Adaptive Operator Selection via Online Learning and Fitness Landscape Metrics

Pietro Consoli Leandro L. Minku Xin Yao

CERCIA, School of Computer Science

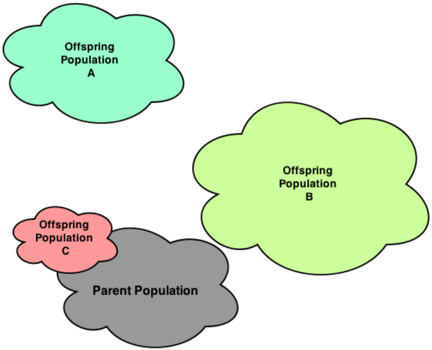
University of Birmingham, United Kingdom

www.cs.bham.ac.uk/~pac265

p.a.consoli@cs.bham.ac.uk

Outline

Adaptive Crossover Selection



Different crossover operators might lead to offspring with **different characteristics**:

- Exploration
- Fitness
- Good traits transmission

We can expect **different search results** on certain instances

Adaptive Crossover Selection

Inst	Op A	Op B	Op C	Op D
1	best	x	x	x
2	best	x	x	x
3	x	x	x	best
4	x	best	x	x
5	x	x	x	best
6	x	x	best	x
7	x	x	best	x
8	x	x	x	best

$\Rightarrow$

Inst	ACS(Op)
1	A
2	A
3	D
4	B
5	D
6	C
7	C
8	D

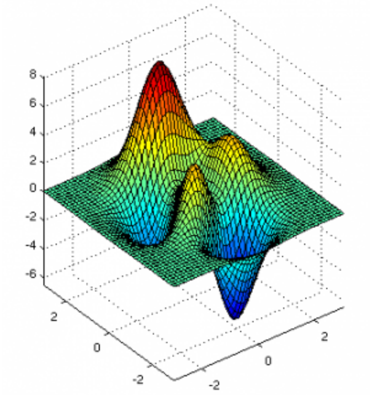
Adaptive Crossover Selection

Adaptively select the best crossover operator to use during the search process

Adaptive Crossover Selection: Dynamic Scenario

Dynamic scenario:

- **Different periods** of the search might have different best crossover operators;
- **Dynamic** ACS potentially better than static scenario



Research Questions

1. State-of-the art approaches for Credit Assignment consider the use of just one measure (usually fitness). Enough to **characterize** the current population distribution?
2. What Operator Selection Rule can handle a set of measures?

RQ1: Population Charachterization through FLA

Fitness Landscape Analysis (FLA): create a more “aware” snapshot of the current population distribution.

1. perform a set of 4 online FLA techniques during each generation;
   1. Average Escape Probability[1] (Evolvability);
   2. Average $\Delta-$Fitness of the neutral networks [2] (Neutrality);
   3. Average neutrality ratio [2] (Neutrality);
   4. Dispersion Metric[3] (Population Distribution);
2. FLA not to predict hardness but to learn more the current population distribution.

[1] Lu, G., Li, J., Yao, X. - "Fitness-probability cloud and a measure of problem hardness for evolutionary algorithms" - 2011

[2] Vanneschi L., Pirola Y., Collard P. - "A Quantitative Study of Neutrality in GP Boolean Landscapes" - 2006

[3] Lunacek M., Whitley D., - "The Dispersion Metric and the CMA Evolution Strategy" - 2006

RQ2: Credit Assignment through Online Learning

- Detection of changes **analogous** to Concept Drift tracking in Online Learning;
- Concept Drift: change of the underlying distribution of the samples during the learning process;
- Online learning can be used to learn the relationship between FLA results (input features) and the credit measure (output feature);
- Dynamic Weighted Majority (DWM) using Regression Trees as base learners.

Dynamic Weighted Majority

```
DWM(p, β, θ,, τ);
initialize a set of experts and assign an initial weight w_j = 1 to each;
create a window of the last training instances wTS(x̄_i);
forall the instances (x̄_i, y_i) do
    update wTS;
    forall the expert e_j do
        λ^i = predict(e^j, x̄_i);
        if |λ^i − y_i| < τ and i mod p = 0 then
            w_j = β ∗ w_j;
        end
        if w_j < θ and i mod p = 0 then
            delete expert e_j;
        end
        normalize weights (maximum weight equal to 1);
        calculate global prediction σ_i (weighted average prediction);
        if |σ^i − y_i| < τ and i mod p = 0 then
            create new expert e_j and train with wTS;
        end
        train all experts with the new instance (x̄_i, y_i);
        return σ_i;
    end
end
```

Capacitated Arc Routing Problem

- Case Study: Crossover Operator Selection using the MAENS algorithm for Capacitated Arc Routing Problem [4];
- Considers the use of a suite of **four different crossover operators**;
- Credit Assignment Mechanism: Proportional Reward (PR);
- we exploit the Local Search of MAENS* to perform the FLA techniques without extra computational cost.

