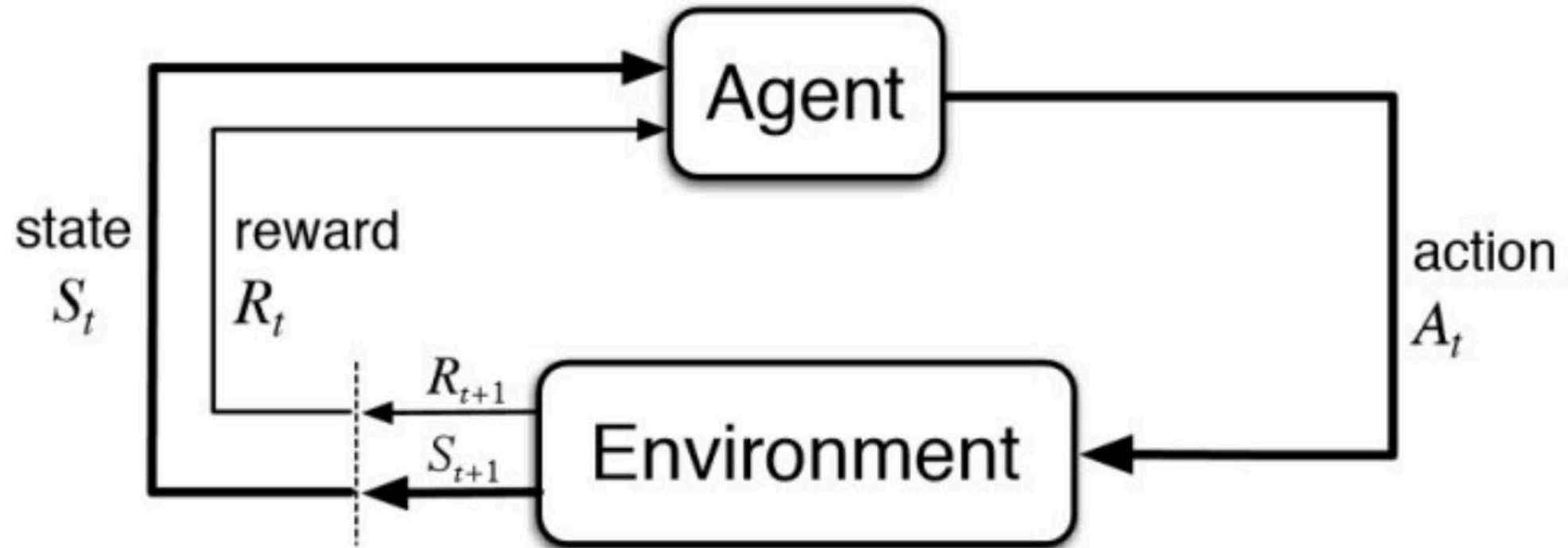


# RLgraph: Modular Computation Graphs for Deep Reinforcement Learning

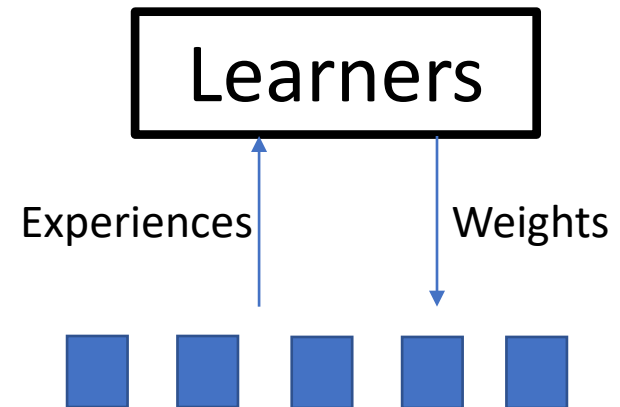
Michael Schaarschmidt, Sven Mika, Kai Fricke, Eiko Yoneki

# Reinforcement Learning (RL)



# Supervised Learning vs RL

- Supervised Learning
  - Training data beforehand
- Reinforcement Learning
  - Learn and collect data at the same time
  - No labeled dataset
  - Sensitive to hyper parameters



