

Towards a Framework for Designing Full Model Selection and Optimization Systems

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Motivations

End-users of ML/DM now have to face the new problem of how to choose a combination of data processing tools and algorithms.

This problem is usually termed the **Full Model Selection** problem.



Full Model Selection (FMS)

The FMS problem consists of the following¹:

Given a pool of preprocessing methods, feature selection and learning algorithms, select the combination of these that obtains the lowest classification error for a given data set.

FMS tasks also include the selection of hyperparameters for the considered methods, resulting in a vast search space.

¹Escalante et al., Particle Swarm Model Selection. JMLR (2009)

Data Mining Operators

We attempt to define a search space that consists of all data mining actions (operators) that are available to a given data set for a user-specified goal, such as:

- a set of outlier filters
- a set of feature generation, transformation and selection methods
- a set of learning algorithms
- ...

In this sense, we call the subject of interest “the space of data mining operators (DMO)”, or simply “the DMO space”.

The DMO Space

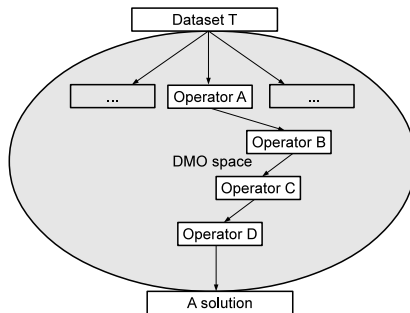


Figure: An illustration of the DMO space

Due to the resources at hand, usually we do not search in an infinite DMO space, and, moreover, we can make the DMO space a finite space by defining the DMOs that are to be included.

- The PSMS system (Escalante et al., JMLR, 2009) is an application of Particle Swarm Optimization (PSO) to the problem of FMS for binary classification problems.
- In total, 3 feature transformation objects, 13 feature selection objects and 10 classifier objects are used in the PSMS system.
- A full PSMS model is defined as a 16-dimensional particle position.

From the system architecture point of view, PSMS assumes a full model has three components: feature transformation, feature selection, and learning algorithm.

In the DMO framework, we can define the following DMO template for the search space covered by the PSMS system:

$$\text{solution} \Leftarrow \text{DMO}_{\text{chain-search}}(\text{DMO}_{\text{random-topology-search}}(\text{DMO}_{[\text{feature-transformation}]}, \text{DMO}_{[\text{feature-selection}]}, \text{DMO}_{[\text{algorithm}]})$$

The GPS Search Strategy

We propose a search strategy, which combines both a genetic algorithm (GA) and particle swarm optimization (PSO).

- GA is used for searching the optimal template structure of a DMO solution (structure space)
- PSO is used for searching the optimal parameter set for a particular solution instance (parameter space)

The algorithm is named GPS (**GA-PSO FMS**). It can be seen as a realization and an application of the DMO framework.

The GPS Search Strategy

We assume a FMS solution consists of five DMOs:

$DMO_{[data-cleansing]}$, $DMO_{[data-sampling]}$, $DMO_{[feature-transformation]}$,
 $DMO_{[feature-selection]}$, and $DMO_{[algorithm]}$.

A DMO template for the FMS problem covered by GPS is defined as:

solution \Leftarrow

$DMO_{chain-search}(\$
 $DMO_{random-topology-search}(\$
 $DMO_{[data-cleansing]}$, $DMO_{[data-sampling]}$,
 $DMO_{[feature-transformation]}$, $DMO_{[feature-selection]}$),
 $DMO_{[algorithm]}$)

