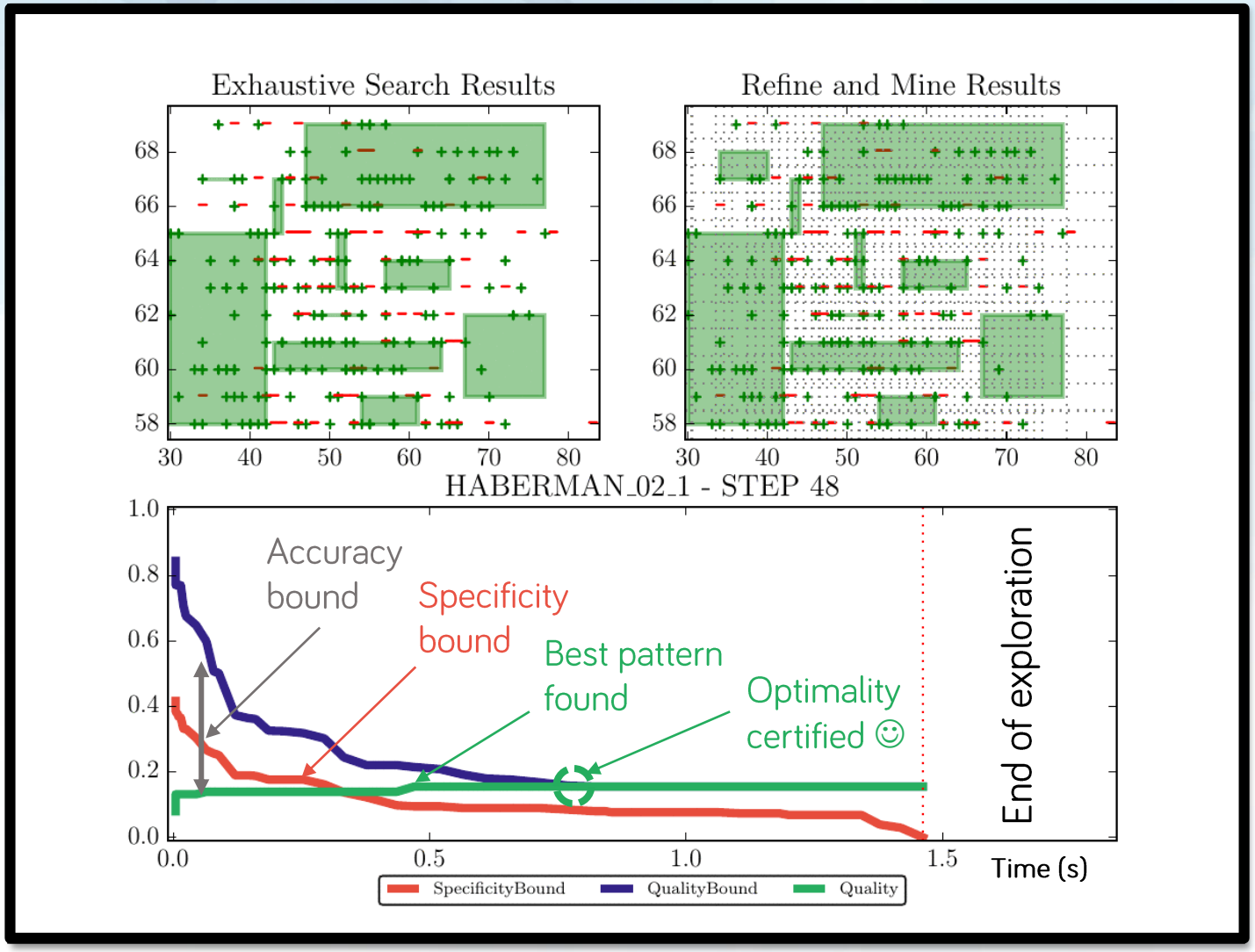
5. **Post-processing** (Optional). Output the desired concise set of patterns (e.g. diversified top-k pattern set).