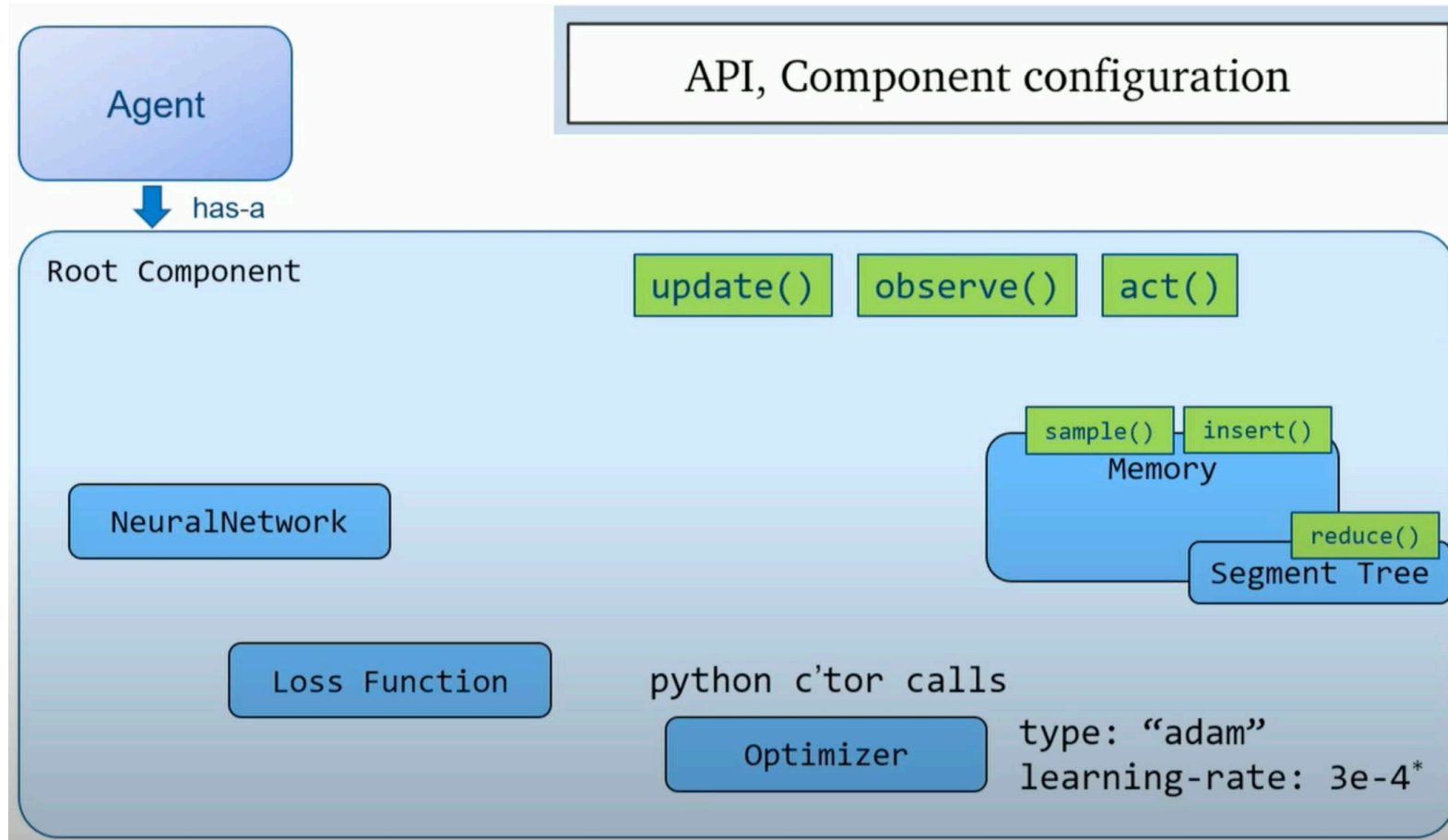
# Related Works

- Existing RL Libraries
  - OpenAI baselines, TensorForce, Ray RLlib
- Pros
  - Present good results on existing environments in library
  - Code is concise
- Cons
  - Hard to adapt other environments since components tightly coupled
  - Restricted to a single backend
  - Unable to test a subcomponent individually