[4] K. Tang, Y. Mei, X. Yao - "Memetic Algorithm with Extended Neighborhood Search for Capacitated Arc Routing Problems" - 2009

Credit Mechanism

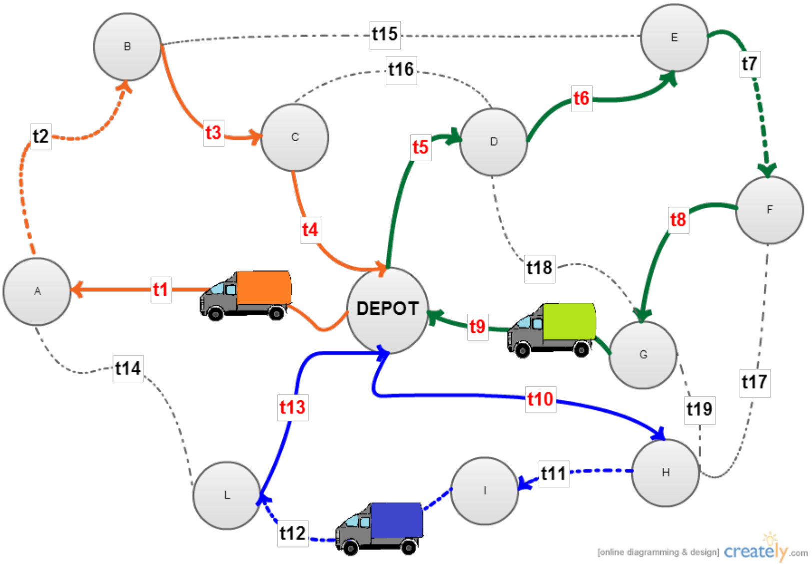
Credit Assignment Mechanism: percentage of offspring generated by each operator surviving to the next generation.

Proportional Reward

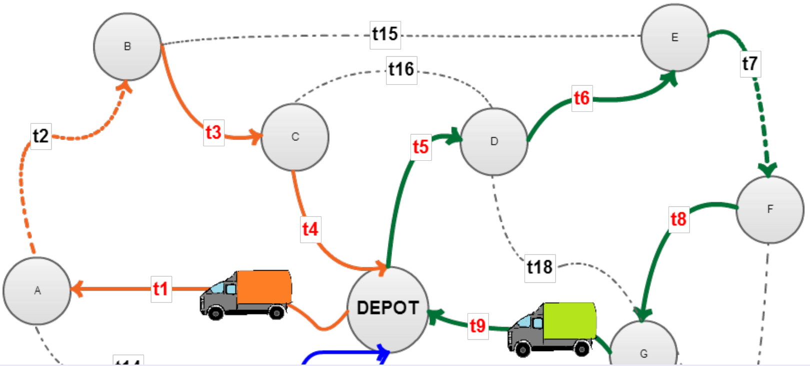
$$PR(i)^t = \frac{|x \in pop^{t+1} : x \text{ generated by operator i}|}{|pop^{t+1}|}$$

- Indirect effect of crossover operator;
- We entrust the selection/ranking operator of the algorithm to evaluate the individuals.

CARP - instance

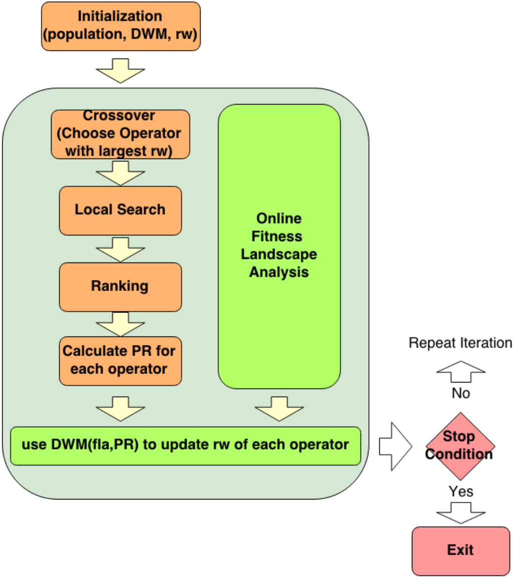


CARP - instance



- each arc (task) has a service cost and a demand;
- constraints: number of vehicles and capacity;
- objective function: minimize the total service cost;
- proved NP-Hard in 1981;
- many real-world applications (e.g. waste collection, road gritting).

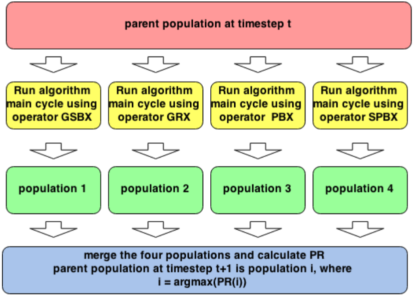
MAENS*-II



- FLA is performed during each iteration;
- basic Operator Selection Rule: largest **instantaneous** reward in order to reduce bias of previous performances;
- Credit Assignment through DWM.