The GPS Search Strategy

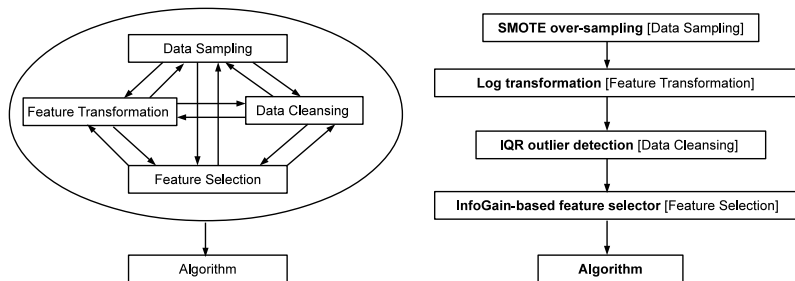


Figure: Left: a graphical representation of the DMO template used by GPS; Right: a DMO solution instance

The GPS Algorithm

Algorithm 1 Pseudocode of the GPS strategy for searching a FMS solution

procedure GPS(T, P, M, W, G)

Input:

T (number of generations for GA), P (population size for GA), M (number of evolutions for PSO), W (swarm size for PSO), G (goal metric)

Get P random template instances based on template (3).

Populate template instances with objects in the DMO pools (Table 2)

for $i \leftarrow 1$ to T **do**

Use a standard PSO procedure **PSO**(M, W, G, I) to search for the optimal parameters for each template instance I (optimising the goal metric G), and assign an evaluation score to each template instance I . This procedure is similar to the PSMS system [3].

Do *crossover* // single point crossover among the top 20% template instances.

Do *mutation* // randomly choose 30% template instances from the population, and randomly change one DMO in each template instance.

Replace the worst N template instances with the N new template instances generated in above two steps, here we use $N = (20\% + 30\%) \times P$.

$solution_{best} \leftarrow population_{best}$

end for

return $solution_{best}$

end procedure

Generate initial solution structures and instances

Optimize a solution instance

Generate new solution structures and instances

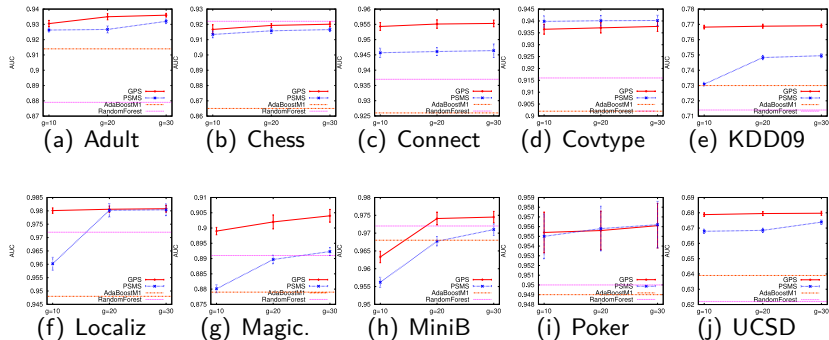
Experiments

- 1 Comparing GPS to PSMS and other algorithms
- 2 Speeding up the GPS system

Experiments: Datasets

Original data sets			Final binary data sets
Data set with release year	#Insts	Atts:Classes	Class distribution (#Insts)
Adult 96	48,842	14:2	23% vs 77% (10,000)
Chess 94	28,056	6:18	48% vs 52% (8,747)
Connect-4 95	67,557	42:3	26% vs 74% (10,000)
Covtype 98	581,012	54:7	43% vs 57% (10,000)
KDD09 Customer Churn 09	50,000	190:2	8% vs 92% (10,000)
Localization Person Activity 10	164,860	8:11	37% vs 63% (10,000)
MAGIC Gamma Telescope 07	19,020	11:2	35% vs 65% (10,000)
MiniBooNE Particle 10	130,065	50:2	28% vs 72% (10,000)
Poker Hand 07	1,025,010	11:10	45% vs 55% (10,000)
UCSD FICO Contest 10	130,475	334:2	9% vs 91% (10,000)

Experiment 1: Comparing GPS to PSMS



- GPS wins in 83% (25 out of 30) evaluation setups (**benefit of combining GA and PSO** for the FMS problem)
- The best performance of both GPS and PSMS outperform AdaBoost. and RF on 9 datasets (**advantage of a full model** over the single algorithm model)
- GPS outperforms the baseline algorithms with big margin on imbalanced datasets

Experiment 2: Speeding Up the GPS System

Some observations

- The training complexity of the GPS algorithm depends on the base learners found and evaluated during the search.
- The main cost for GPS is the cost for estimating a base learner's performance (e.g., cross-validation).

