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 reduction, instance reduction **(IR),** and discretisation are important for a data mining process. Data reduction is also important in the context of Big Data as it helps reduce storage, runtime and computation.

Research about **IR** can be categorised into instance selection (**IS**) and instance generation (**IG**). **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**. Integrating **IS** and **IG** within a single search framework has not been found in the literature, which will be proposed in this study and proved saving more runtime.

Benefits of RS over TR

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

Training Set

TR

IR techniques

Reduced Set

RS

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

```
INPUT $x$
while local budget and precision conditions are not met do
    for $h = 1 : p$ do
        $\mathbf{x}_h = \mathbf{x}$ after removing the elements $b_{h1}, b_{h2}, \ldots, b_{hm}$
        if $f(\mathbf{x_h}) \geq f(\mathbf{x})$ then
            $x = \mathbf{x_h}$
        end if
    end for
    for $i = 1 : n \ (n = m \cdot p)$ do
        $\mathbf{x^t} = \mathbf{x} - \rho \cdot \mathbf{e}^i$
        if $f(\mathbf{x^t}) \geq f(\mathbf{x})$ then
            $\mathbf{x} = \mathbf{x^t}$
        else
            $\mathbf{x^t} = \mathbf{x} + \frac{\rho}{2} \cdot \mathbf{e}^i$
            if $f(\mathbf{x^t}) \geq f(\mathbf{x})$ then
                $\mathbf{x} = \mathbf{x^t}$
            end if
        end if
        if $\mod (i, m) = 0$ then
            $\mathrm{j = i\ /\ m}$        ▷ Get index of the generated example
            $\mathbf{x}^{t'} = \mathbf{x}^t$ after removing the elements $b_{j1}, b_{j2}, \ldots, b_{jm}$
            if $f\left(\mathbf{x}^{t'}\right) \geq f(\mathbf{x}^t)$ then
                $\mathbf{x} = \mathbf{x}^{t'}$
            end if
        end if
    end for
    if $x$ has not been updated then
        halve the exploratory radius $\rho$
        if $\rho < \epsilon$ then
            Randomly generate a candidate solution $\mathbf{x^r}$
            Apply Crossover between $x$ and $\mathbf{x^r}$ to generate $x^t$
            Reinitialise $\mathbf{x} = \mathbf{x^t}$
        end if
    end if
end while
RETURN $x$
```

LS^eli: Local search in combinatorial space

LS^cont: Local search in continuous space

LS^asc: Local search in combinatorial space

Restart the search or halve the exploratory radius

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 and datasets

❑ $P_{init} = 10\%$ size (TR)
❑ exploratory step $\rho = 0.4$
❑ 44 small and 17 medium datasets from KEEL (https://sci2s.ugr.es/)

