APS-VSS: Accelerated Pattern Search with Variable Solution Size for Simultaneous Instance Selection and Generation

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Introduction

With the explosion in the size of training set (**TR**), potentially having more valuable information but also more noise and imperfections. Data reduction techniques including feature selection, instance reduction (**IR**), and discretisation are important for a data mining process.

Training Set
TR

IR techniques

Reduced Set
RS
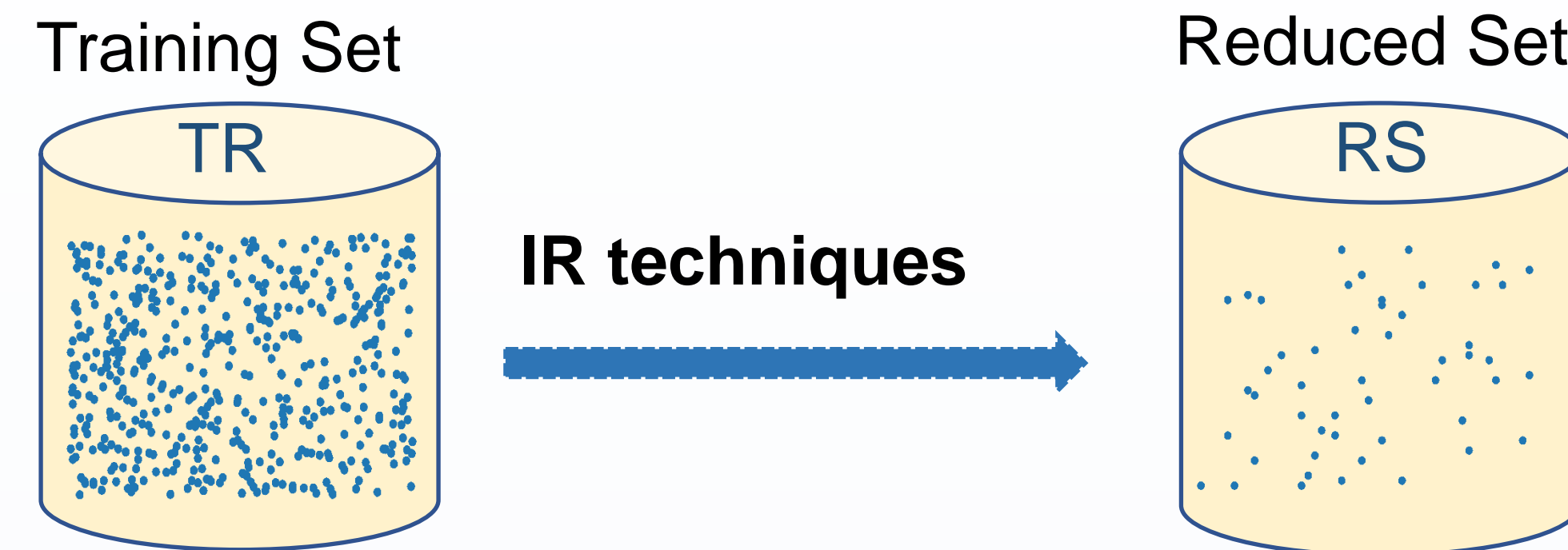
Research about **IR** can be categorised into instance selection (**IS**) and instance generation (**IG**). **IS** chooses representative examples in the available source while **IG** creates artificial ones, if needed. **IS** has frequently been modelled as a binary combinatorial optimisation problem as it deals with the decision whether or not to include a sample in the final subset, whilst **IG** can be modelled as a continuous optimisation problem, considering generating new examples non-existing in the source but better to represent **TR**.