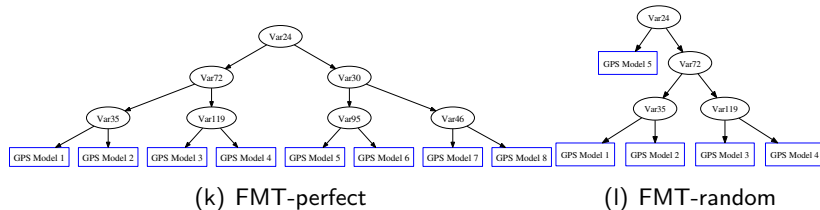
Users may have to wait for several hours, or even days on relatively large data sets. Therefore, in this work we also present a strategy for speeding up the GPS algorithm.

Experiment 2: Speeding Up the GPS System

Full Model Trees (FMT):

Instead of training the GPS algorithm on the full training data, we build GPS models at the leaves of a tree structure.

Experiment 2: Speeding Up the GPS System



We compare GPS to Full Model Tree with two different tree structures, namely, the perfect binary tree and the random binary tree.

Experiment 2: Speeding Up the GPS System

Theoretically (theorem 1 and 2, pp. 9-10), the two Full Model Tree variants are faster than GPS-0 in the case that the (empirical) training complexity of GPS-0 is worse than linear.

Experiment 2: Speeding Up the GPS System

Table: Performance and runtime of the GPS and the Full Model Tree algorithms; A “ \ominus ” indicates that in terms of AUC, the GPS algorithm is significantly better than the respective algorithm; A “ \diamond ” indicates that in terms of runtime, the GPS algorithm is significantly slower than the respective algorithm

Dataset	GPS	FMT-perf.	FMT-rand.	GPS	FMT-perf.	FMT-rand.
	AUC			Runtime (mins)		
Adult	0.94	0.93	0.93 \ominus	45 \pm 6	37 \pm 4 \diamond	48 \pm 11
Connect-4.	0.95	0.95	0.95 \ominus	91 \pm 5	77 \pm 9 \diamond	74 \pm 14 \diamond
KDD Cup.	0.77	0.77	0.76 \ominus	178 \pm 9	157 \pm 11 \diamond	189 \pm 8
Mini.B.E.	0.98	0.98 \ominus	0.97 \ominus	124 \pm 7	123 \pm 9	135 \pm 12
UCSD.	0.68	0.68 \ominus	0.67 \ominus	487 \pm 16	417 \pm 19 \diamond	476 \pm 17

- The DMO framework for designing new FMS algorithms
- The GPS algorithm for FMS
- Speeding up GPS with the perfect-binary-tree structure

A GUI for FMS

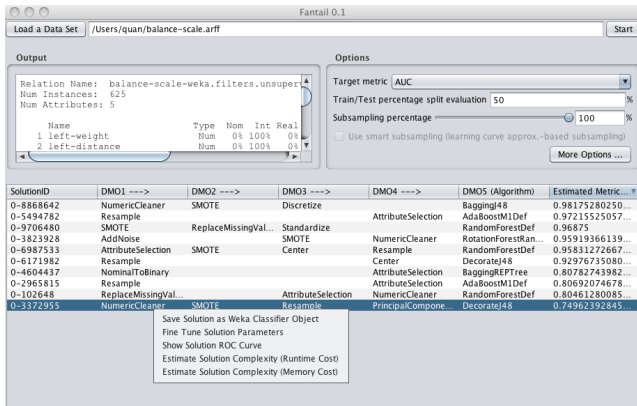


Figure: A proof-of-concept system based on the DMO framework using the GPS algorithm as the optimisation engine.

Thank you :-)