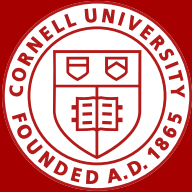


# LLM-Driven Composite Neural Architecture Search for Multi-Source RL State Encoding

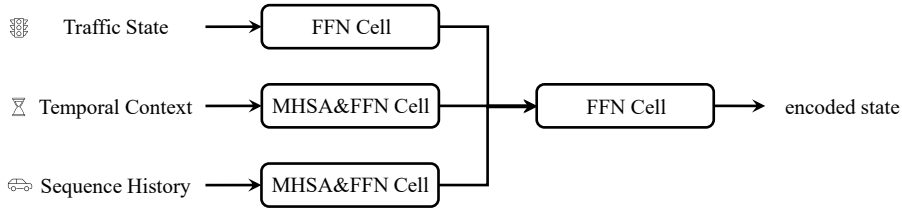


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<sup>1</sup>Shanghai Jiao Tong University <sup>2</sup>Cornell University <sup>3</sup>New York University

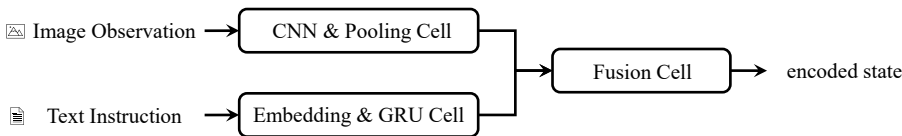


## Multi-Source RL State Encoding

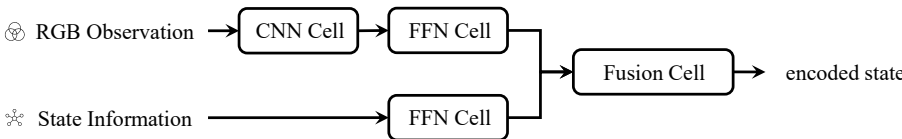
Mixed-autonomy traffic control:



MiniGrid goal-oriented tasks:



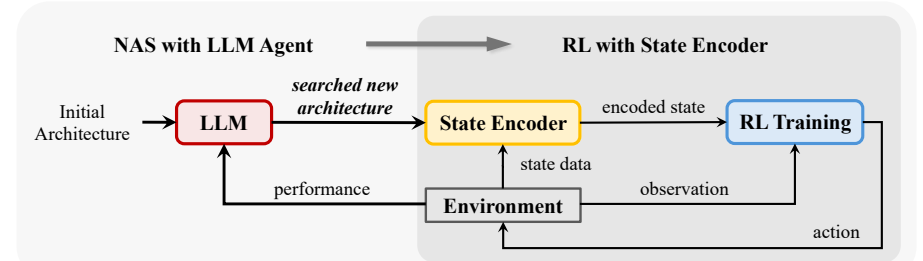
ManiSkill robotic control:



Designing state encoders for multi-source-RL remains underexplored.

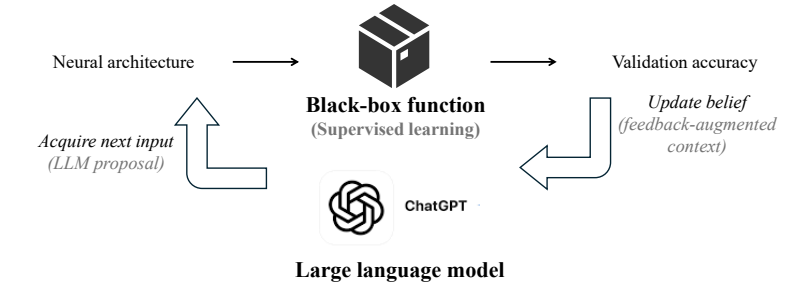
## Pipeline

LLM-driven Neural Architecture Search for Composite State Encoders in RL (LACER):