Benefits of RS over TR

- ❑ Cleaner and smaller
- ❑ Freer of noise, redundant or irrelevant samples (the so-called **Smart Data**)
- ❑ Green AI, sustainable AI

Challenges

State-of-the-art IR solutions are based on evolutionary search methods, which are time-consuming due to:

- High fitness evaluation cost
  ⟶ **Surrogate model** [1]
- Algorithmic design complexity
  ⟶ **Single-Point Memetic Structure** [2]

Pseudo-code of APS-VSS

```
1:  INPUT x
2:  while local budget and precision conditions are not met do
3:      for h = 1 : p do
4:          x_h = x after removing the elements b_{h1}, b_{h2}, ..., b_{hm}
5:          if f(x_h) ≥ f(x) then        LS^eli: Local search in
6:              x = x_h                   combinatorial space
7:          end if
8:      end for
9:      for i = 1 : n (n = m · p) do
10:         x^t = x − ρ · e^i
11:         if f(x^t) ≥ f(x) then
12:             x = x^t                   LS^cont: Local search
13:         else                          in continuous space
14:             x^t = x + ρ/2 · e^i
15:             if f(x^t) ≥ f(x) then
16:                 x = x^t
17:             end if
18:         end if
19:         if mod (i, m) = 0 then
20:             j = i / m      ▷ Get index of the generated example
21:             x^{t'} = x^t after removing the elements b_{j1}, b_{j2}, ..., b_{jm}
22:             if f(x^{t'}) ≥ f(x^t) then   LS^asc: Local search in
23:                 x = x^{t'}               combinatorial space
24:             end if
25:         end if
26:     end for
27:     if x has not been updated then
28:         halve the exploratory radius ρ
29:         if ρ < ε then
30:             Randomly generate a candidate solution x^r
31:             Apply Crossover between x and x^r to generate x^t
32:             Reinitialise x = x^t        Restart the search or halve
33:         end if                          the exploratory radius
34:     end if
35: end while
36: RETURN x
```

Motivation

State-of-the-art **IR** techniques employed **IS** and **IG** sequentially, usually **IS** first and then **IG**. Typically, **IS** searches for the best distribution of instances per class to feed in **IG** for further optimisation. Unlike previous studies, **Accelerated Pattern Search with Variable Solution Size (APS-VSS)** performs the selection and generation on both continuous and combinatorial search spaces within a single framework.

Algorithmic Description

An iteration of APS-VSS is summarised as follows:

- ❑ LS^eli shrinks the initial RS, discarding any element whose absence does not deteriorate the solution quality
- ❑ LS^cont perturbs features and seeks an accurate solution
- ❑ LS^asc is embedded within LS^cont and confirms whether the presence of the newly generated instance is necessary.
- ❑ The crossover re-initialises the candidate solution to explore another search region when the LS^cont seems to be no longer effective.
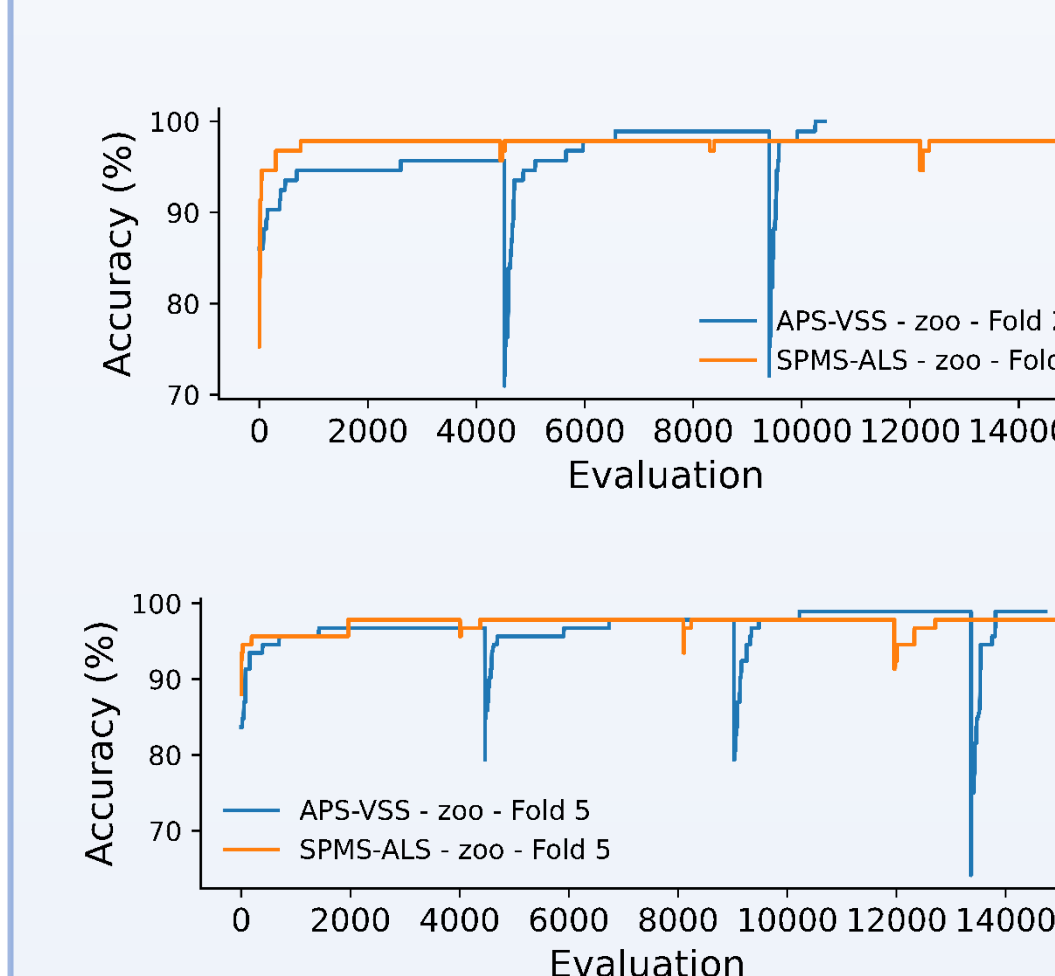
Parameters of APS-VSS
$P_{init} = 10\%$ size (TR)
exploratory step $\rho = 0.4$

Compared Algorithms [2]
- ❑ LSIR
- ❑ SPMS-ALS
- ❑ APS-VSS
- ❑ SSMA-LSHADE
- ❑ SSMA-SFLSDE
- ❑ SSMA-SPMS-ALS

Single-Point Search

Instance **I** has m features and belongs to class w:

$$I = a_1, a_2, \ldots, a_m$$

$$TR = \begin{bmatrix} & f_1 & f_2 & \ldots & f_m \\ I_1 & a_{11} & a_{12} & \ldots & a_{1m} \\ I_2 & a_{21} & a_{22} & \ldots & a_{2m} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ I_l & a_{l1} & a_{l2} & \ldots & a_{lm} \end{bmatrix} \quad RS = \begin{bmatrix} & f_1 & f_2 & \ldots & f_m \\ I_1 & b_{11} & b_{12} & \ldots & b_{1m} \\ I_2 & b_{12} & b_{22} & \ldots & b_{2m} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ I_p & b_{p1} & b_{p2} & \ldots & b_{pm} \end{bmatrix}$$

with $p \ll l$

Flatten **RS** into a n-dimensional vector, n = m * p:

$$x = (b_{11}, b_{12}, \ldots, b_{1m}, b_{21}, b_{22}, \ldots, b_{2m}, \ldots, b_{p1}, b_{p2}, \ldots, b_{pm})$$

e^i is an n-dimensional vector with all zeros, but 1 at the ith element

$$e^i = (0, 0, \ldots, 1, \ldots, 0, 0)$$

i = 1: indicating the first variable of x: b_{11}

$x^1 = x - \rho \cdot e^1$ First Attempt: Move one exploratory step

$x = (b_{11}, b_{12}, \ldots, b_{1m}, b_{21}, b_{22}, \ldots, b_{2m}, \ldots, b_{p1}, b_{p2}, \ldots, b_{pm})$

