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

Challenges

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

- High fitness evaluation cost
  $\longrightarrow$ **Surrogate model** [1]
- Algorithmic design complexity
  $\longrightarrow$ **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
        x_h = x after removing the elements b_h1, b_h2, ..., b_hm
        if f(x_h) ≥ f(x) then
            x = x_h
        end if
    end for                                   [LS^eli: Local search in combinatorial space]
    for i = 1 : n (n = m · p) do
        x^t = x − ρ · e^i
        if f(x^t) ≥ f(x) then
            x = x^t
        else
            x^t = x + (ρ/2) · e^i
            if f(x^t) ≥ f(x) then
                x = x^t
            end if
        end if                                [LS^cont: Local search in continuous space]
        if mod(i, m) = 0 then
            j = i / m          ▷ Get index of the generated example
            x^t' = x^t after removing the elements b_j1, b_j2, ..., b_jm
            if f(x^t') ≥ f(x^t) then
                x = x^t'
            end if
        end if                                [LS^asc: Local search in combinatorial space]
    end for
    if x has not been updated then
        halve the exploratory radius ρ
        if ρ < ε then
            Randomly generate a candidate solution x^r
            Apply Crossover between x and x^r to generate x^t
            Reinitialise x = x^t
        end if
    end if                                    [Restart the search or halve the exploratory radius]
end while
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 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*:

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

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

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 i^{th} 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

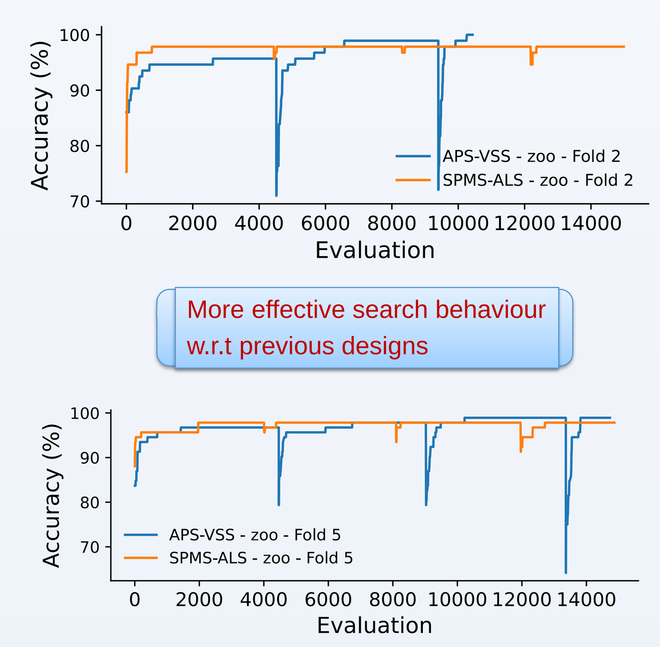
Accelerating Fitness Computation

- ❑ Accuracy $\longleftarrow$ 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					
	–					
	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]*

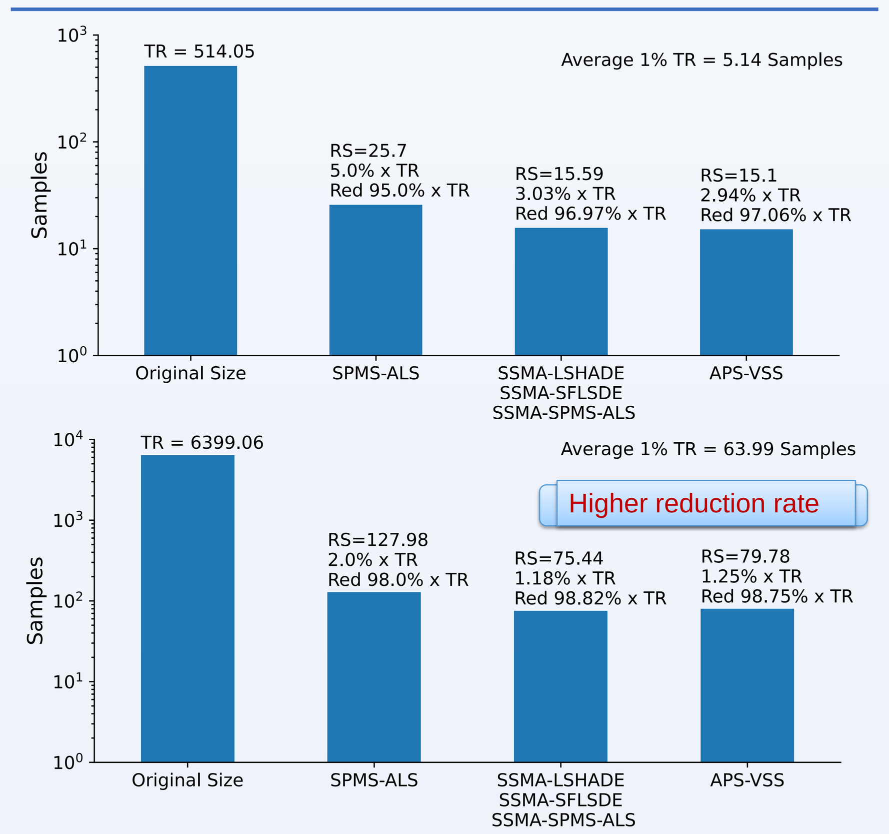
Search Behaviour



- ❑ 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

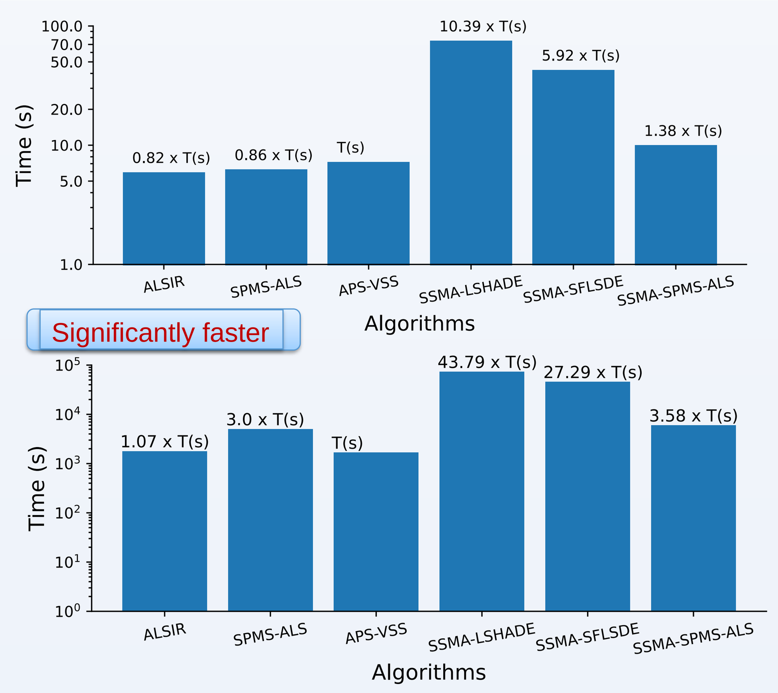


For small and medium, respectively:

- ❑ 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.