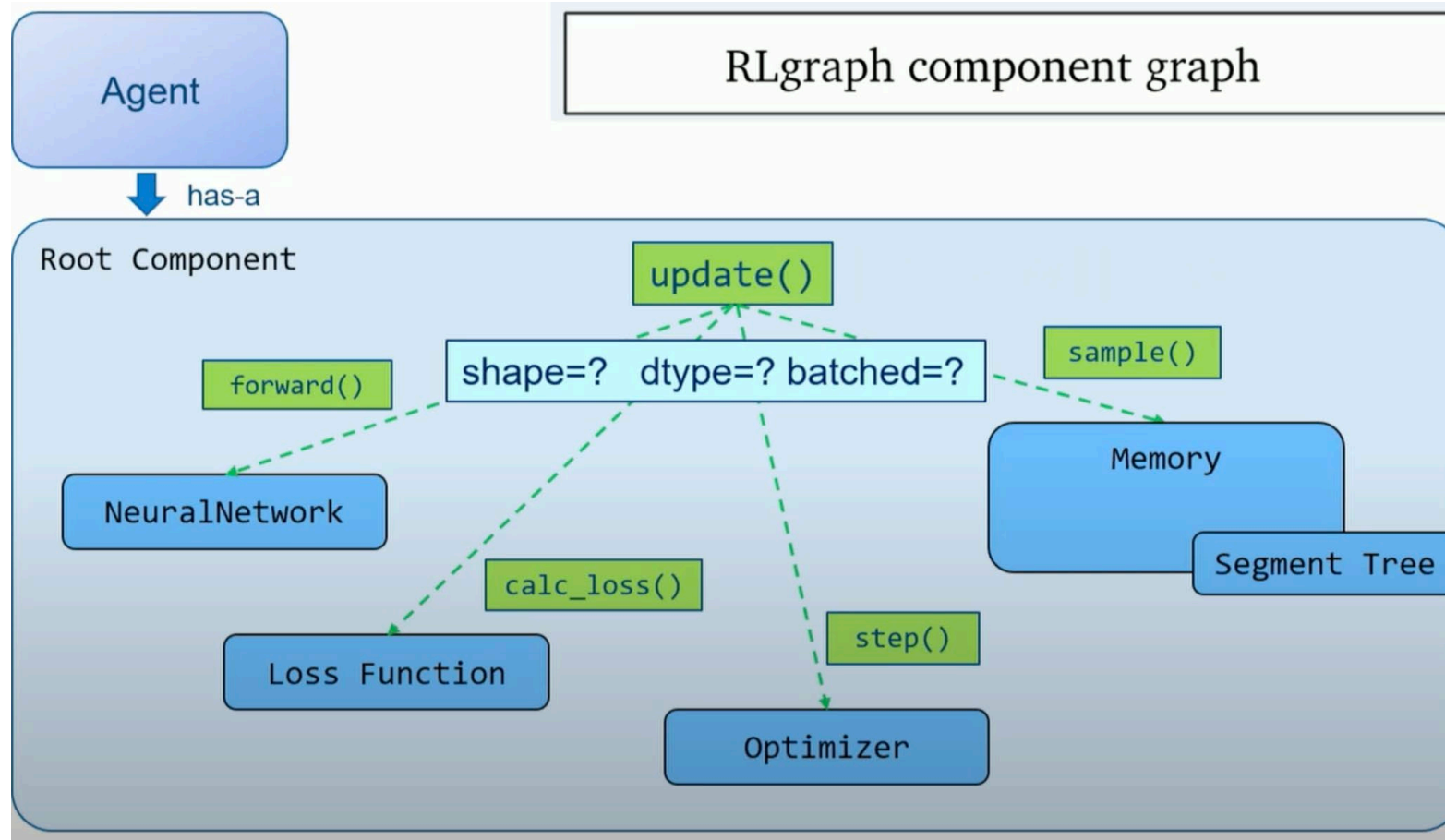
# RLgraph

API, Component configuration	Prebuilt models, inference		
RLgraph component graph	Model design, dataflow composition		
TensorFlow	PyTorch	...	Local backends variables/operations
Distributed TF	Horovod	Ray	Distributed execution engine
Hardware: CPU, GPU, TPU, FPGAs...			Execution, orchestration

