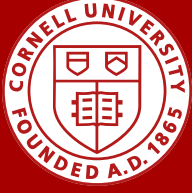# LLM-Driven Composite Neural Architecture Search
for Multi-Source RL State Encoding
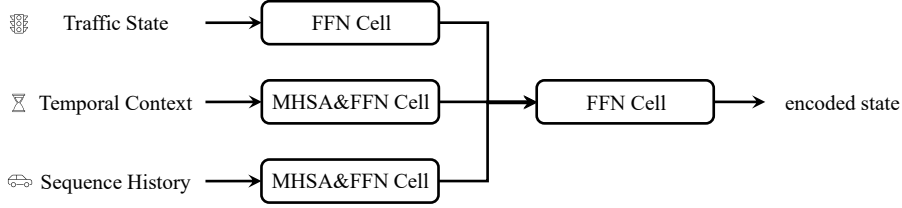
Yu Yu[1], Qian Xie[2†], Junping Li[1], Aghamatlab Akbarzade[1], Nairen Cao[3], Li Jin[1†]

[1]Shanghai Jiao Tong University   [2]Cornell University   [3]New York University
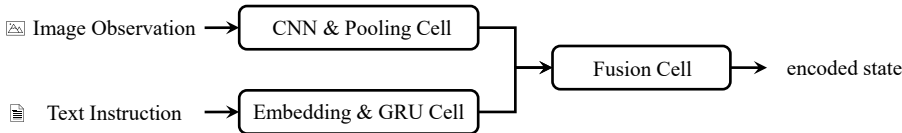
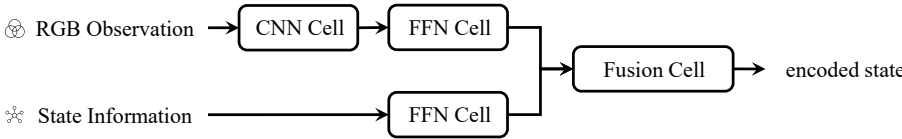## Multi-Source RL State Encoding

Mixed-autonomy traffic control:
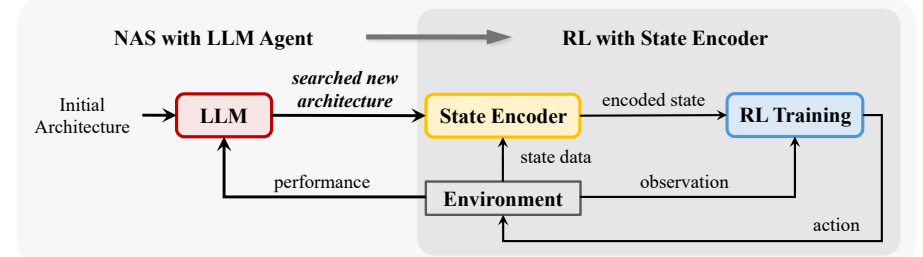

MiniGrid goal-oriented tasks:

ManiSkill robotic control:

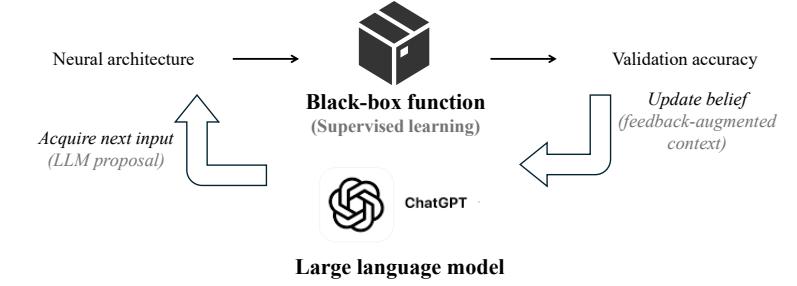💡 Designing state encoders for multi-source-RL remains underexplored.

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.