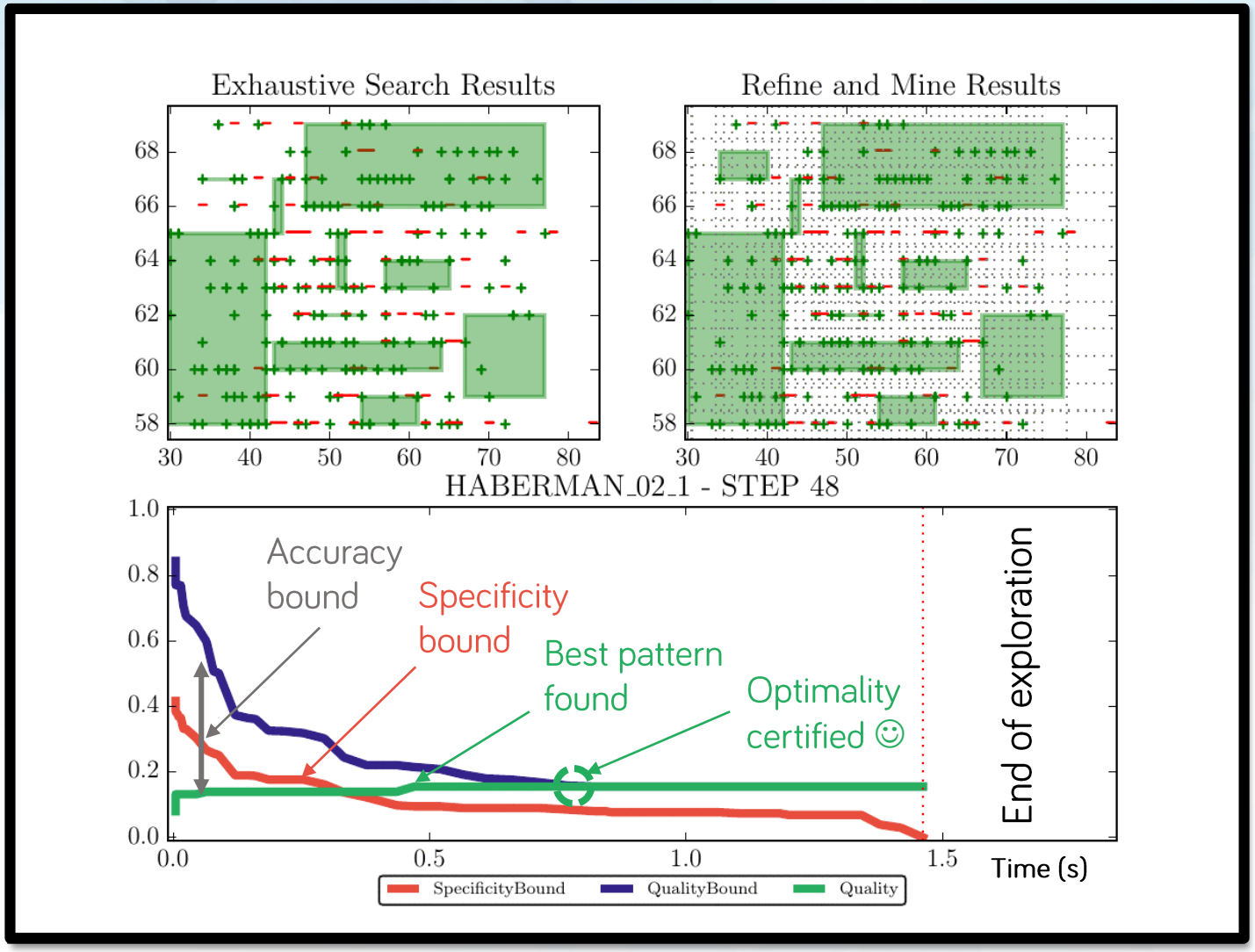
Refine&Mine

Wrap-up

REFINE&MINE: Wrap-up



REFINE&MINE: Wrap-up

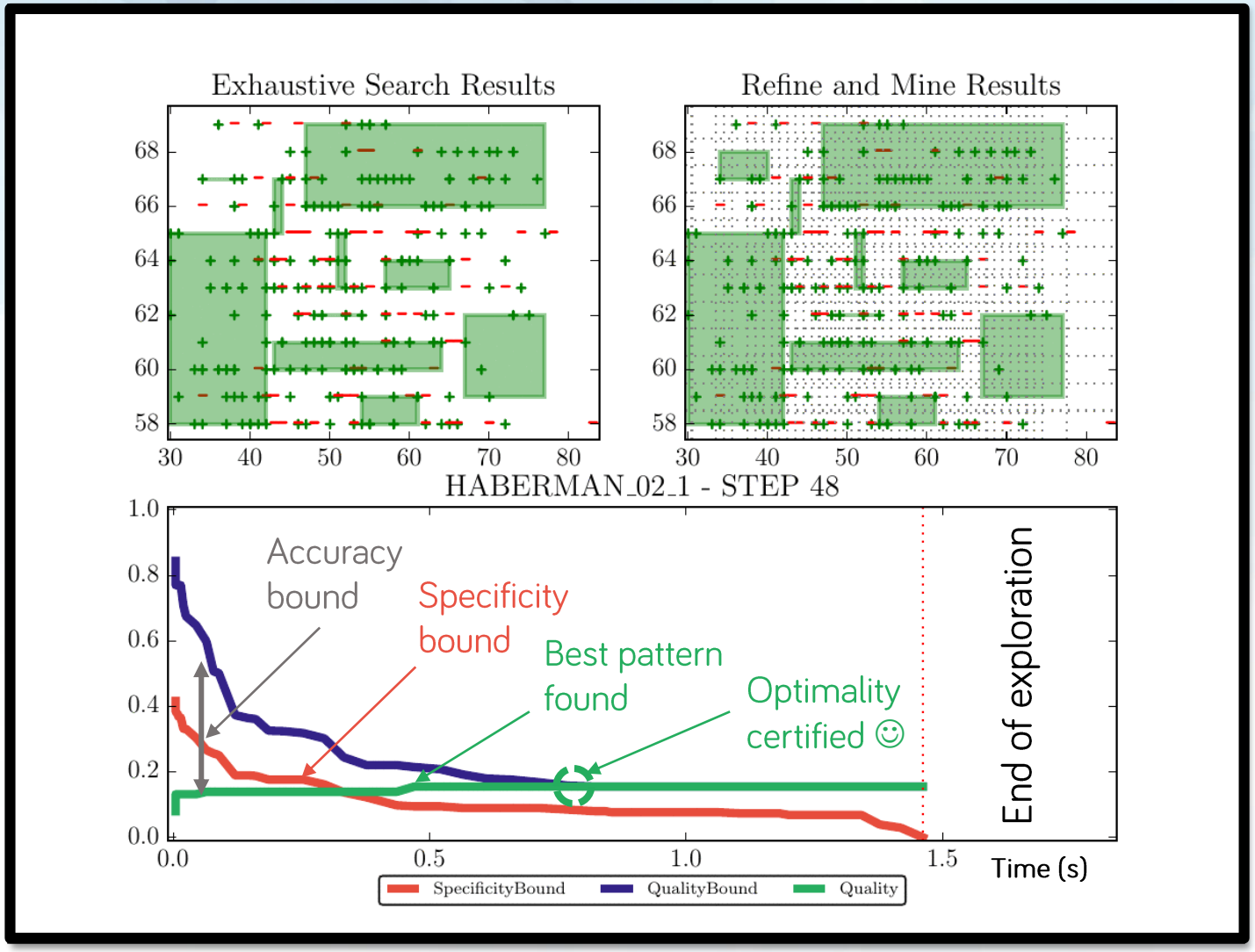


Empirical Evaluation

Experiments were performed over

25 UCI Datasets

REFINE&MINE: Wrap-up



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- Refine&Mine achieves to find a 80% ground truth in less than 20% of the time required for the exhaustive search algorithm to finish

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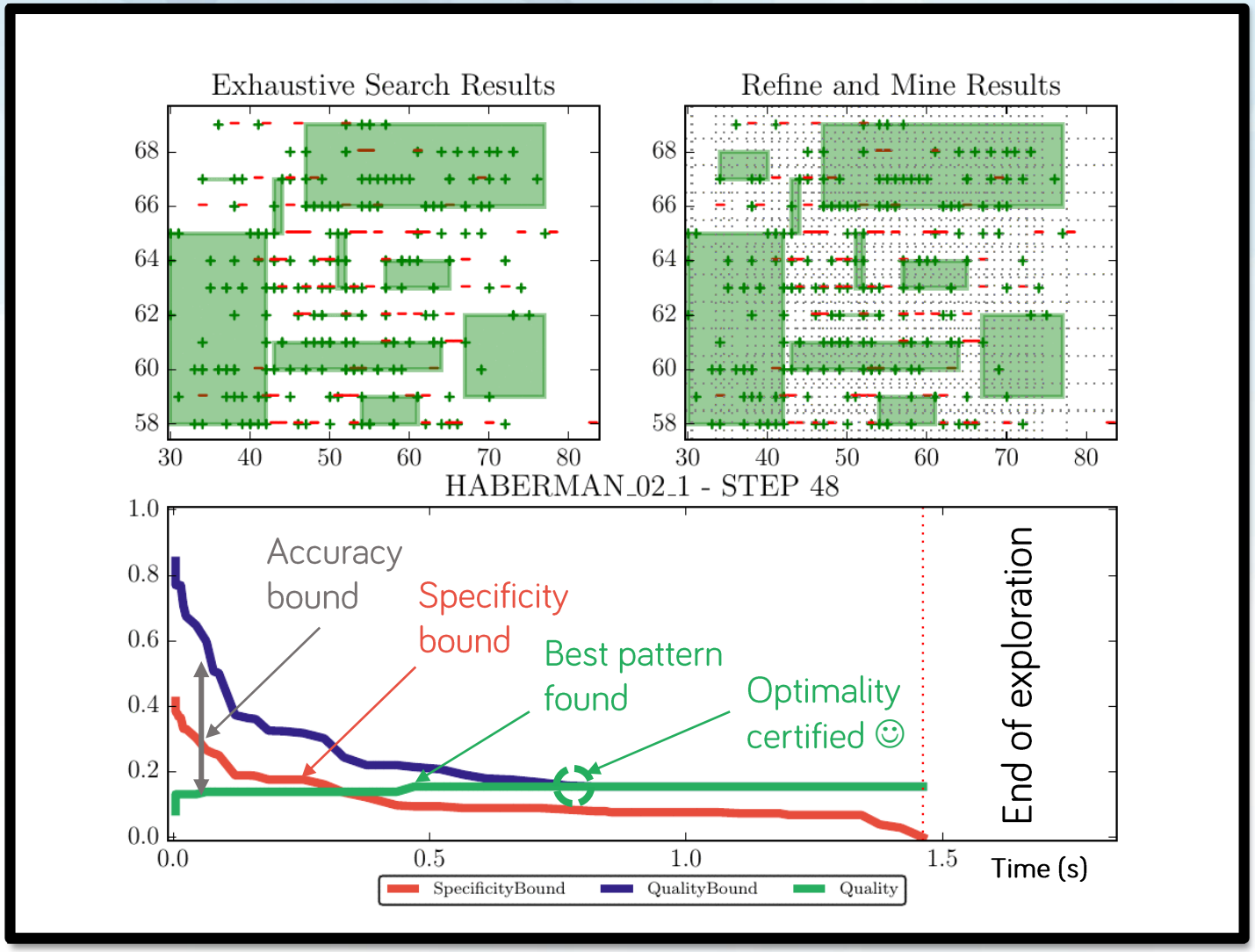

Empirical Evaluation

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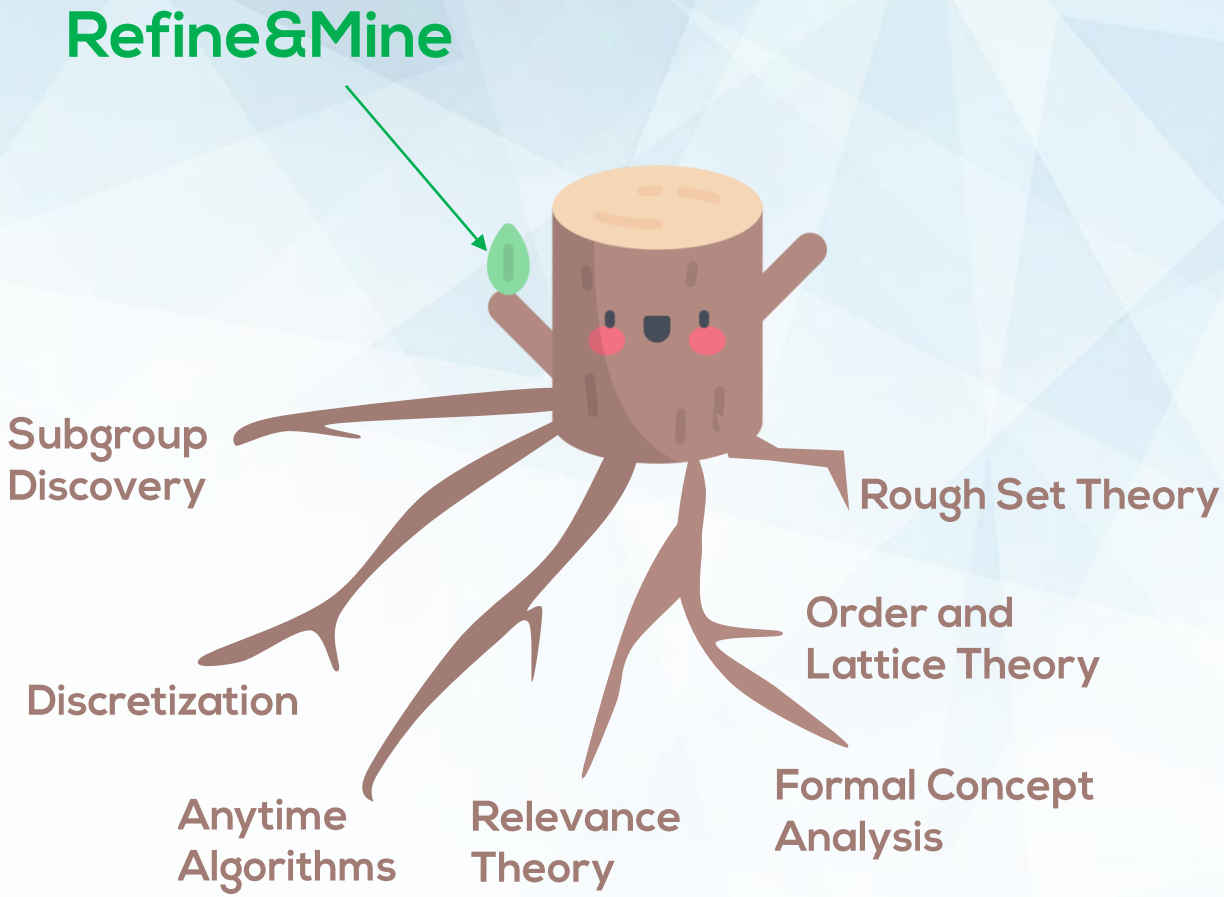
- Refine&Mine achieves to find a 80% ground truth in less than 20% of the time required for the exhaustive search algorithm to finish
- Refine&Mine achieved better results both in finding the best pattern and a high diversified results set compared to MCTS4DM [*]

[*] *G. Bosc, J.F. Boulicaut, C. Raïssi, M. Kaytoue. Anytime discovery of a diverse set of patterns with MCTS. In DMKD 2018.*