Experimental studies

- Experiments conducted on a set of 42 non-easy CARP instances belonging to *egl*, *val* and Beullen's benchmark sets;
- Average fitness values calculated over 30 independent runs;
- In order to provide a lower bound and a term of comparison for the results, an Oracle using only the Proportional Reward is built;



1. Tested **optimization** results against MAENS*, Oracle;
2. Tested **prediction** ability against Oracle.

MAENS*-II vs MAENS*

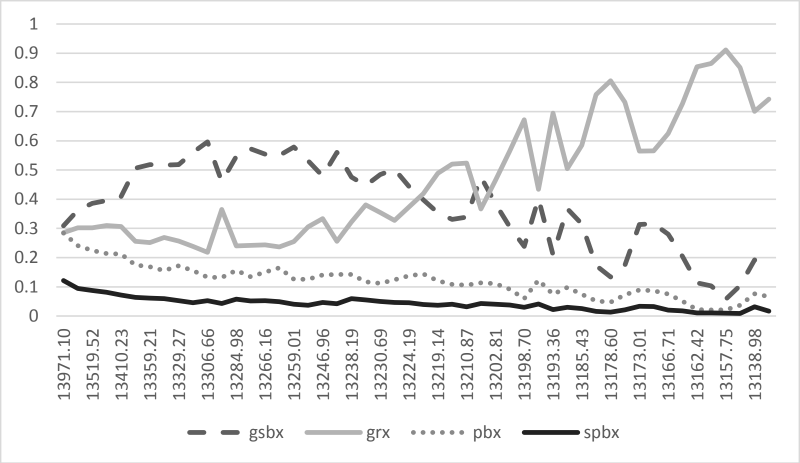
- MAENS* - uses MAB and Proportional Reward;
- MAENS*-II wins the comparisons with MAENS* on 20 instances and loses on 18 out of 42 instances;
- Wilcoxon signed-rank test over the set of the instances suggests that there is no statistical difference between the results achieved by the two algorithms;
- 6 instances show statistically different results using Wilcoxon rank-sum test on each couple of results.

Instance	MAENS*-II		MAENS*	
	avg fitness	std	avg fitness	std
D23	**767.67**	7.39	769.83	12.28
E15	1604.33	5.59	**1602.50**	6.68
E19	**1442.00**	4.58	1442.67	4.23
F19	**732.50**	9.64	735.17	9.35
egl-s1-B	**6397.59**	12.70	6399.90	16.38
egl-s2-B	**13171.41**	29.49	13179.07	26.11

MAENS*-II vs Oracle

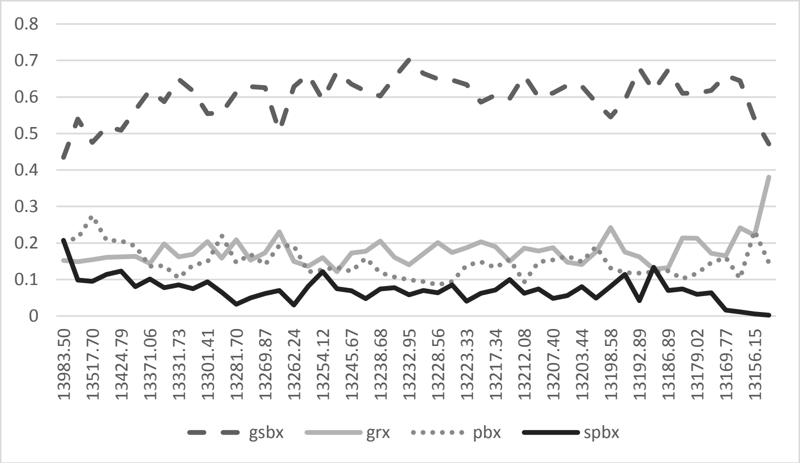
- Oracle achieves better results on 40 instances;
- On 2 instances MAENS*-II managed to achieve better results than the Oracle;
- If Oracle shows bound using only PR, then the use of **FLA+PR can enhance of the optimization ability** of the algorithm.

Prediction Ability: Oracle



Prediction Ability: MAENS*

Prediction Ability: MAENS*-II



Future work

- Integrated with a Reinforcement Learning mechanism with concurrent use of the operators;
- Tested the use of a diversity-based reward measure;
- Improved results when using RL;
- outperformed state-of-the-art on Large Scale CARP instances.

Conclusions

Conclusions:

- Novel Adaptive Operator Selection strategy based on a set of FLA measures and online learning;
- Achieved comparable results w.r.t. MAB and outperformed the oracle in a few instances but still non optimal detection of changes in environment;

Future Directions:

- Improving the detection of changes in the environment;
- Test on Software Engineering Problems?

References

- Consoli, P.; Minku, L. L; Yao, X.; **"Dynamic Selection of Evolutionary Algorithm Operators Based on Online Learning and Fitness Landscape Metrics"**, Proceedings of the 10th International Conference on Simulated Evolution And Learning (SEAL'14), LNCS 8886, pp. 359-370, December 2014
- Consoli P., Yao, X.; **"Diversity-Driven Selection of Multiple Crossover Operators for the Capacitated Arc Routing Problem"**, Evolutionary Computation in Combinatorial Optimisation, Proceedings of the 14th European Conference, EvoCOP 2014, Granada, Spain, April 23-25, 2014, LNCS 8600, 2014, pp 97-108

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Thank You!