

# Multi Armed Bandits for Many Task Optimization

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# Agenda

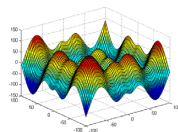
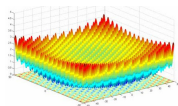
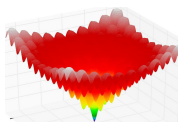
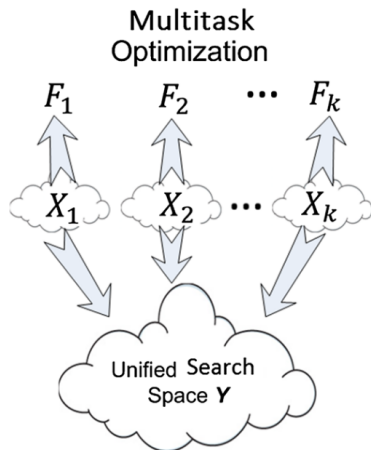
- 1 Introduction
- 2 Related works
- 3 Proposed method
- 4 Experimental results

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# Many task optimization - MaTSOO benchmark

## Single Objective Optimization (SOO)



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# MFEA

## MFEA

A. Gupta, Y.-S. Ong, and L. Feng, "Multifactorial evolution: Toward evolutionary multitasking," *IEEE Transactions on Evolutionary Computation*, vol. 20, no. 3, pp. 343–357, 2015

## Problem

- Do not group ideal assist tasks

# MaTGA

## MaTGA

Y. Chen, J. Zhong, L. Feng, *et al.*, “An adaptive archive-based evolutionary framework for many-task optimization,” *IEEE Transactions on Emerging Topics in Computational Intelligence*, 2019

## Problem

- Store past solutions
- Measure KLD between past solutions
- Complex, many parameters

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# Task selection as a Multi Armed Bandit (MAB) problem

## Action

- Given a  $K$  task MTO problem
- Given a parent  $p_1$ , skill factor  $\tau_{source}$
- **Action** is  $\tau_{target} \in \{1, \dots, K | \tau_{source} \neq \tau_{source}\}$
- Then, select  $p_2$  from  $P_{\tau_{target}}$  to reproduce.

## Reward

- Given  $y_{\tau_{source}}$ , list of fitness of  $P_{\tau_{source}}$
- **Reward**

$$r = \begin{cases} 1 & \text{if } y_c < \min(y_{\tau_{source}}) \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

# UCB function to solve MAB

## Estimate expected reward

Each source task  $\tau_{source}$  estimate the expected reward of selecting a target task

$$Q[\tau_{target}] = Q[\tau_{target}] + \alpha(r - Q[\tau_{target}]) \quad (2)$$

where  $Q \in \mathbb{R}^{K-1}$  is the estimated expected reward,  $r$  is the given reward,  $\alpha$  is the discount factor.

## UCB function

Each source task  $\tau_{source}$  select target task by

$$\tau_{target} = \operatorname{argmin}_k Q[k] + c \sqrt{\frac{\log(t)}{N[k]}} \quad (3)$$

where  $c$  is exploration-exploitation trade off coefficient,  $t$  is the total number of selection,  $N[k]$  is number of times task  $k$  is selected.

## Linear decay of $rmp$

High  $rmp$  first, low  $rmp$  after

$$rmp = \frac{rmp_{max} - rmp_{min}}{T} \times (T - t) \quad (4)$$

# Basic structure of MAB-MFEA

## Parameters

- $\alpha$  - discounted factor,  $c$  - exploration exploitation trade-off
- $rpm_{max}$ ,  $rpm_{min}$

## MAB-MFEA evolution step

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### Algorithm 1 Multi-step SR