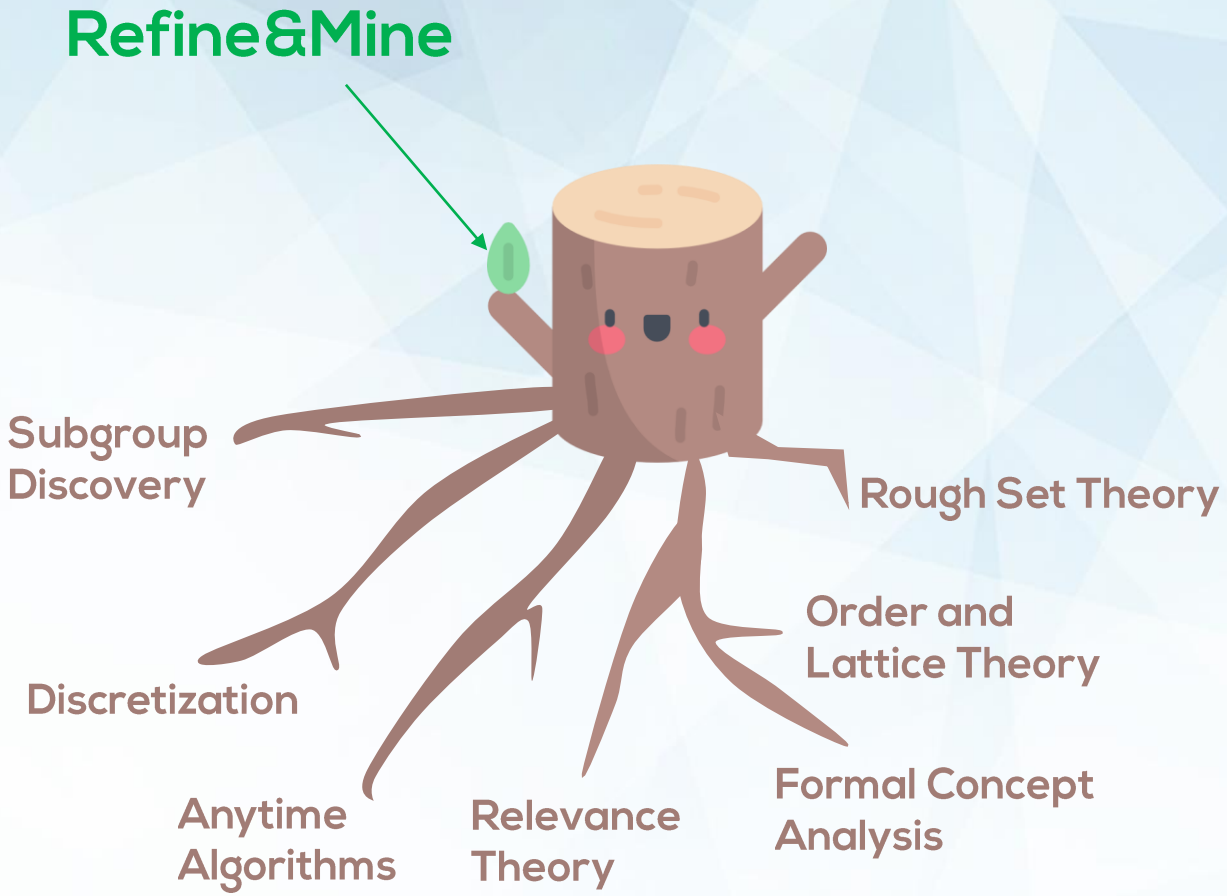
CONCLUSION & PERSPECTIVES

Conclusion



Proposed the new algorithm **Refine&Mine**

Conclusion



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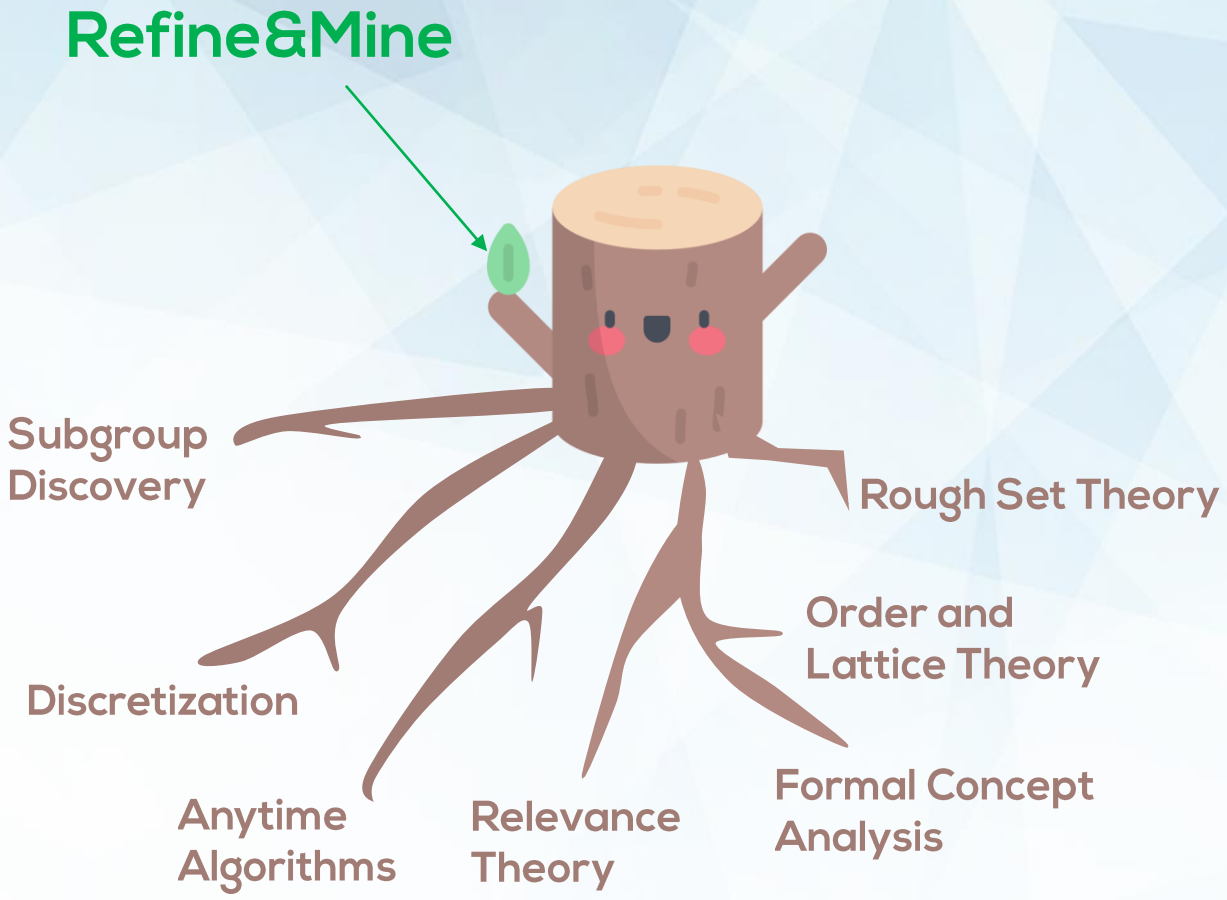
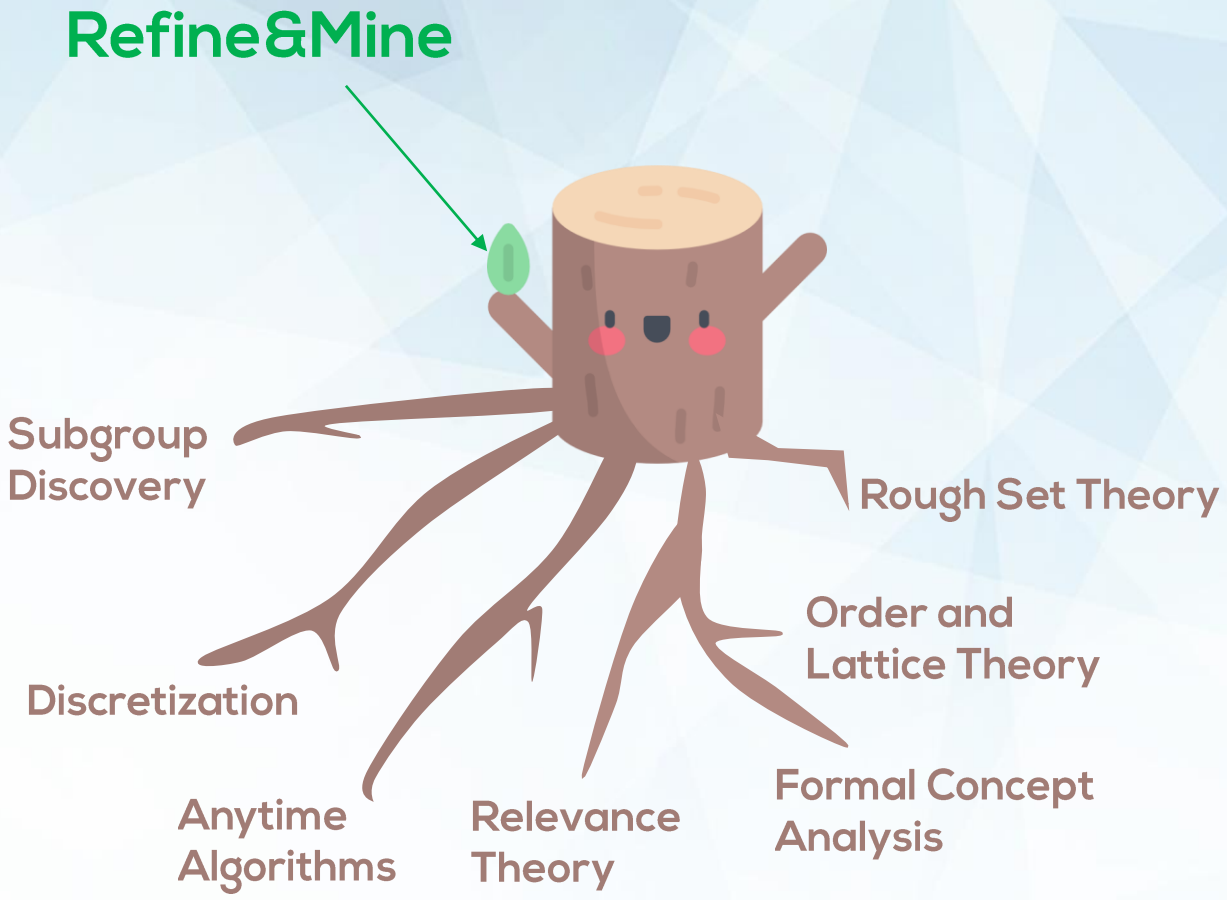


Proposed the new algorithm **Refine&Mine**

Anytime Algorithm

Guarantees on the found patterns anytime

Conclusion



Proposed the new algorithm **Refine&Mine**

Anytime Algorithm

Guarantees on the found patterns anytime

It performs an exhaustive search If given enough time

Future works

Handle High dimensional data.

