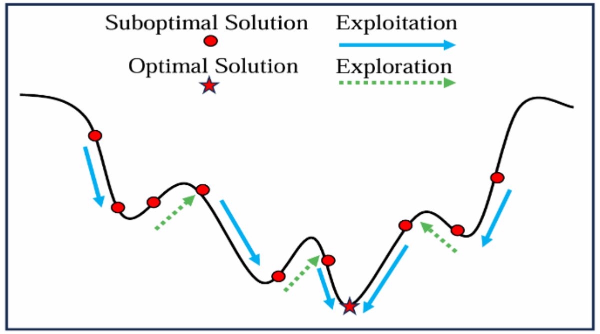
AutoEP: LLMs-Driven Automation of Hyperparameter Evolution for Metaheuristic Algorithms

Zhenxing Xu[1†], Yizhe Zhang[1†], Weidong Bao[1*], Hao Wang[1], Ming Chen[2], Haoran Ye[3] and Wenzheng Jiang[1], Hui Yan[1] 1 and Ji Wang[1]

[1] National University of Defense Technology [2] Tsinghua University [3] Peking University

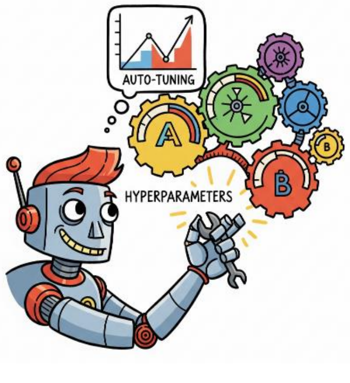
Motivation & Chanllenge

What is the core of metaheuristic algorithms?



- The performance of metaheuristic algorithms primarily depends on the balance between exploration and exploitation, which is precisely governed by hyperparameters.
- How can we design an efficient, versatile, and adaptive framework for automated hyperparameter optimization?

Current Bottlenecks in Hyperparameter Optimization

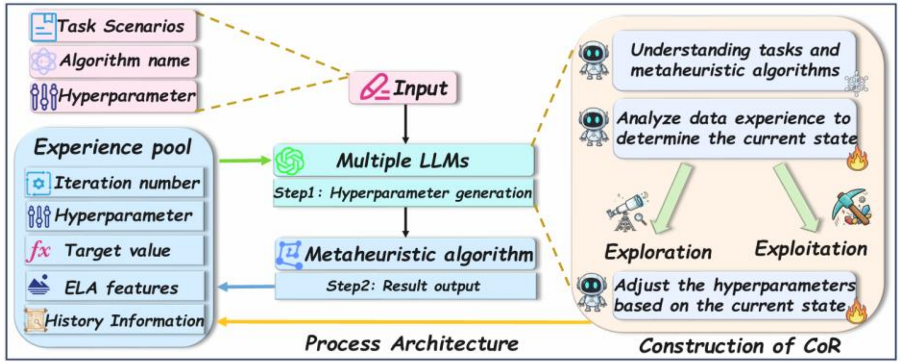


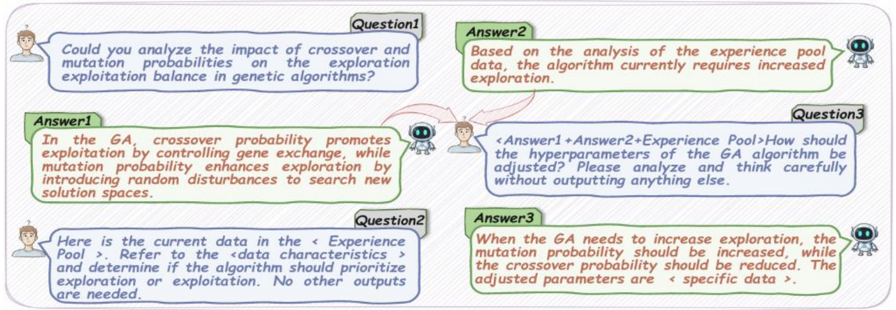
- Manual hyperparameter tuning necessitates extensive domain expertise and exhaustive trial-and-error. Consequently, this time-consuming process frequently falls short of discovering optimal configurations.
- Learning-based approaches incur prohibitive training costs and demand substantial computational resources. Moreover, their limited generalization hinders effective transfer across diverse problem domains and algorithmic frameworks.

Proposed Method

Core idea: Integrating the reasoning capabilities of Large Language Models (LLMs) with quantitative algorithmic analysis enables dynamic and intelligent hyperparameter tuning..

AutoEP: A Framework for Hyperparameter Optimization





Component I: Exploratory Landscape Analysis (ELA).

This component quantitatively characterizes the algorithm's state during optimization, informing the decision-making process of the LLM.

Component II: Multi-LLM Collaborative Chain of Reasoning (CoR)

This mechanism decomposes complex tuning tasks and resolves them through the collaboration of multiple LLMs, thereby improving both decision accuracy and efficiency.

Experiments

Method	Kroa150		rd300		rat575		dsj1000	
	Gap(%)↓	Time	Gap(%)↓	Time	Gap(%)↓	Time	Gap(%)↓	Time
DACT	0.13	7.9	0.93	18.7	2.55	26.3	4.97	71.5
LEHD	0.96	0.3	1.38	0.4	2.64	0.6	5.54	1.8
GA	5.26	1.7	11.33	2.8	14.75	3.3	21.94	5.3
GA+PT	3.94	1.7	8.82	2.8	9.43	3.3	19.25	5.3
GA+GLEET	3.23	2.4	7.11	3.7	8.06	4.9	16.23	6.8
GA+BEA	3.76	1.8	7.28	2.9	9.07	3.5	16.91	5.5
GA+EoH	3.61	1.9	7.16	3.1	8.32	3.4	19.39	5.3
GA+ReEvo	3.39	1.9	7.58	3.0	8.39	3.4	16.53	5.4
GA+AutoEP	**2.15**	**4.2**	**6.27**	**5.3**	**6.92**	**5.8**	**14.02**	**7.8**
GA-2opt	0.87	29.4	1.62	56.3	3.35	167.6	7.14	309.8
GA-2opt+PT	0.24	29.9	0.54	56.7	1.46	168.1	6.07	310.3
GA-2opt+GLEET	0.09	30.9	0.33	57.8	0.91	171.2	5.47	311.5
GA-2opt+BEA	0.25	30.8	0.41	57.7	1.03	169.0	5.86	311.2
GA-2opt+EoH	0.27	29.7	0.63	56.5	2.91	167.9	5.83	310.0
GA-2opt+ReEvo	0.16	30.2	0.48	57.2	2.68	168.5	5.95	310.7
GA-2opt+AutoEP	**0.01**	**31.9**	**0.09**	**58.9**	**0.08**	**170.2**	**3.58**	**312.8**
GA-2opt+EoH+AutoEP	0.01	32.5	0.11	59.1	0.08	169.6	3.61	312.6
GA-2opt+ReEvo+AutoEP	0.01	32.1	0.10	59.8	0.07	170.1	3.59	312.3