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

Hoang Lam Le[1,*], Ferrante Neri[2], Dario Landa-Silva[1], Isaac Triguero[1,3]

[1]COL, School of Computer Science, University of Nottingham, UK
[2]NICE, Department of Computer Science, University of Surrey, UK
[3]DaSCI Andalusian Institute in Data Science and Computational Intelligence, University of Granada, Spain
*Email: hoang.le@nottingham.ac.uk
lehoanglam20000@gmail.com

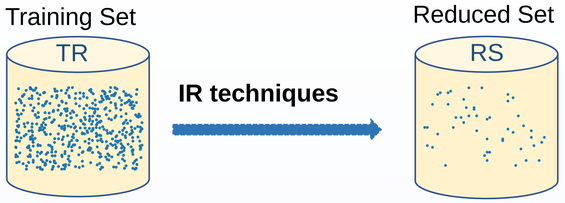
Poster Digital Copy

University of Nottingham UK | CHINA | MALAYSIA

Computational Optimisation & Learning Lab

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.



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]

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:

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

$\mathbf{e}^i$ 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

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

Distance matrix

	1	2	3	–	p
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]*

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**
      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 $f(\mathbf{x}^{t'}) \geq f(\mathbf{x}^t)$ **then**
        $\mathbf{x} = \mathbf{x}^{t'}$
      end if
    end if
  end for
  if x has **not** been updated **then**
    halve the exploratory radius ρ
    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.

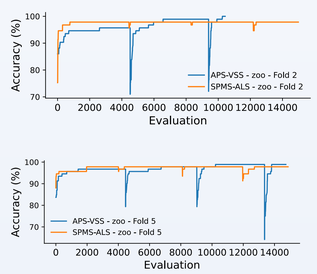
Parameters of APS-VSS

$\boldsymbol{P_{init}} = \mathbf{10\%}$ size (TR)
exploratory step $\boldsymbol{\rho = 0.4}$

Compared Algorithms [2]

- ❑ LSIR
- ❑ SPMS-ALS
- ❑ APS-VSS
- ❑ SSMA-LSHADE
- ❑ SSMA-SFLSDE
- ❑ SSMA-SPMS-ALS

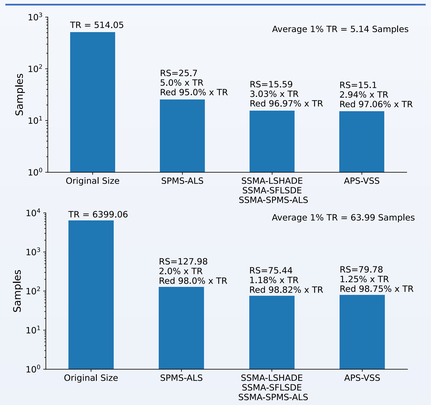
Search Behavior



- ❑ 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

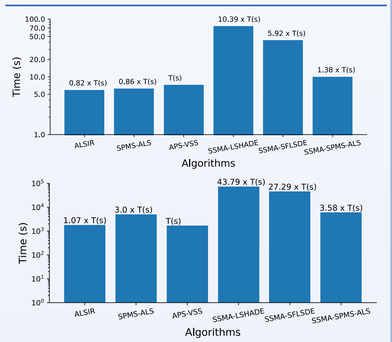


For small and medium, respectively:

- ❑ 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.