Limit. We need **2 cut points in each dimension** to compute the first guarantees:

d attributes $\Leftrightarrow 6^d$ *patterns*

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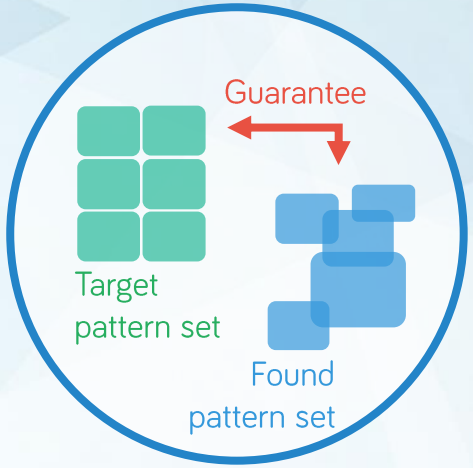


Provide guarantees on pattern sets rather than all patterns.

THANKS

FOR YOUR TIME

QUESTIONS

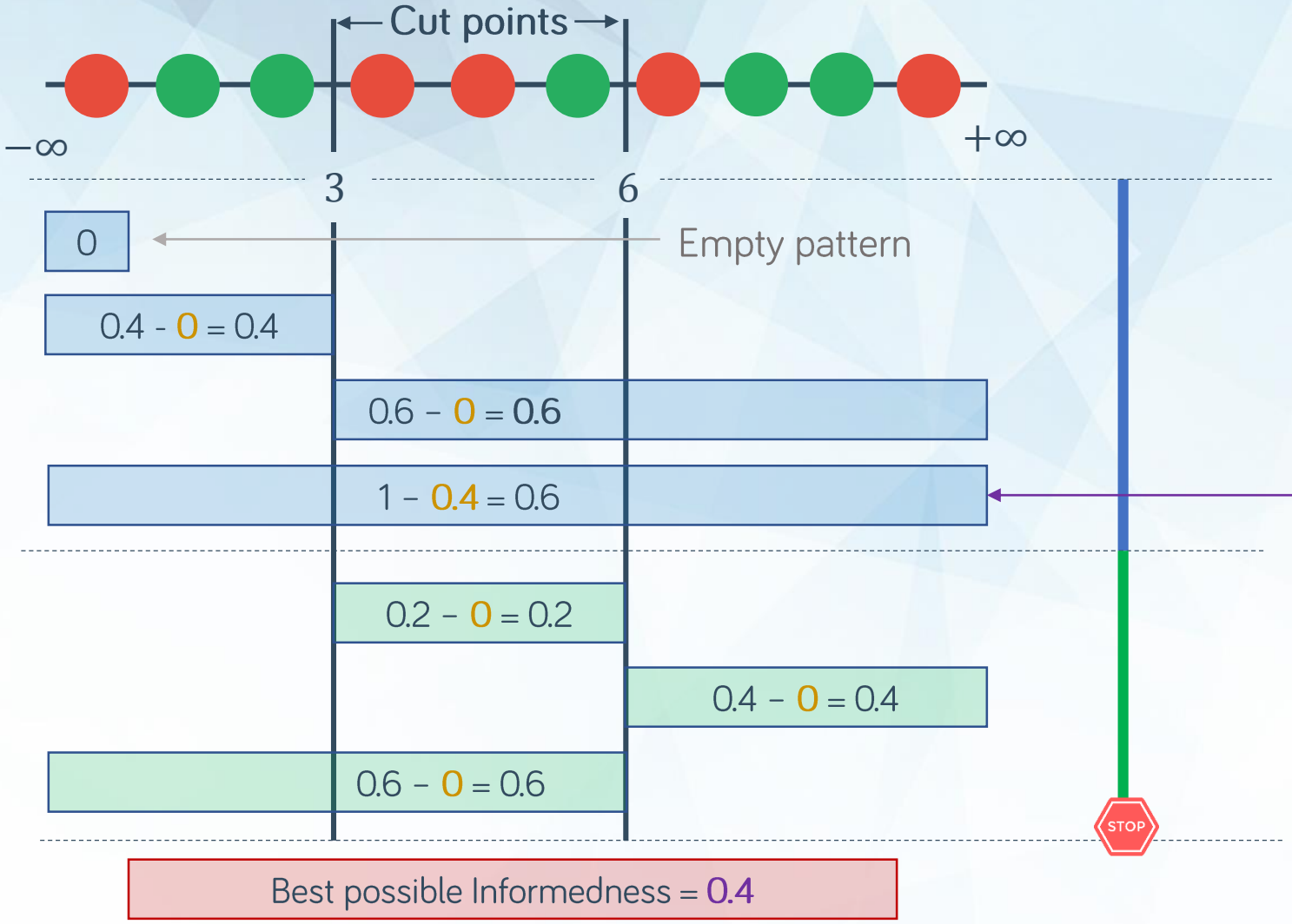
Contact : adnene.belfodil@insa-lyon.fr & aimene.belfodil@insa-lyon.fr

Materials: https://github.com/Adnene93/RefineAndMine

Looking forward to meeting up with you during the poster session :-)

ADDITIONAL DETAILS

Accuracy Guarantee – Example



$$tpr(pattern) - fpr(core(pattern)) = informedness\ bound(pattern)$$

- Best found Informedness = 0.2
- Best unseen Informedness = 0.4
- Highest Informedness bound = 0.6

- Accuracy = **0.4** − 0.2 = 0.2

- Accuracy bound = 0.6 − 0.2 = 0.4

First guarantee

Specificity Guarantee

$$\text{Specificity} = \overrightarrow{distance}(\text{All found patterns}, \text{All pattern in the dataset})$$

$$\text{Specificity} \leq \text{Specificity bound}$$

Refine&Mine computes this bound using only already found patterns.

Specificity Guarantee – Directed Distance

$$distance(c, d) = \frac{|c \,\Delta\, d|}{n} \in [0,1]$$

Symmetric difference

Pattern extents

Dataset size

The set of found patterns is compared to the set of ground truth patterns in this **direction** as follow:

- Each possible pattern is compared to its nearest found pattern.
- The top nearest distance is then the specificity

$$\overrightarrow{distance}(Found, All) = \sup_{d \in all} \inf_{c \in found} distance(c, d)$$

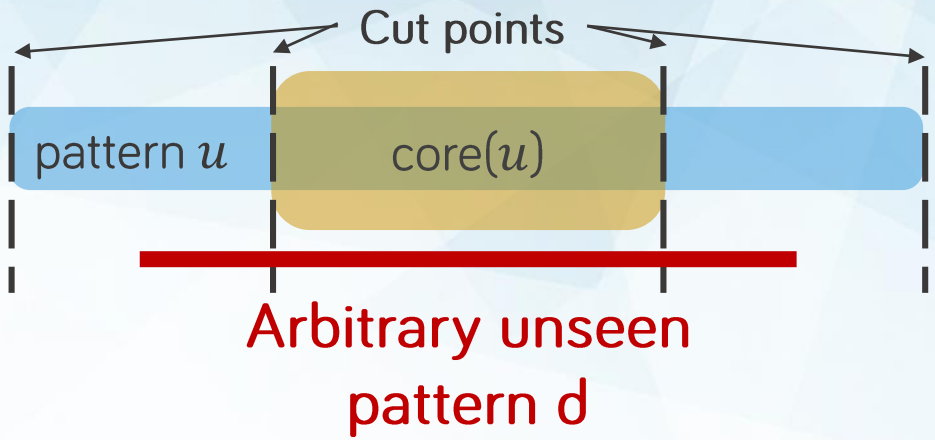
Specificity = Directed Hausdorff distance

Distance to the nearest found pattern

*The lower the **specificity** , the better found patterns are diversified

$Specificity = 0 \iff$ Found Patterns $\supseteq$ All Patterns.