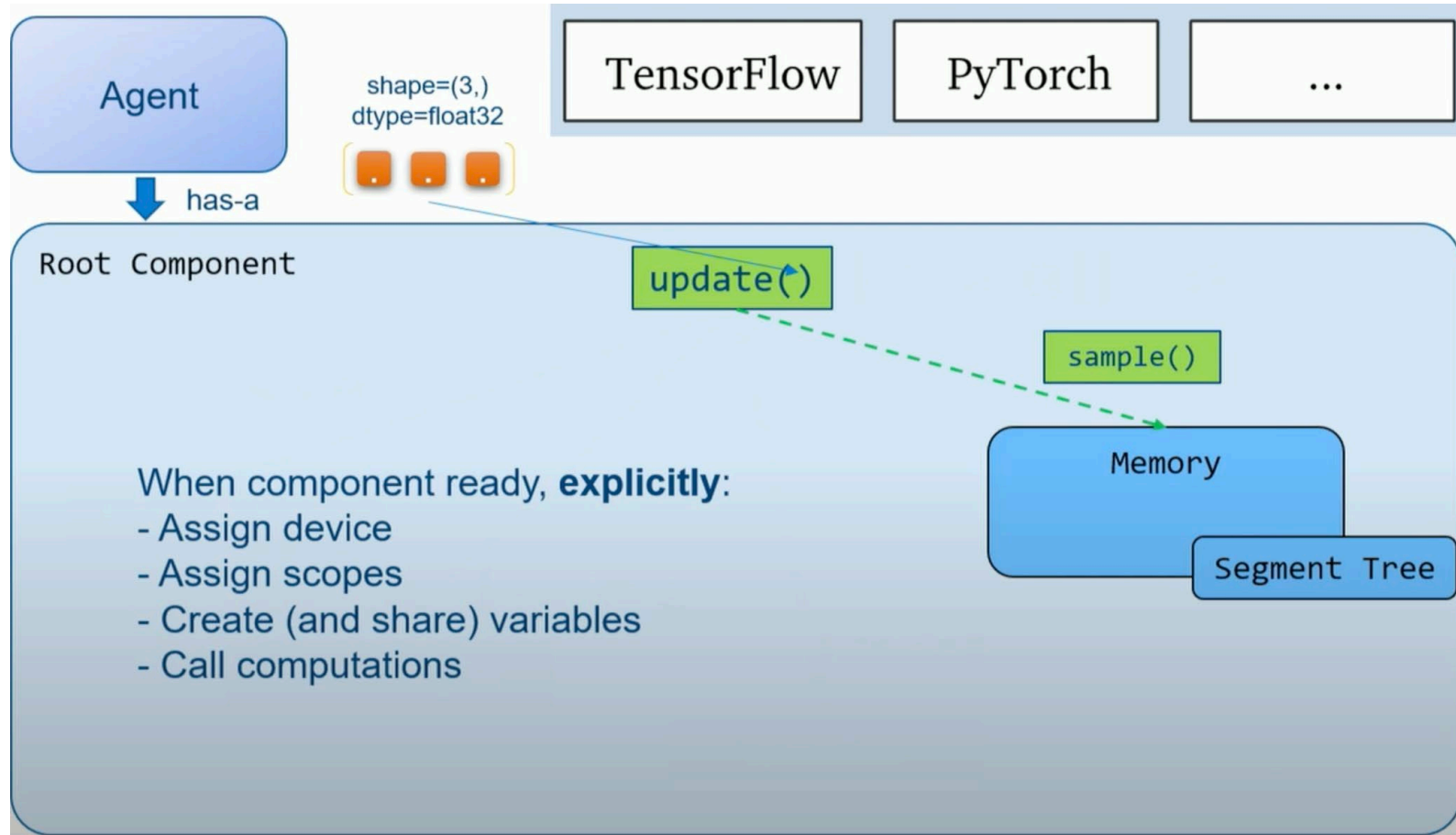
# The First Layer



# The