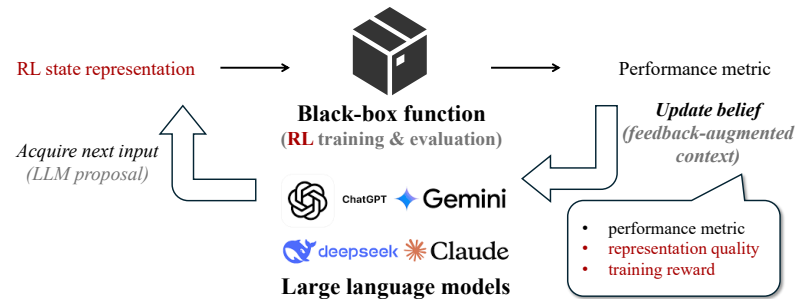


## LLM-Based Method Comparisons

GENIUS (existing LLM-based NAS):



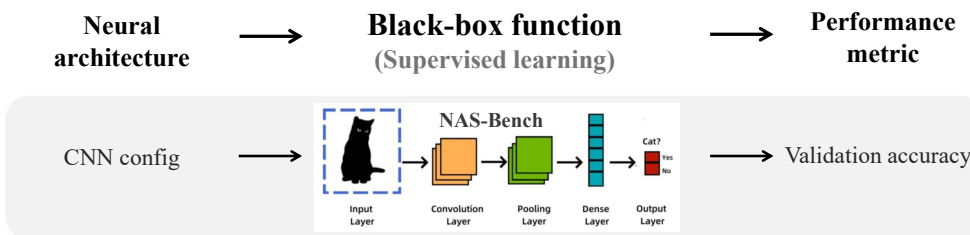
LACER (ours):



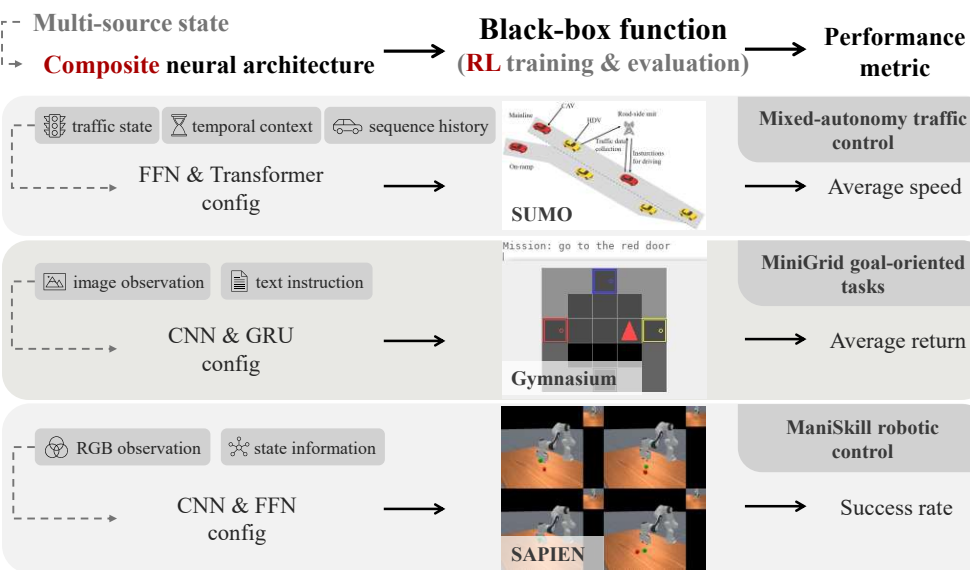
Exploit side info on source-specific encoders beyond performance metric.

## Composite Neural Architecture Search

NAS for supervised learning:

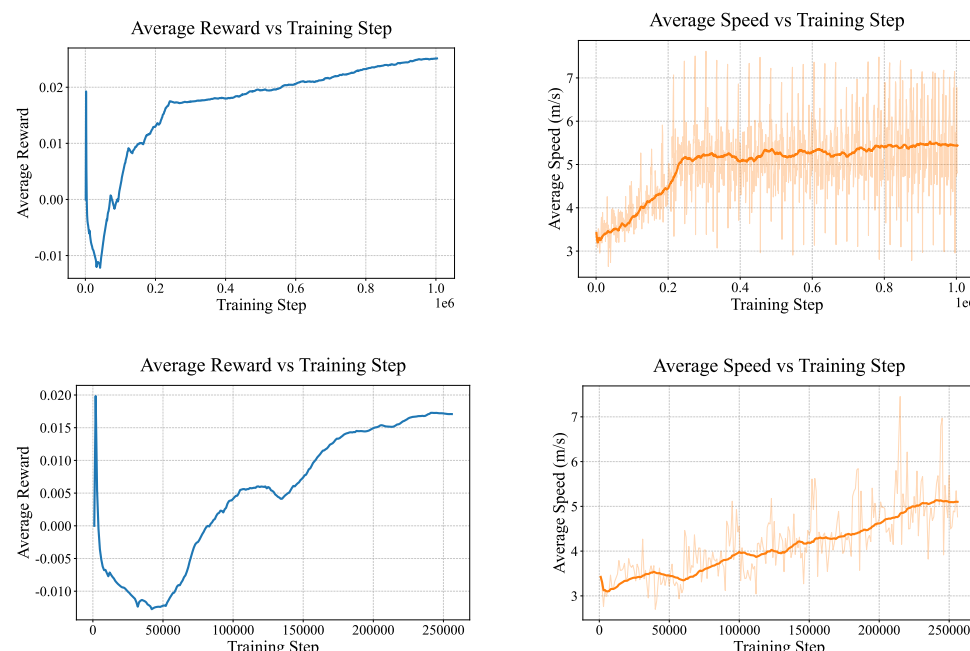


NAS for multi-source RL state encoding:



Unlike supervised learning, multi-source RL requires composite NAS.

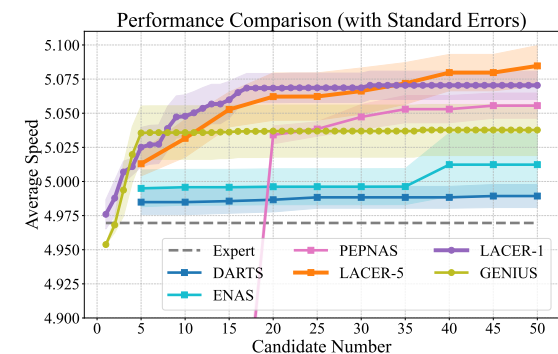
RL training and evaluation:



Balance convergence stability and training cost for efficient, reliable NAS.

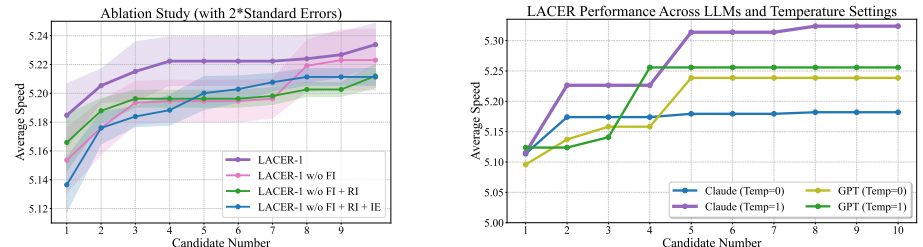
## Performance

Comparison between LACER and baselines:



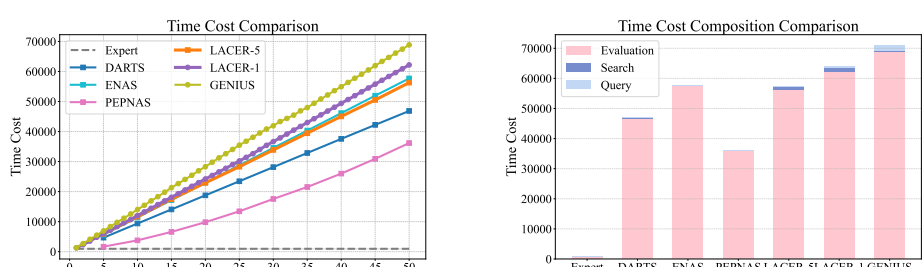
LACER-5 denotes the batch variant (five candidates per iteration).

Ablation study on LLM feedback, model choice, and temperature:



LLM priors and richer feedback enable sample-efficient composite NAS.

## Computation Time



LLM query time is negligible relative to encoder candidate eval time.