Specificity Guarantee – Computation



$$\text{Specificity} = \sup_{d \in all} \inf_{c \in found} |c \,\Delta\, d|/n$$

- Core(found pattern) $\subseteq$ some unseen patterns $\subseteq$ found pattern

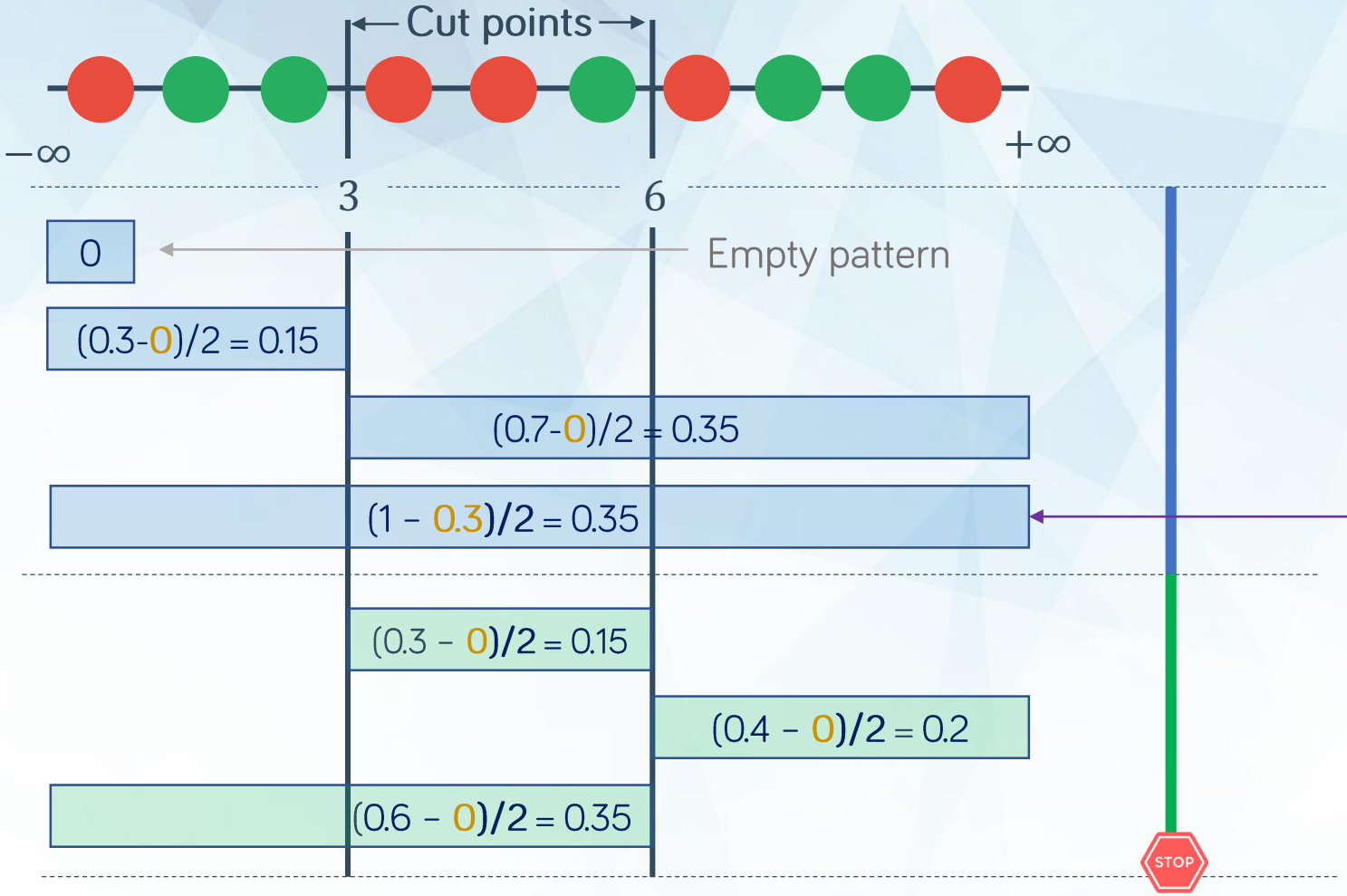
Upper approximation

- $\inf_{d \in all} \text{distance}(c,d) \leq \text{distance}(u,d) = \frac{|u|-|d|}{n}$
- $\inf_{d \in all} \text{distance}(c,d) \leq \text{distance}(core(u),d) = \frac{|d|-|core(u)|}{n}$

$$\text{Specificity} \leq \sup_{u \in found} \frac{|u| - |core(u)|}{2 \cdot n}$$

*This is a simplified formula.

Specificity Guarantee – Example



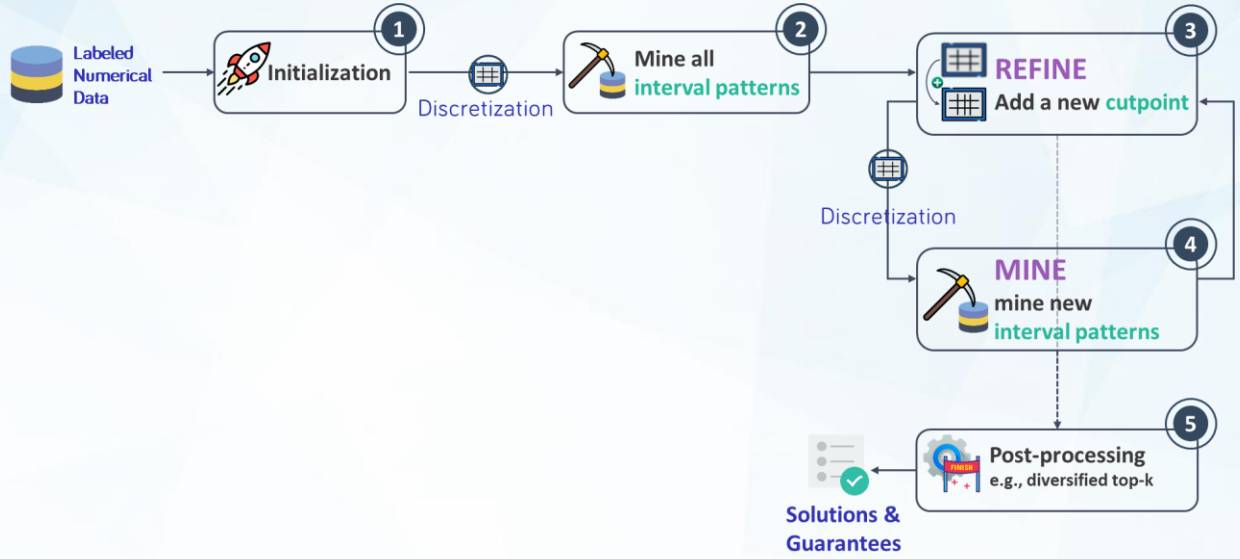
$$(|pattern| - |core(pattern)|)/2 \cdot 10 = \textbf{\textit{nearest distance bound}}(pattern)$$

- Specificity bound = 0.35

Second guarantee

Refine&Mine

Step-by-step



REFINE&MINE: Step-by-step (1)

1 Initialization

Compute an initial discretization [10,11]. e.g. Entropy based discretization, frequency based discretization...

[10] U.M. Fayyad, K.B. Irani. Multi-Interval discretization of continuous-valued attributes for classification learnings. In IJCAI 1993.
[11] Y. Yang, G.I. Webb, X., Wu: Descretization methods. In DMKD 2010.

REFINE&MINE: Step-by-step (2)

2 Mine

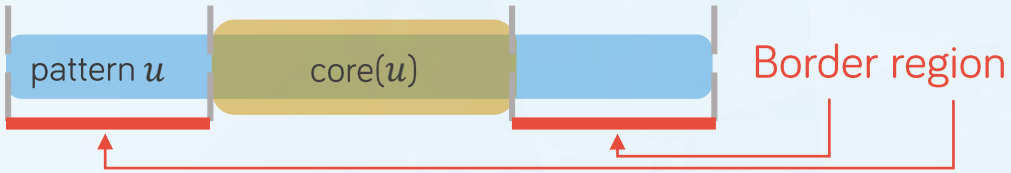
- Compute all interval patterns using MinIntChange algorithm [6] considering only the input-discretization selected points
- Compute the first guarantees.

[6] M. Kaytoue, Sergei O. Kuznetsov, Amedeo Napoli. Revisiting Numerical Pattern Mining with Formal Concept Analysis. In IJCAI 2011.

REFINE&MINE: Step-by-step (3)

3 Refine

- Add one cutpoint in one dimension generating a new discretization, this can be done by:
  - Adding a random cut-point on a random dimension.
  - Adding a cut-point belonging to the border region of the pattern yielding the highest accuracy bound.



REFINE&MINE: Step-by-step (4)

4 Mine

- Mine new interval patterns using [6]

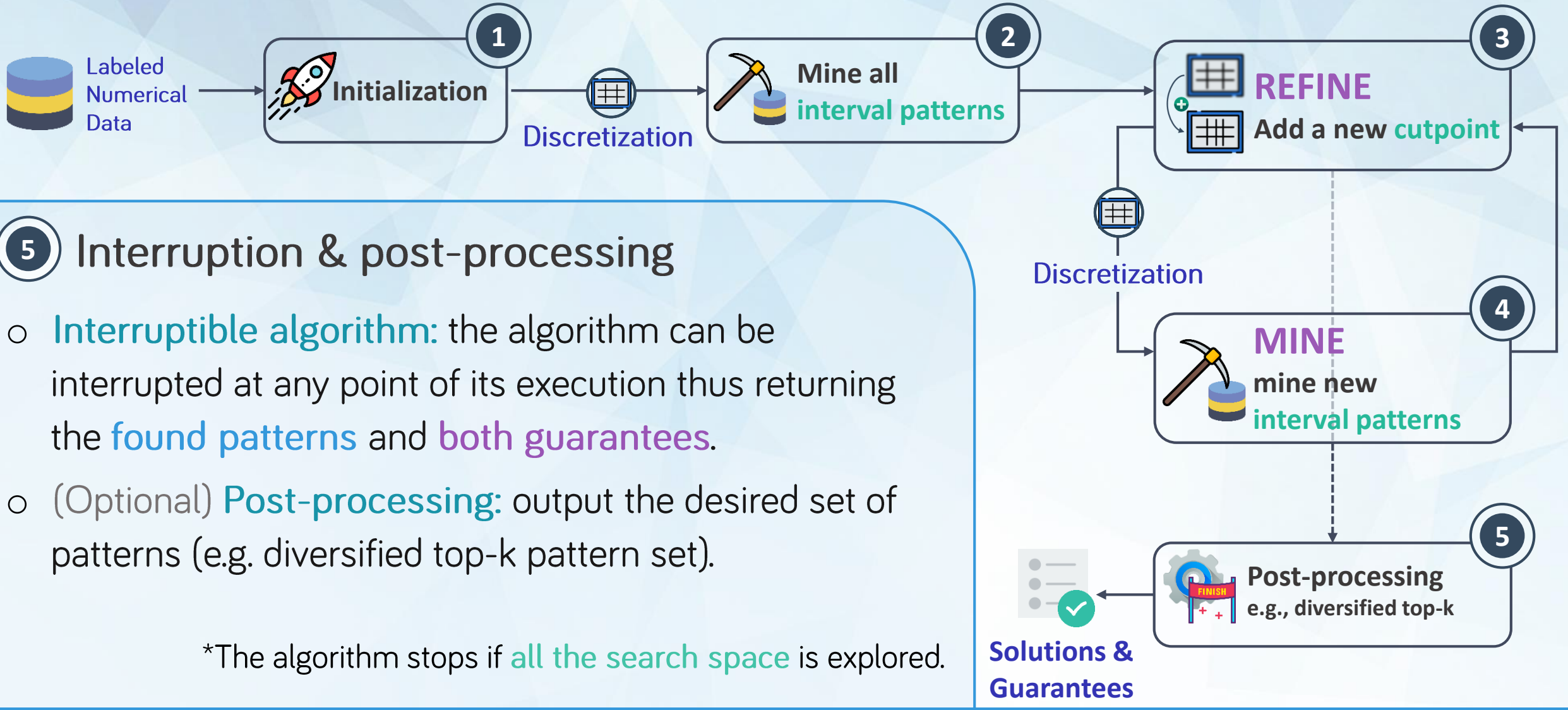
  by only visiting those whose left or right bound on the split dimension is the new selected cut-point.