Second Layer

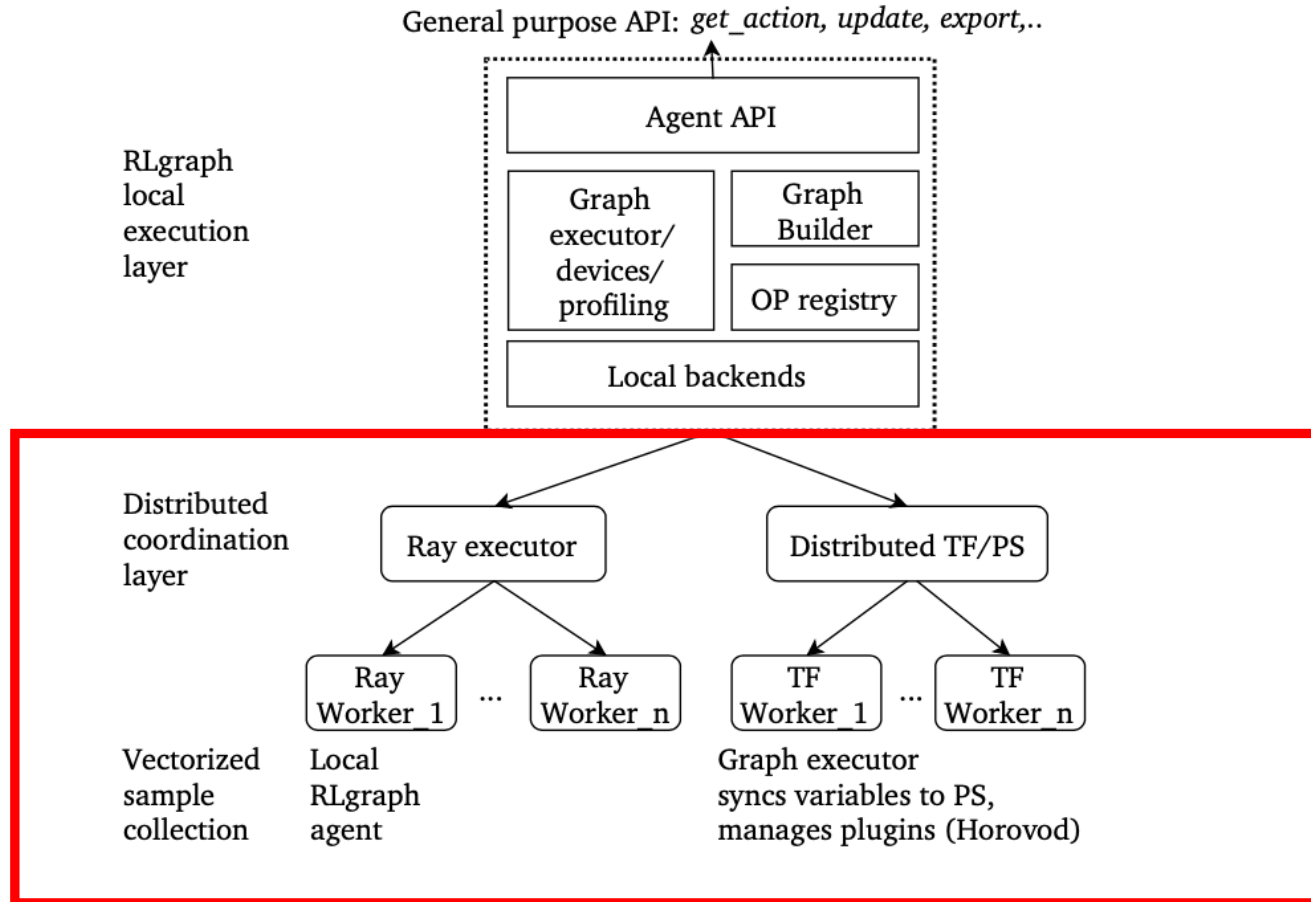