$x^1 = x + \frac{\rho}{2} \cdot e^1$ Second Attempt: Move a half-size exploratory step in the other direction

Acceleration of Fitness Computation

- ❑ Accuracy ⟵ considering **RS** as training data to classify **TR** as the test set
- ❑ Maintains a global distance matrix **D**: length = size (TR), width = size (RS)
- ❑ **D** can be initialised large (10% size (TR)), but is gradually reduced and remains small (1%-3% size (TR))
- ❑ Tailored to the k-nearest neighbour rule and the logic of pattern search

		1	2	3	–	p
	1	0.55	0.12	0.85		1.2
Distance	2					
matrix	3					
	–					
	1	0.21	1.02	3.2		0.98

At each trial of x, only recomputing values of one column, thus saving $l \times (p - 1)$ times of Euclidean distance calculation [2]

Search Behavior

Accuracy (%) vs Evaluation — APS-VSS - zoo - Fold 2, SPMS-ALS - zoo - Fold 2

Accuracy (%) vs Evaluation — APS-VSS - zoo - Fold 5, SPMS-ALS - zoo - Fold 5
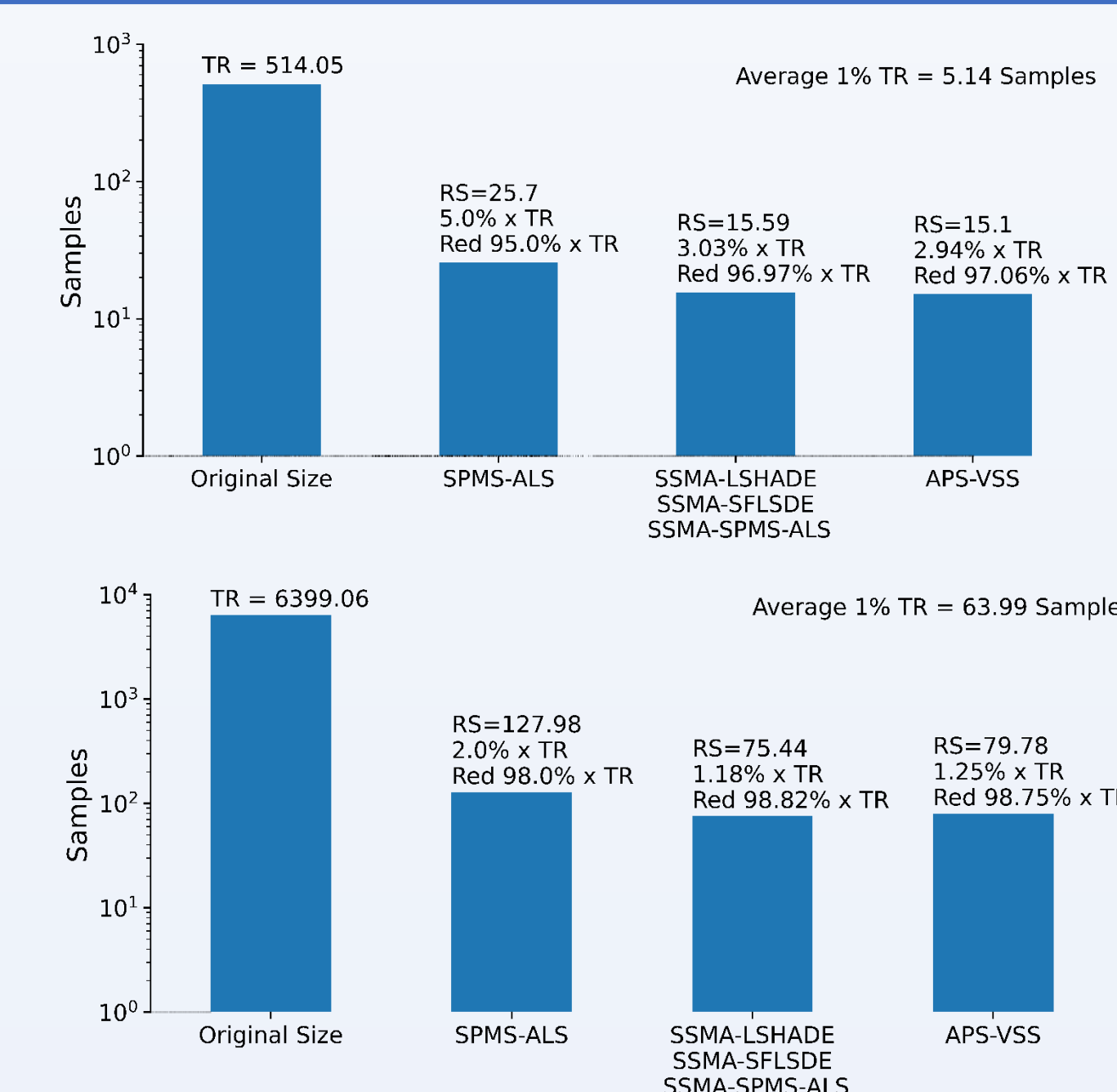
- ❑ Restart mechanism is effective to prevent premature convergence
- ❑ APS-VSS gradually develops the accuracy whilst SMPS-ALS goes back to its previous peak. This can be attributed to the impact of LS^eli and LS^asc