- Update both guarantees

  An index structure is used to update quickly the guarantees

[6] M. Kaytoue, Sergei O. Kuznetsov, Amedeo Napoli. Revisiting Numerical Pattern Mining with Formal Concept Analysis. In IJCAI 2011.

REFINE&MINE: Step-by-step (5)



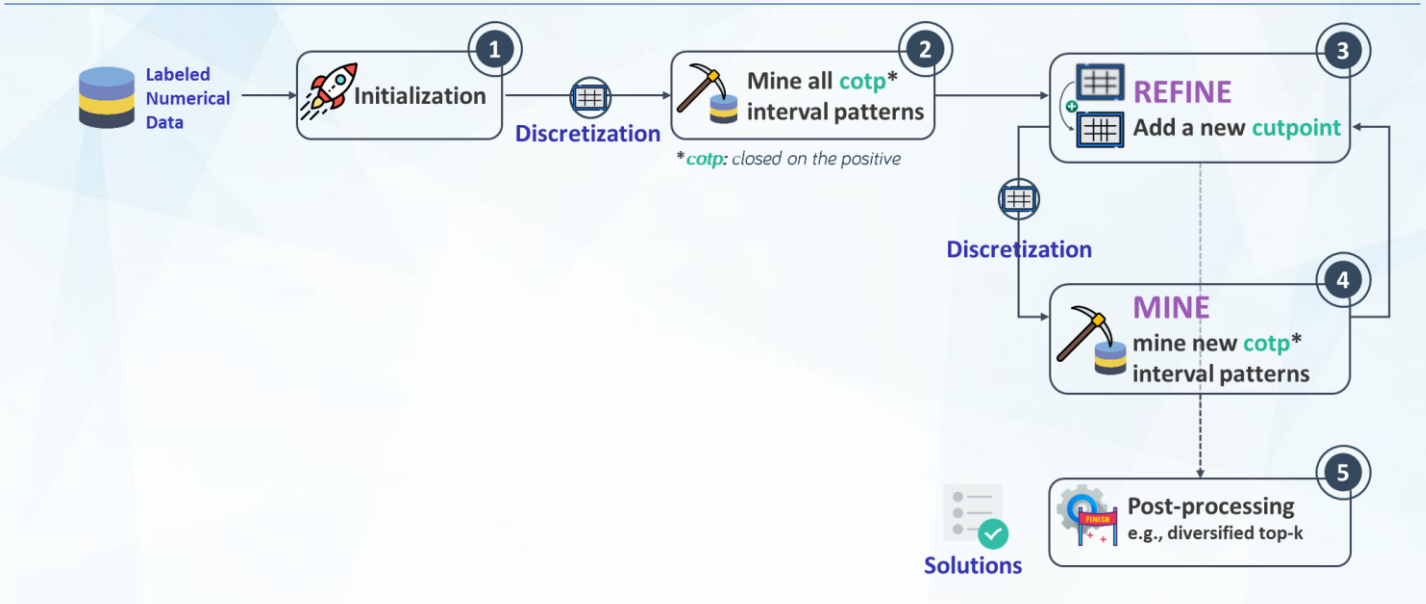
5 Interruption & post-processing

- Interruptible algorithm: the algorithm can be interrupted at any point of its execution thus returning the found patterns and both guarantees.
- (Optional) Post-processing: output the desired set of patterns (e.g. diversified top-k pattern set).

*The algorithm stops if all the search space is explored.

Refine&Mine

Step-by-step



REFINE&MINE: Step-by-step (1)

1 Initialization

- Compute relevant cuts [10] (cuts separating two classes).

- Compute an initial discretization [11].

[10] U.M. Fayyad, K.B. Irani. Multi-Interval discretization of continuous-valued attributes for classification learnings. In IJCAI 1993.
[11] Y. Yang, G.I. Webb, X., Wu: Descretization methods. In DMKD 2010.

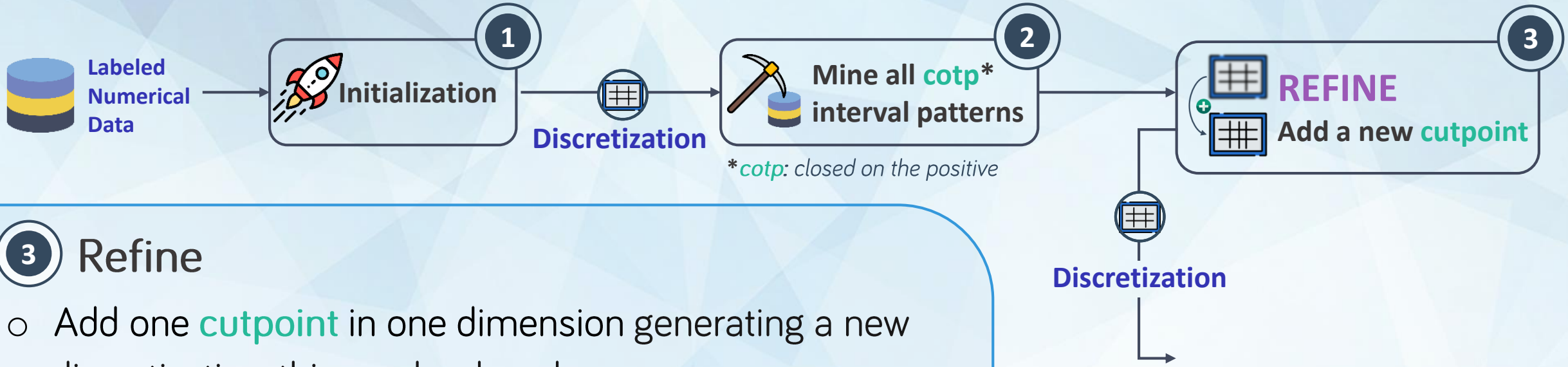
REFINE&MINE: Step-by-step (2)

2 Mine

- Compute all closed-on-the-positive (cotp [12]) patterns using MinIntChange algorithm [6].
- Compute the first guarantees.

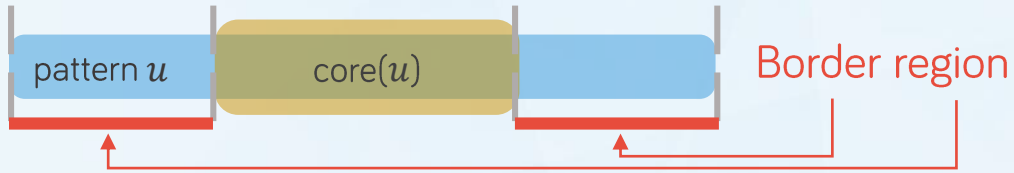
[6] M. Kaytoue, Sergei O. Kuznetsov, Amedeo Napoli. Revisiting Numerical Pattern Mining with Formal Concept Analysis. In IJCAI 2011.
[12] C.G.. Garriga, P. Kralj, N. Lavrac. Closed sets for labeled data. In JMLR 2008.

REFINE&MINE: Step-by-step (3)

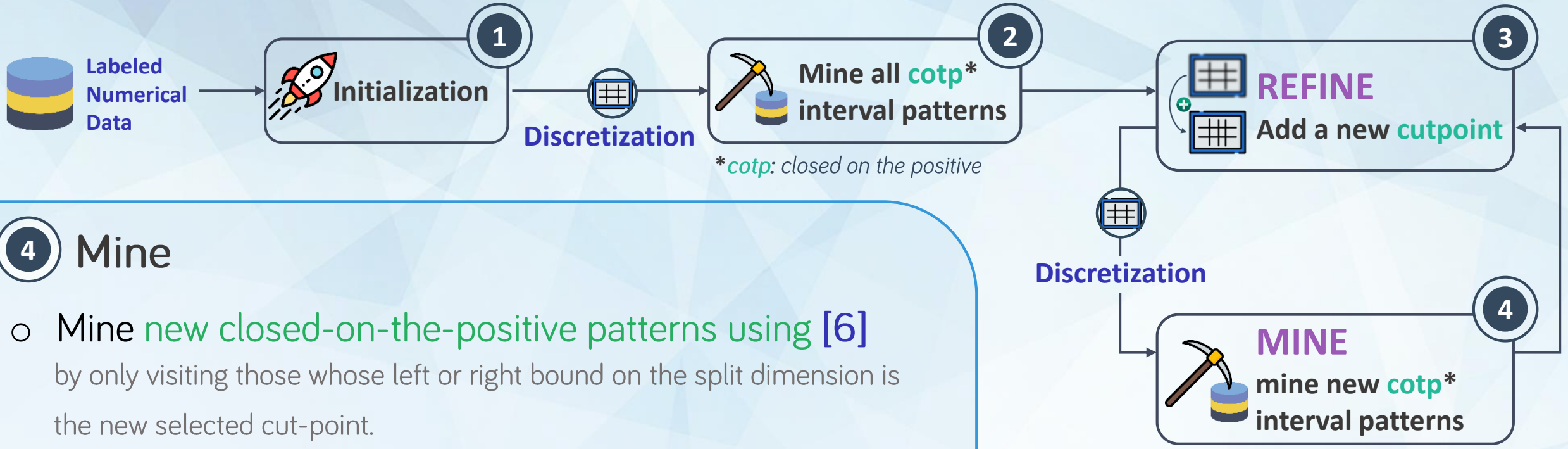


3 Refine

- Add one cutpoint in one dimension generating a new discretization, this can be done by:
  - Adding a random cut-point on a random dimension or,
  - adding a cut-point belonging to the border region of the pattern yielding the highest accuracy bound.