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:*

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

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

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

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

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

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

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

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

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

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

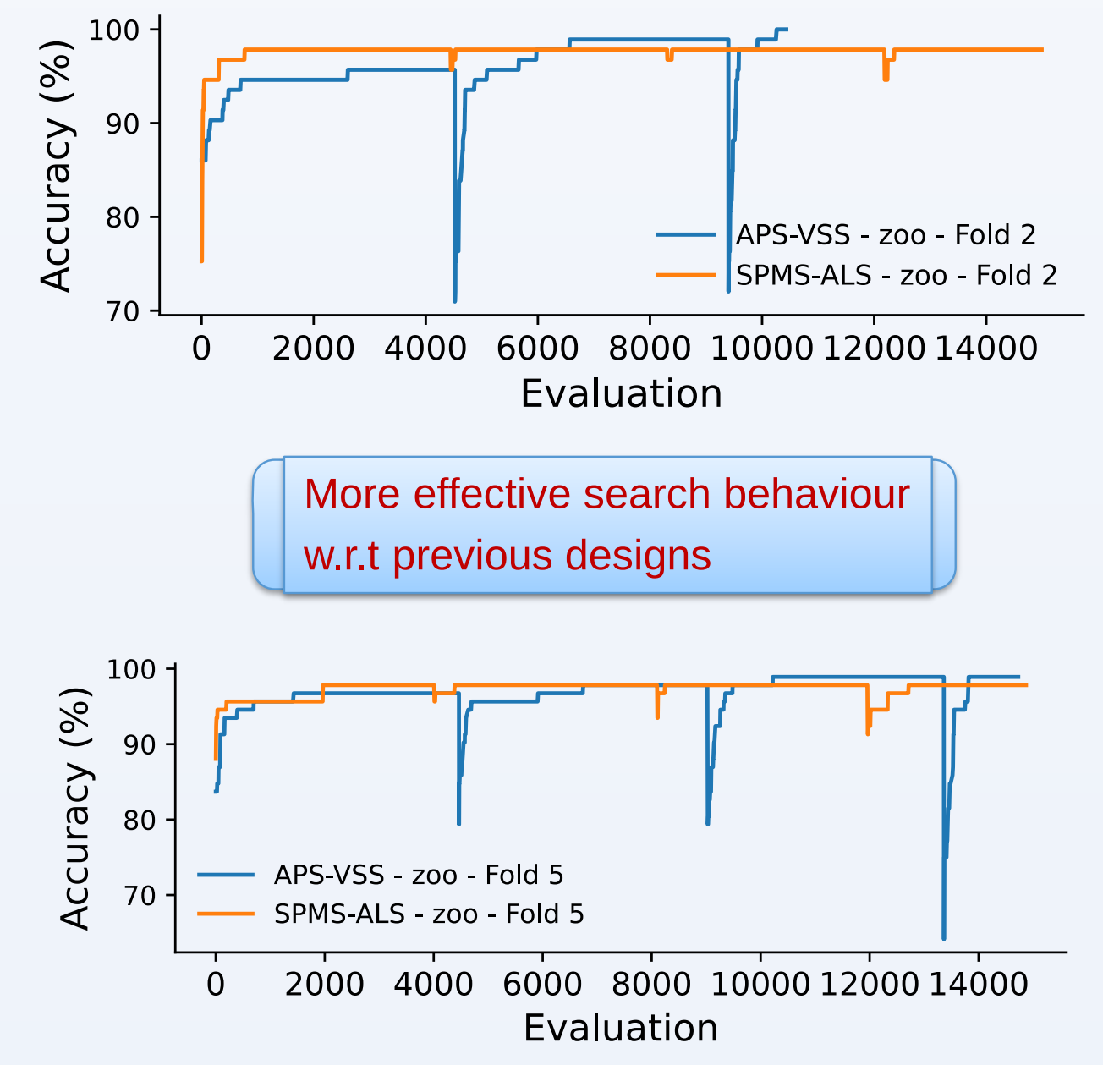
Accelerating Fitness Computation

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

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

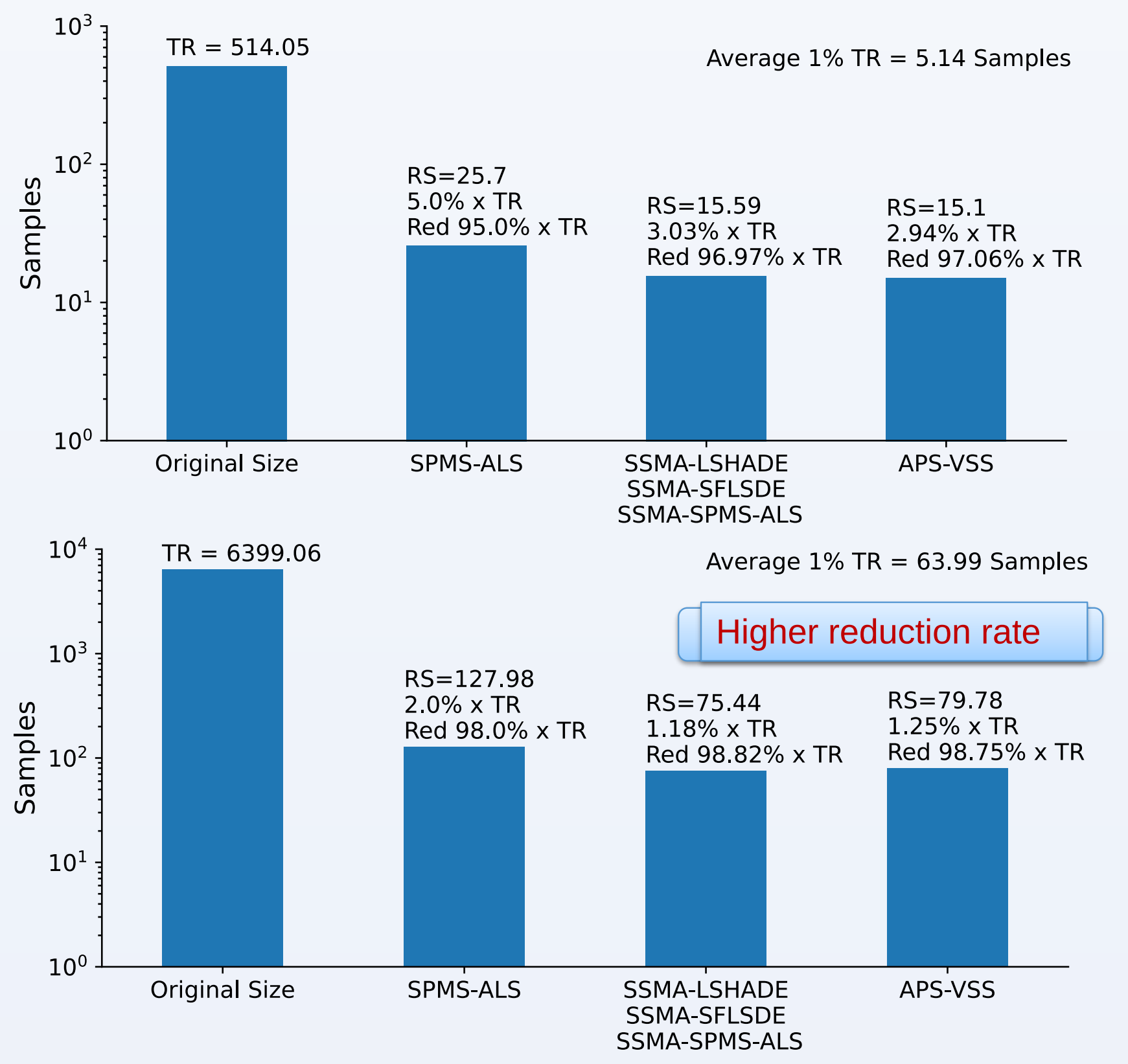
Search Behaviour



❑ 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

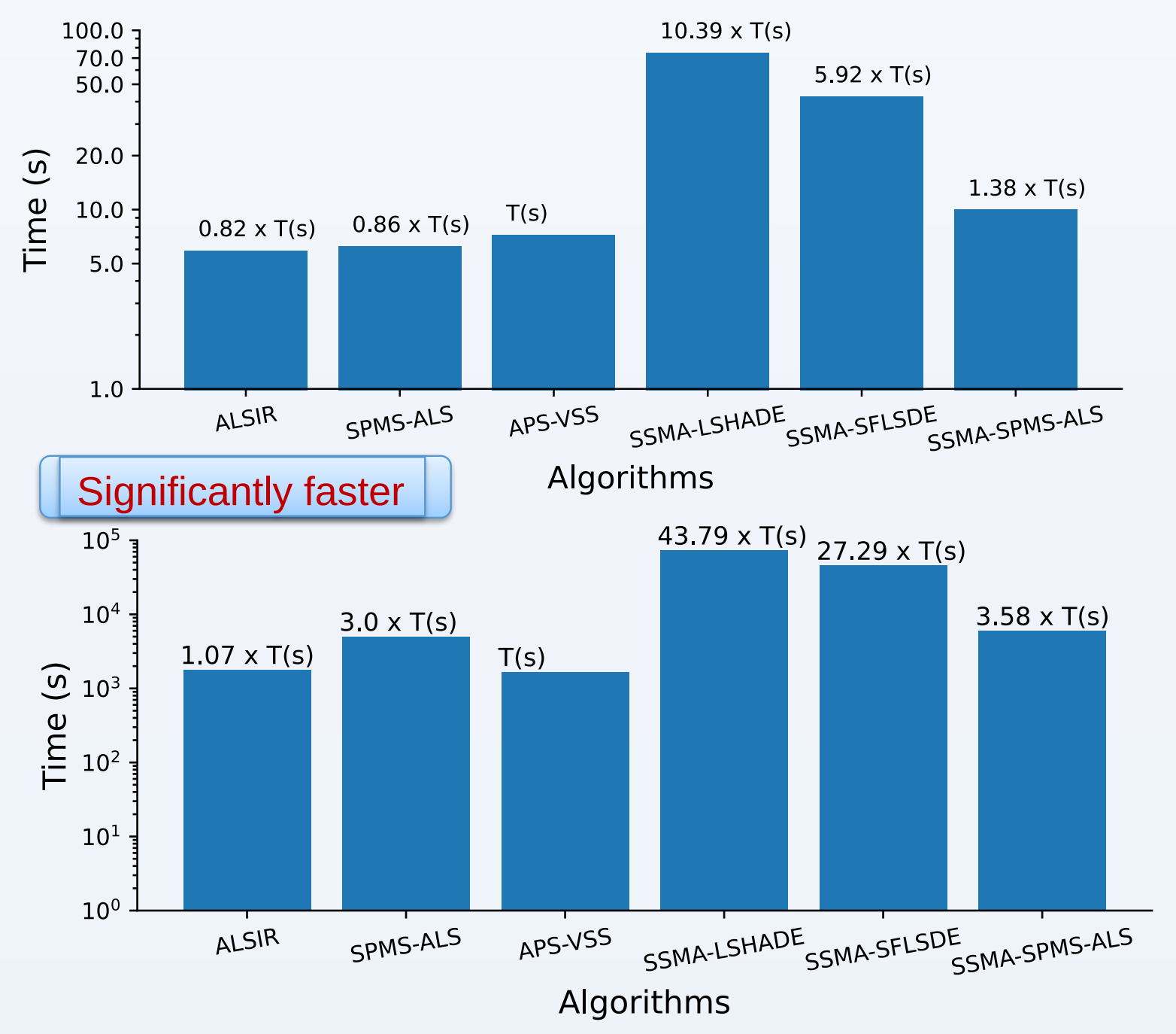
Small datasets: Top
Medium datasets: Bottom



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



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.*