# The Third Layer



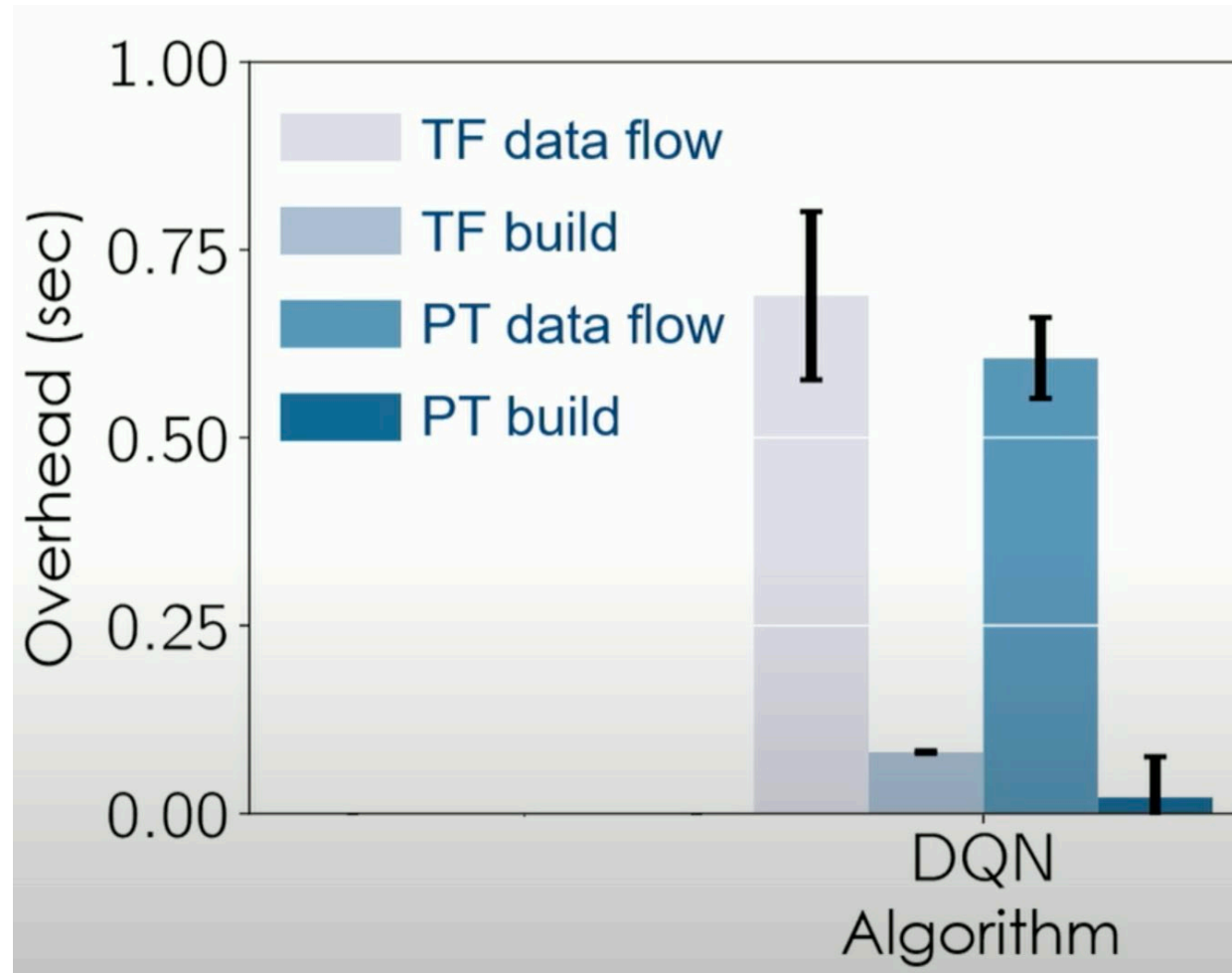