REFINE&MINE: Step-by-step (4)

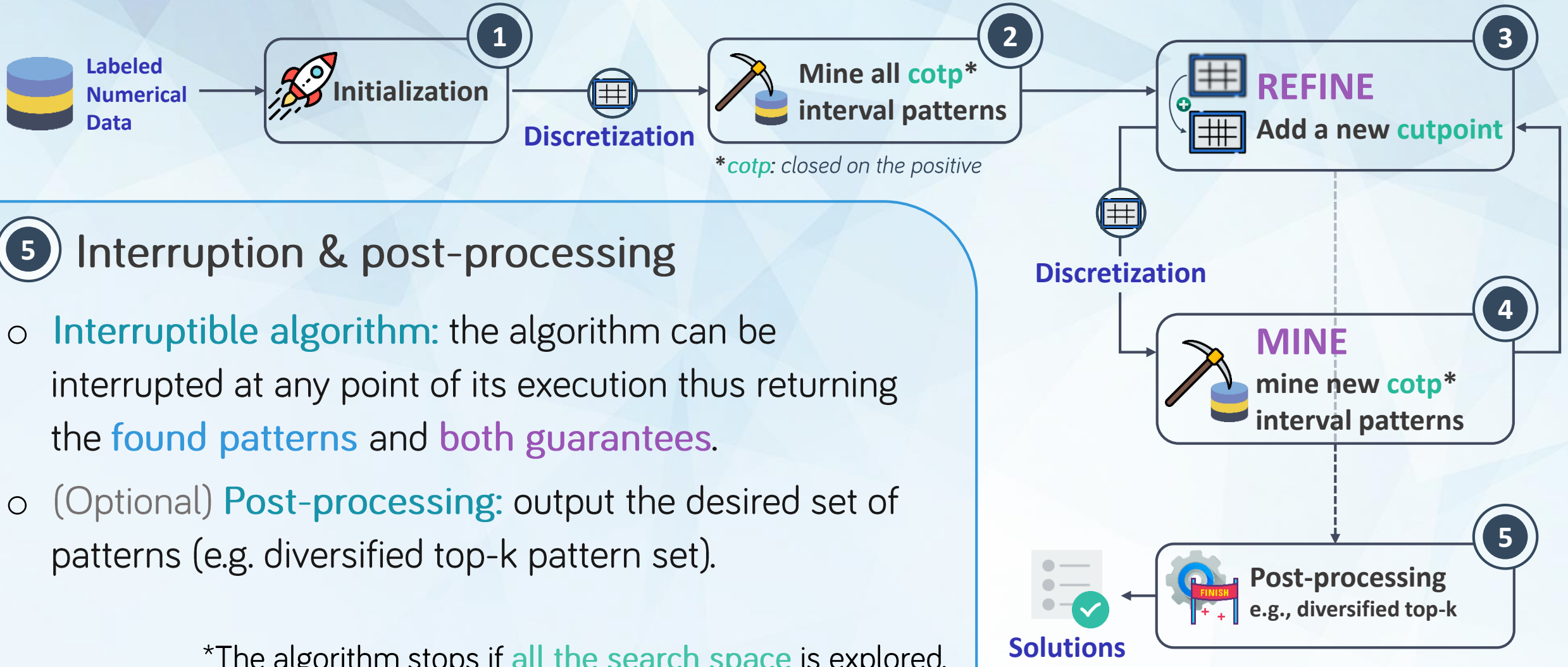


4 Mine

- Mine new closed-on-the-positive patterns using [6]
  by only visiting those whose left or right bound on the split dimension is the new selected cut-point.
- Update both guarantees
  An index structure is used to update quickly the guarantees

[6] M. Kaytoue, Sergei O. Kuznetsov, Amedeo Napoli. Revisiting Numerical Pattern Mining with Formal Concept Analysis. In IJCAI 2011.

REFINE&MINE: Step-by-step (5)



5 Interruption & post-processing

- Interruptible algorithm: the algorithm can be interrupted at any point of its execution thus returning the found patterns and both guarantees.
- (Optional) Post-processing: output the desired set of patterns (e.g. diversified top-k pattern set).

*The algorithm stops if all the search space is explored.

EMPIRICAL EVALUATION

Experiment Plan

Accuracy Guarantee

A bound on the difference of quality between the best quality pattern in D and the best found pattern in S.

Specificity Guarantee

A bound on the distance between the set of all patterns D and the set of already found patterns S.

Comparison with MCTS4DM

MCTS4DM is the closest approach to Refine&Mine in terms of the underlying paradigm, i.e. Anytime Algorithms.

Experiment Plan

Accuracy Guarantee

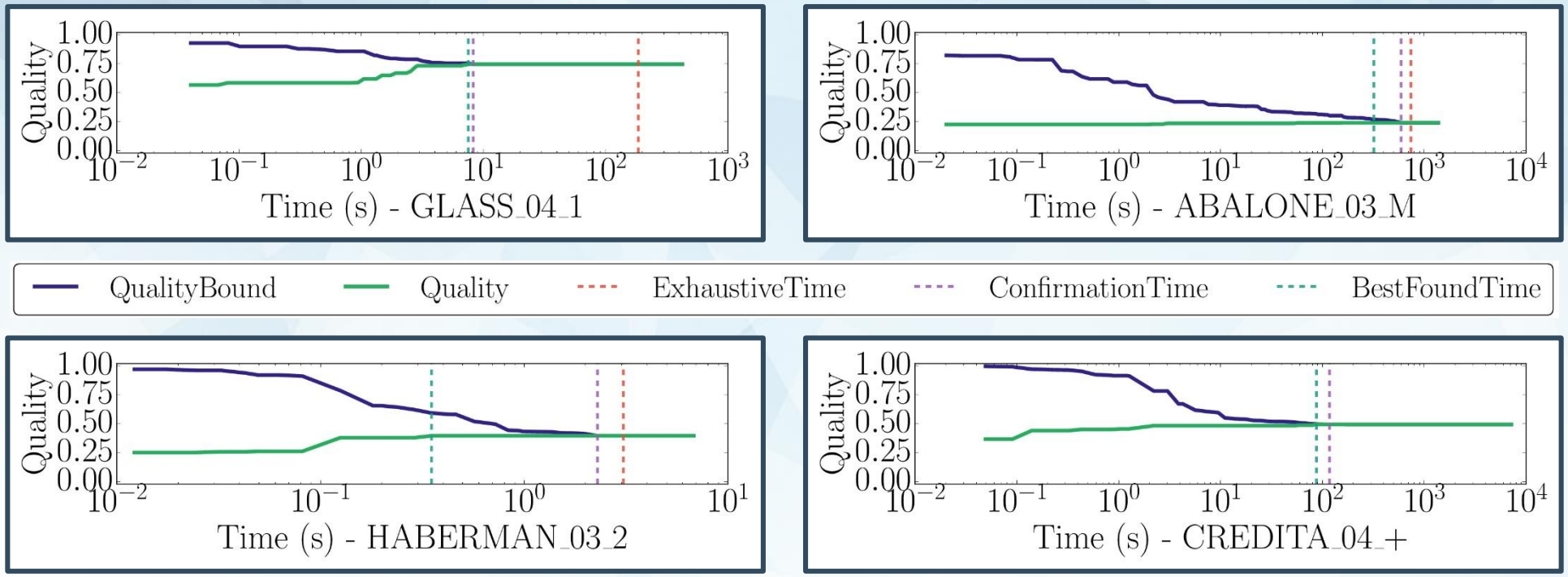
A bound on the difference of quality between the best quality pattern in D and the best found pattern in S.

Bottom line

Experiments were performed over 25 UCI Datasets

- 5 out of 25 Datasets: Exhaustive Algorithm achieved a better time in ensuring the discovery of the best pattern.
- 6 out of 25 Datasets: Exhaustive Algorithm was not able to finish within 2 Hours
- Refine&Mine required in average 40% of the time to guarantee the discovery of the best pattern

Experiment Plan: Accuracy Guarantee



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Experiment Plan

Specificity Guarantee

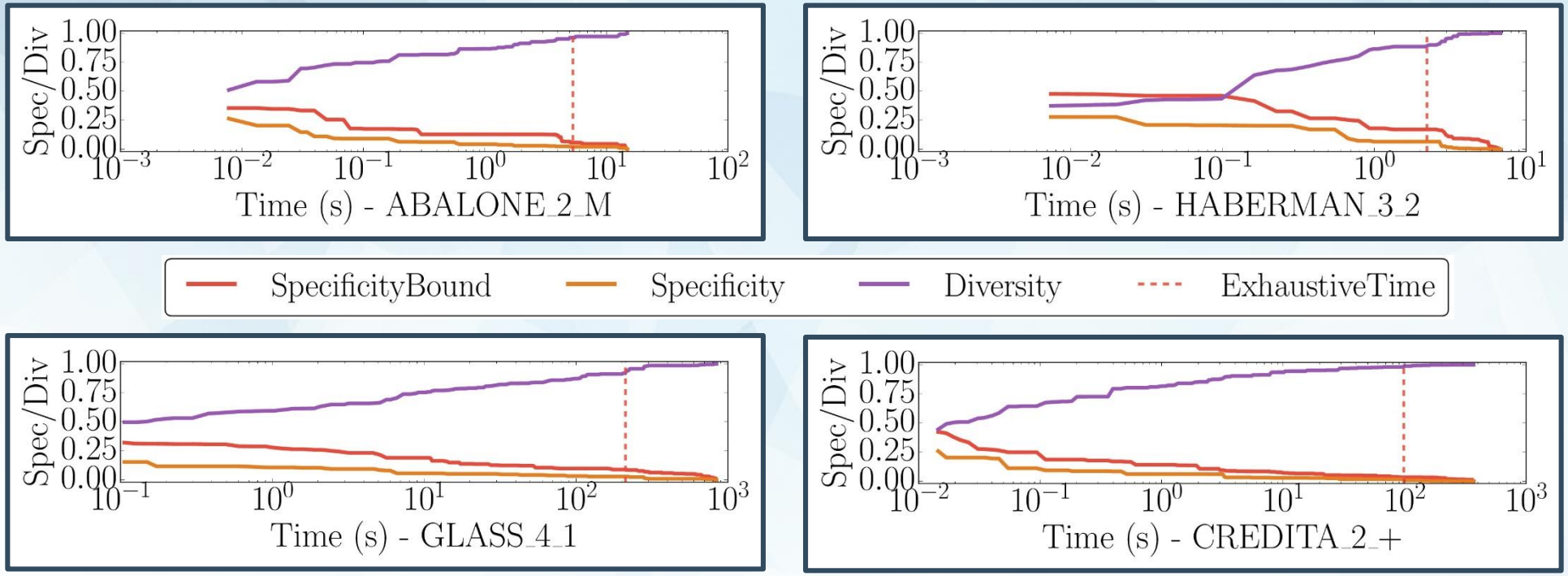
A bound on the distance between the set of all patterns D and the set of already found patterns S.