## Reduction Rate
Small datasets: Top
Medium datasets: Bottom

Average 1% TR = 5.14 Samples
TR = 514.05
RS=25.7 5.0% x TR Red 95.0% x TR
RS=15.59 3.03% x TR Red 96.97% x TR
RS=15.1 2.94% x TR Red 97.06% x TR

Original Size | SPMS-ALS | SSMA-LSHADE SSMA-SFLSDE SSMA-SPMS-ALS | APS-VSS

Average 1% TR = 63.99 Samples
TR = 6399.06
RS=127.98 2.0% x TR Red 98.0% x TR
RS=75.44 1.18% x TR Red 98.82% x TR
RS=79.78 1.25% x TR Red 98.75% x TR

Original Size | SPMS-ALS | SSMA-LSHADE SSMA-SFLSDE SSMA-SPMS-ALS | APS-VSS

For small and medium, respectively:
- ❑ SPMS-ALS: 95% and 98%
- ❑ Hybrid approaches: 96.97% and 98.82%
- ❑ APS-VSS: 97.06% and 98.75%

Runtime
Small datasets: Top
Medium datasets: Bottom

0.82 x T(s) | 0.86 x T(s) | T(s) | 10.39 x T(s) | 5.92 x T(s) | 1.38 x T(s)
ALSIR | SPMS-ALS | APS-VSS | SSMA-LSHADE | SSMA-SFLSDE | SSMA-SPMS-ALS
Algorithms