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1: Get current generation's  $rpm$ 
2: for  $i \in \{1, 2, \dots\}$  do
3:   Select parents  $p_1, p_2$  randomly.
4:   if  $\tau_1 = \tau_2$  then
5:     SBX, Polynomial  $p_1, p_2$  to  $c_1, c_2$ , evaluate them
6:   else if  $rand() < rpm$  then
7:     Select  $\tau_{target}$  for  $\tau_1$  (Equation.3)
8:     Select  $p_2$  from  $\tau_{target}$ 
9:     SBX, Polynomial  $p_1, p_2$  to  $c_1, c_2$ , evaluate them
10:    Update estimate (Equation.2)
11:   else
12:     Select  $p_2$  from  $\tau_1$ 
13:     SBX, Polynomial  $p_1, p_2$  to  $c_1, c_2$ , evaluate them
14:   end if
15: end for
16: Elitist selection

```

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# Benchmark

Task	Function	Ideal Assisted Task
$T_1$	Sphere1	None
$T_2$	Sphere2	None
$T_3$	Sphere3	None
$T_4$	Weierstrass25D	None
$T_5$	Rosenbrock	$T_1$
$T_6$	Ackley	$T_2$
$T_7$	Weierstrass50D	$T_3, T_4$
$T_8$	Schwefel	None
$T_9$	Griewank	$T_4$
$T_{10}$	Rastrigin	None

# Parameter setting

## MFEA

- Population size: 30
- $rmp$ : 0.3
- $sboxdi$ : 2
- $pmdi$ : 5

## MAB-MFEA

- $rmp_{min}$ : 0.1
- $rmp_{max}$ : 0.9
- $\alpha$ : 0.01 - discounted coefficient
- $c$ : 0.5 - UCB explore/exploit trade-off coefficient

## MaTGA

- $NP$ :
- $\lambda$ : 0.8 - reward shrink rate
- $\rho$ : 0.8 - attenuation coefficient
- $\alpha$ : 0.1 - knowledge transfer rate
- $UR$ : 0.2 - archive update rate
- $AcS$ : 300 - archive size

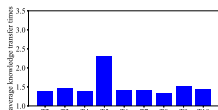
## Table

	MFEA	MaTGA	MAB-MFEA
$T_1$	1.32E+00	<b>2.45E-04</b>	2.85E-03
$T_2$	1.27E+00	4.75E-04	<b>1.15E-12</b>
$T_3$	1.17E+00	<b>0</b>	<b>6.30E-09</b>
$T_4$	3.37E+00	<b>1.00E-06</b>	5.37E-04
$T_5$	8.15E+02	<b>2.16E-02</b>	1.01E+01
$T_6$	1.99E+01	3.61E-03	<b>1.05E-07</b>
$T_7$	1.05E+01	<b>5.57E-04</b>	1.52E-03
$T_8$	2.34E+03	<b>3.40E-02</b>	9.21E+02
$T_9$	4.11E-02	4.52E-03	<b>4.50E-03</b>
$T_{10}$	1.55E+01	1.57E+01	<b>7.77E+00</b>

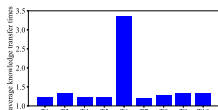
Table 1: The performance of 3 algorithms for 30 independent runs



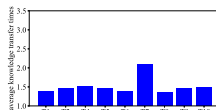
# Analysis



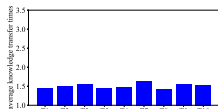
(a) Task 1



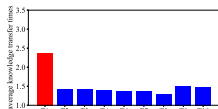
(b) Task 2



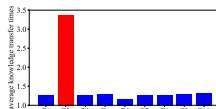
(c) Task 3



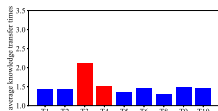
(d) Task 4



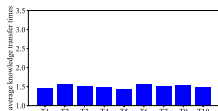
(e) Task 5



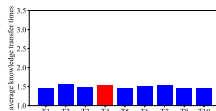
(f) Task 6



(g) Task 7



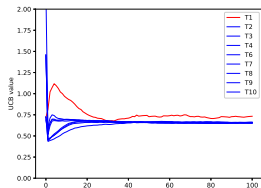
(h) Task 8



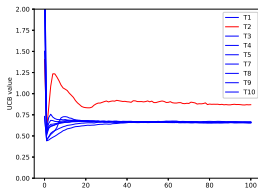
(i) Task 9

Figure 1: The average times of choosing knowledge transfer target, the assisted task is highlighted in red

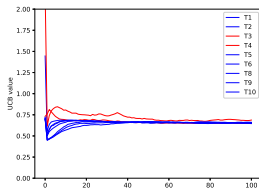
# Analysis



(a) Task 5



(b) Task 6



(c) Task 7

Figure 2: The UCB function value 3 for choosing knowledge transfer target, the assisted task is highlighted in red

# Conclusion

## Contribution

- Trade of between explore and exploit task relationship.
- Better than MFEA, less complex but performs equally well to MaTGA.
- The best on 5/10 tasks.
- Analyse on 10 task benchmark shows MAB-MFEA correctly identify ideal assist task.

## Future task to complete the study

- Adjust *rpm\_min* and *rpm\_max* paramter.
- Finish experiment on CEC Complex 50 tasks benchmark.

Thank you for your attention!