Pipeline

LLM-driven Neural **A**rchitecture Search for **C**omposite State **E**ncoders in **R**L (LACER):
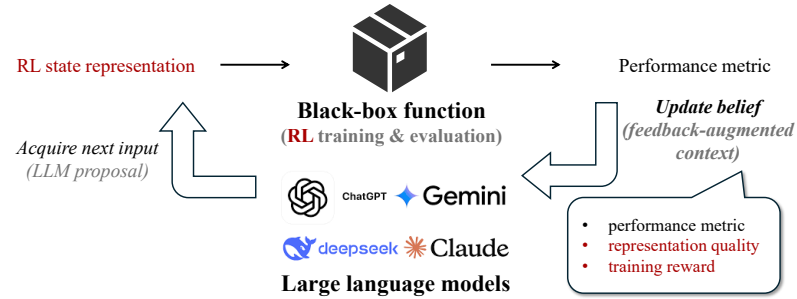

LLM-Based Method Comparisons
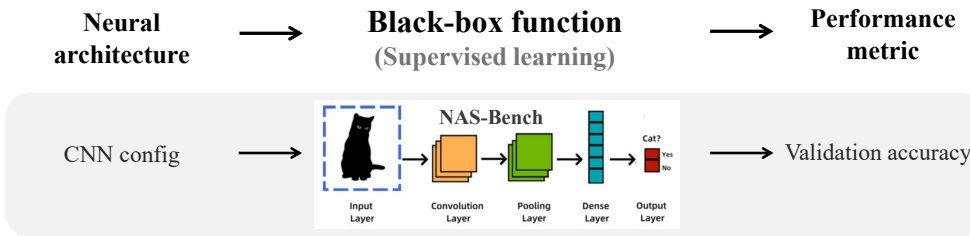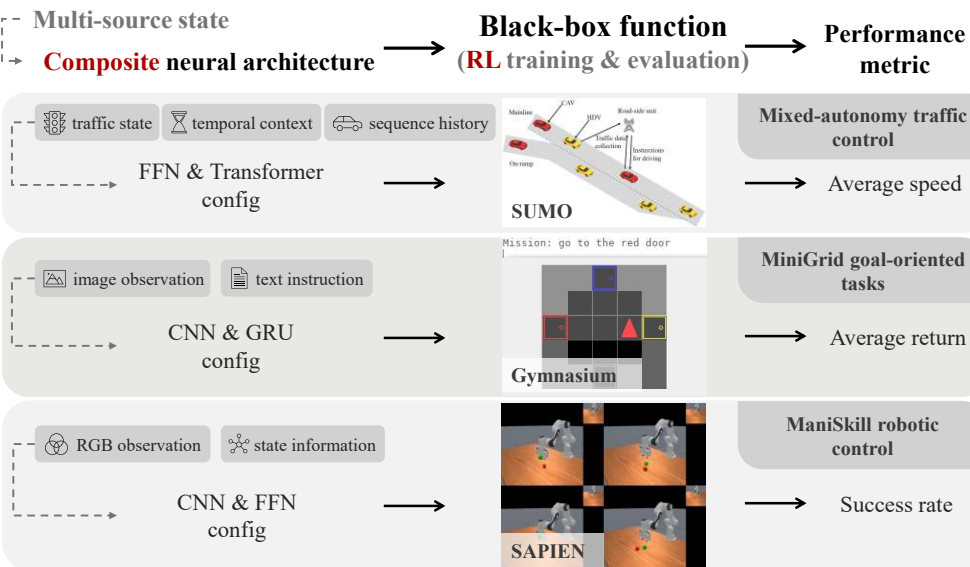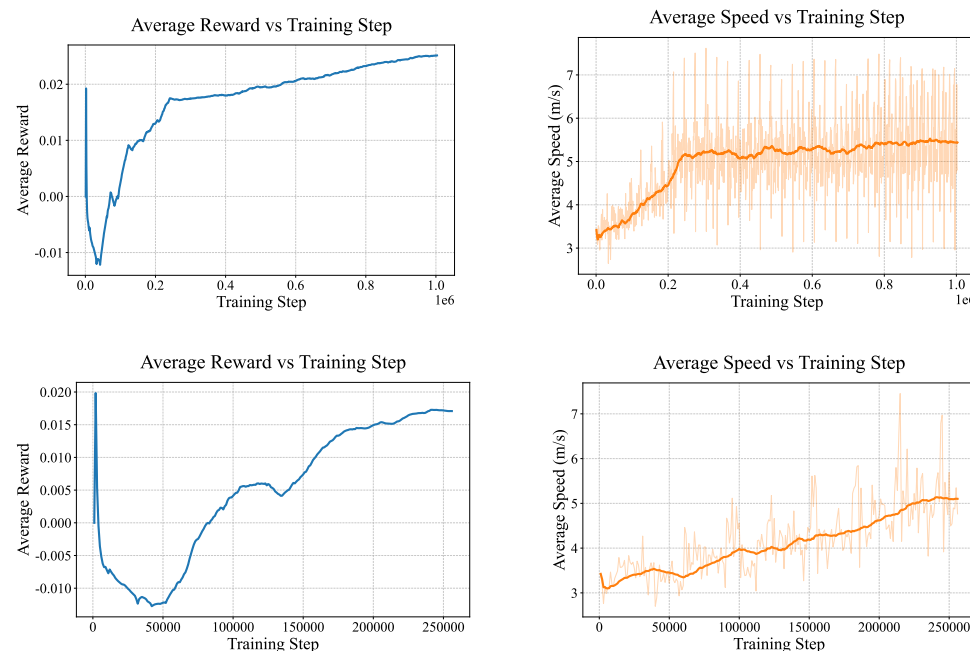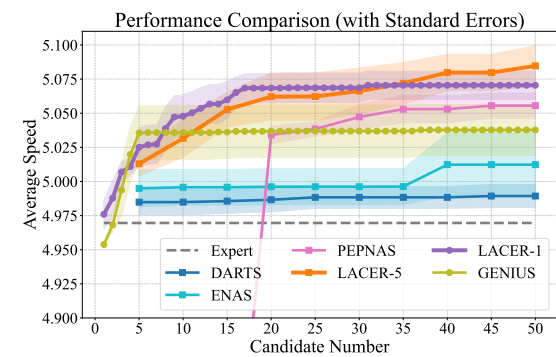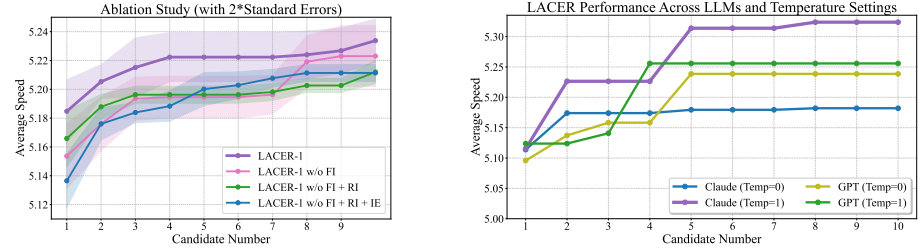
GENIUS (existing LLM-based NAS):

LACER (ours):

💡 Exploit encoder intermediate output beyond performance metric.

Performance

Comparison between LACER and baselines:
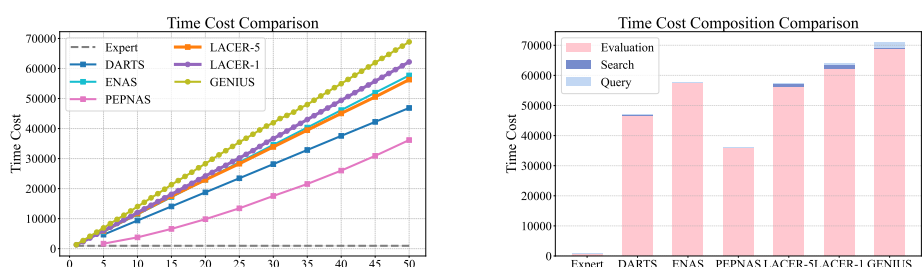

Performance Comparison (with Standard Errors)

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

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

Ablation Study (with 2*Standard Errors)

LACER Performance Across LLMs and Temperature Settings

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

Computation Time

Time Cost Comparison

Time Cost Composition Comparison

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