1.07 x T(s) | 3.0 x T(s) | T(s) | 43.79 x T(s) | 27.29 x T(s) | 3.58 x T(s)
ALSIR | SPMS-ALS | APS-VSS | SSMA-LSHADE | SSMA-SFLSDE | SSMA-SPMS-ALS
Algorithms
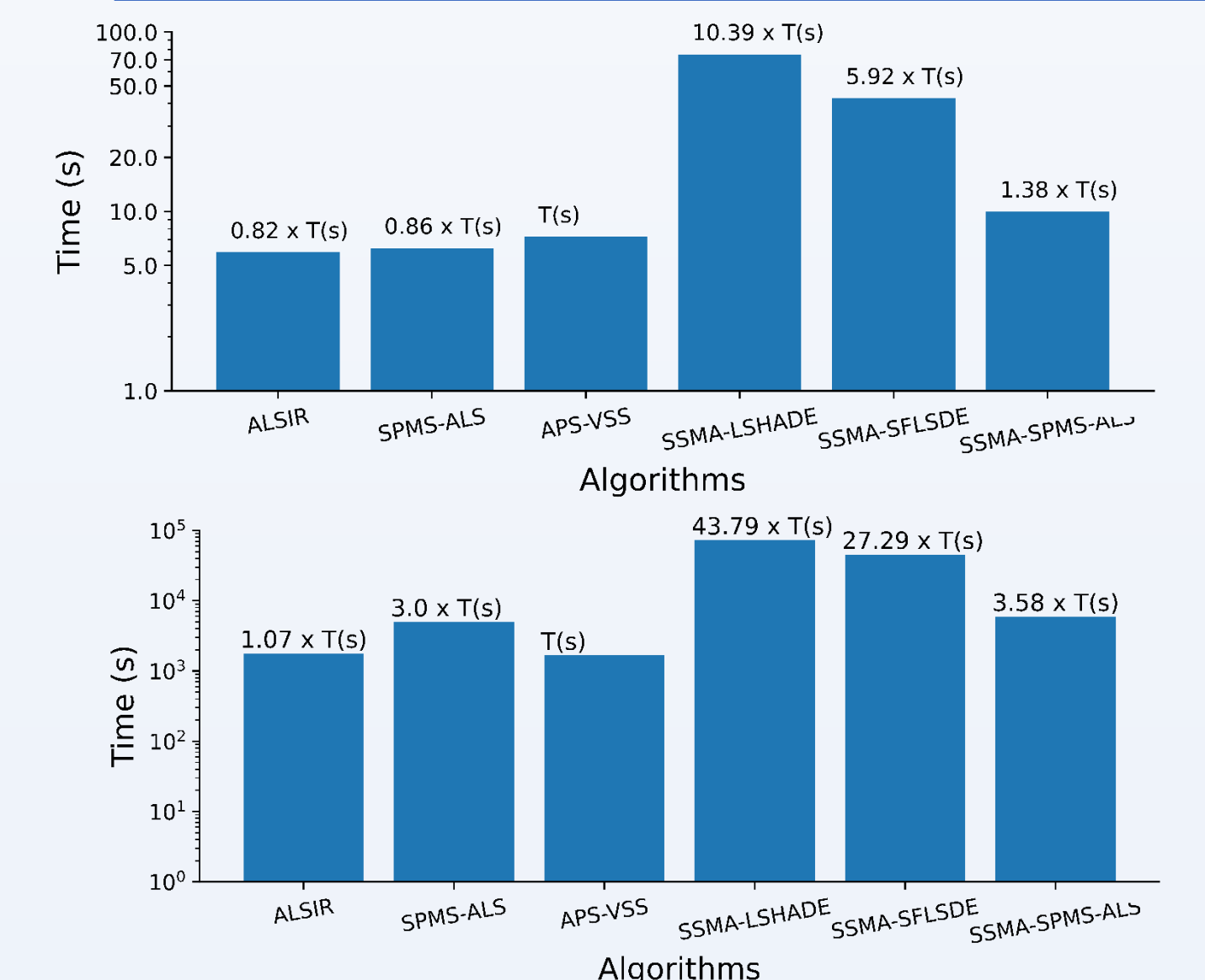
For small and medium, respectively:
- ❑ LSIR: 6s and 1784s
- ❑ SPMS-ALS: 6s and 5007s
- ❑ APS-VSS: 7s and 1669s
- ❑ SSMA-LSHADE: 75s and 73072s
- ❑ SSMA-SFLSDE: 43s and 45547s
- ❑ SSMA-SPMS-ALS: 10s and 5969s

References

[1] Le, H. L., Landa-Silva D., Mikel G., Salvador G., Triguero I. 'EUSC: A Clustering-based Surrogate Model to Accelerate Evolutionary Undersampling in Imbalanced Classification.' Applied Soft Computing 101 (2021):107033.
[2] Le, H. L., Neri F., Triguero I. 'SPMS-ALS: A Single-Point Memetic Structure with Accelerated Local Search for Instance Reduction.' Swarm and Evolutionary Computation 69 (2022): 100991.