Bottom line

Experiments were performed over 15 UCI Datasets

Refine&Mine achieves to find a 80% approximation of the top-k diversified patterns set found by the exhaustive search algorithm in less than 20% of the required time of the exhaustive search algorithm

Experiment Plan: Specificity Guarantee



Specificity Guarantee

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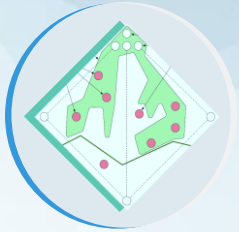
Experiment Plan



Comparison with MCTS4DM

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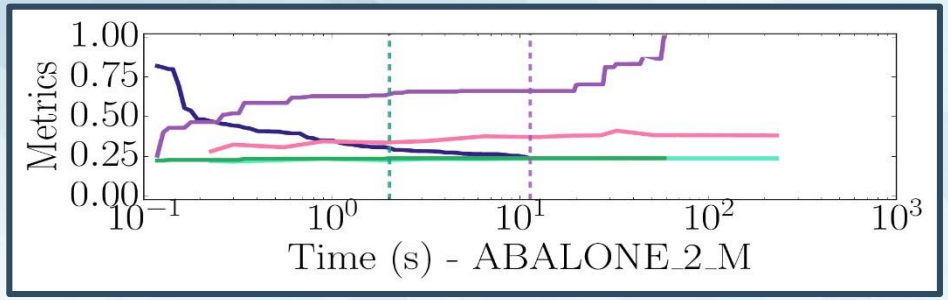
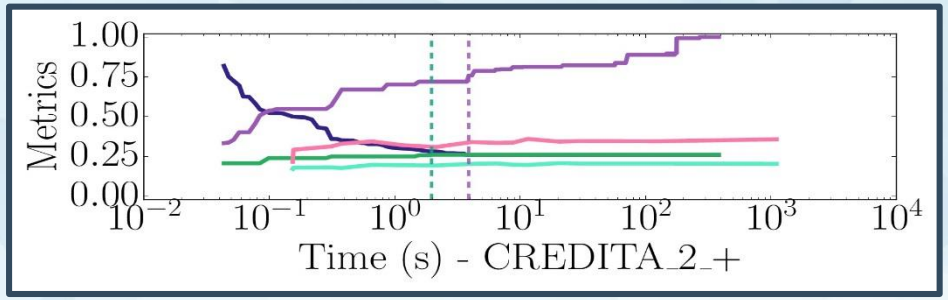
Bottom line

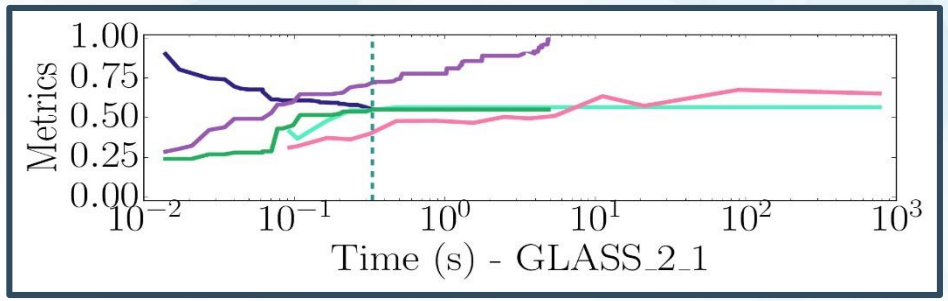
Experiments were performed over 6 UCI Datasets

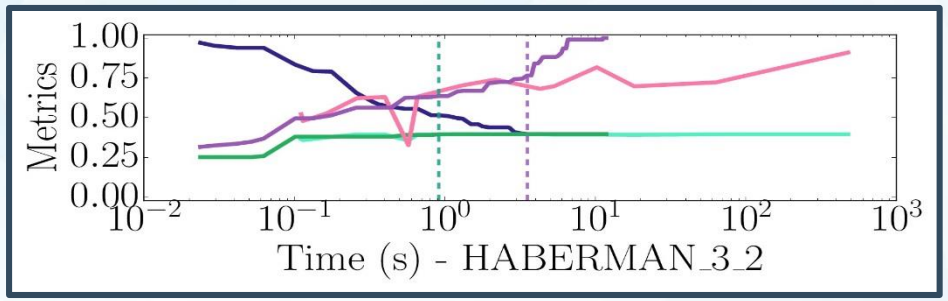
- In all configurations: Refine&Mine ensured a full traversal of the search space before MCTS4DM
- In all configurations: In average, Refine&Mine achieved 25% more diversity (after 10s of execution time) than MCTS4DM

Experiment Plan: Comparison with MCTS4DM









R&M vs. MCTS4DM

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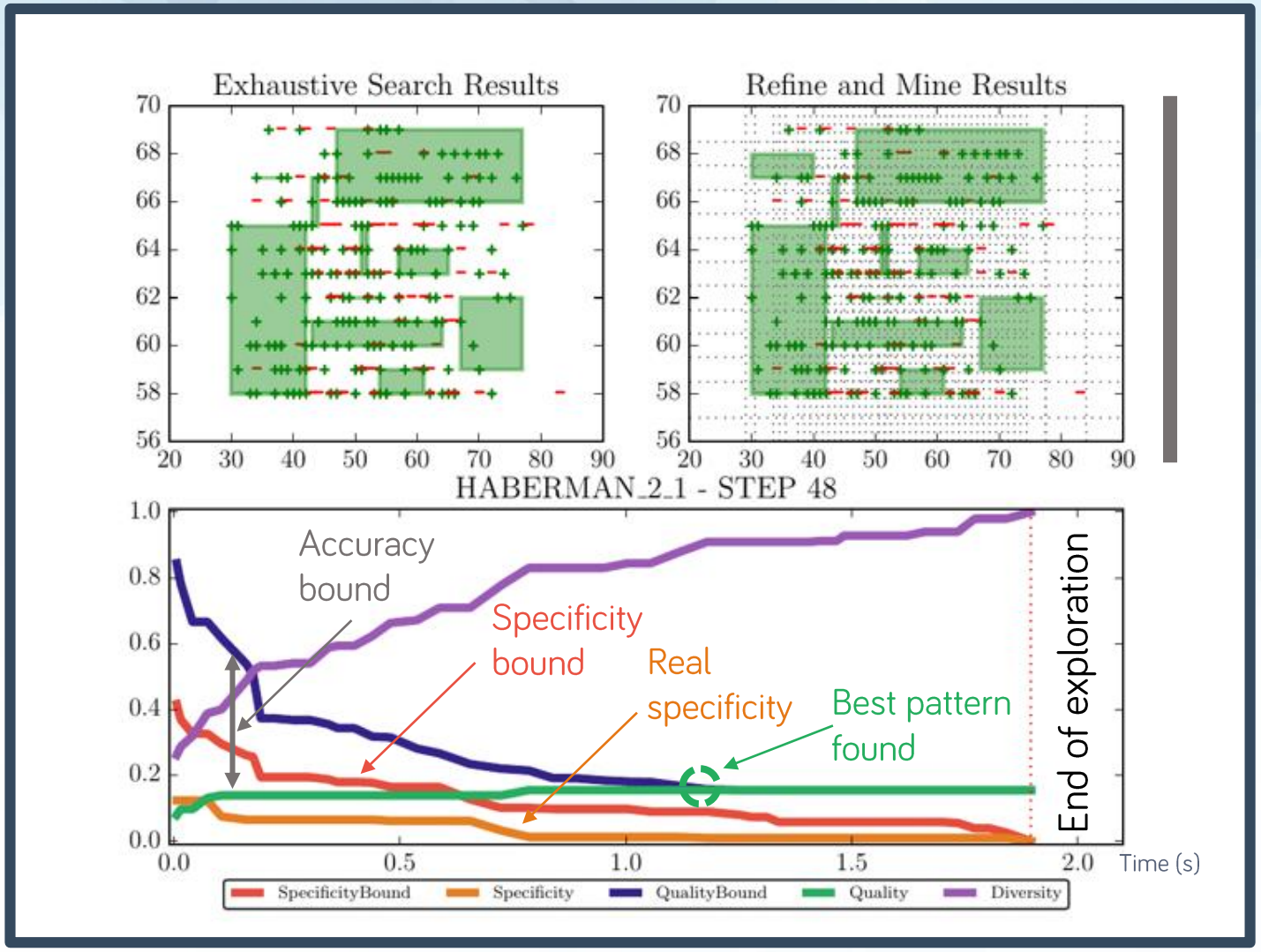
REFINE&MINE: Wrap-up



Empirical Evaluation

Experiments were performed over

25 UCI Datasets

- Refine&Mine achieves to find a 80% ground truth in less than 20% of the time required for the exhaustive search algorithm to finish
- Refine&Mine achieved better results both in finding the best pattern and a high diversified results set compared to MCTS4DM [*]

[*] *G. Bosc, J.F. Boulicaut, C. Raïssi, M. Kaytoue. Anytime discovery of a diverse set of patterns with MCTS. In DMKD 2018.*