# The Fourth Layer

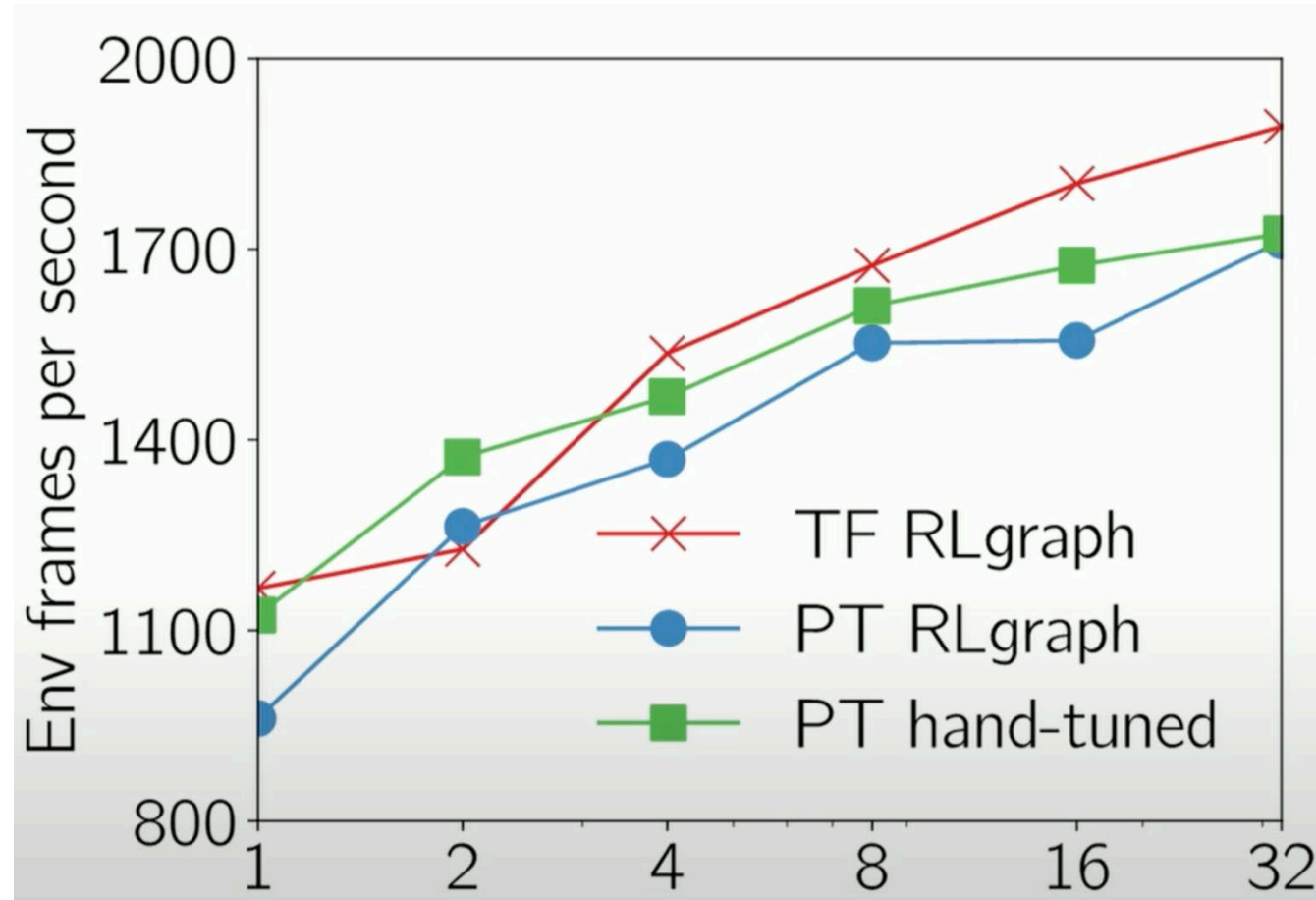


Evaluation

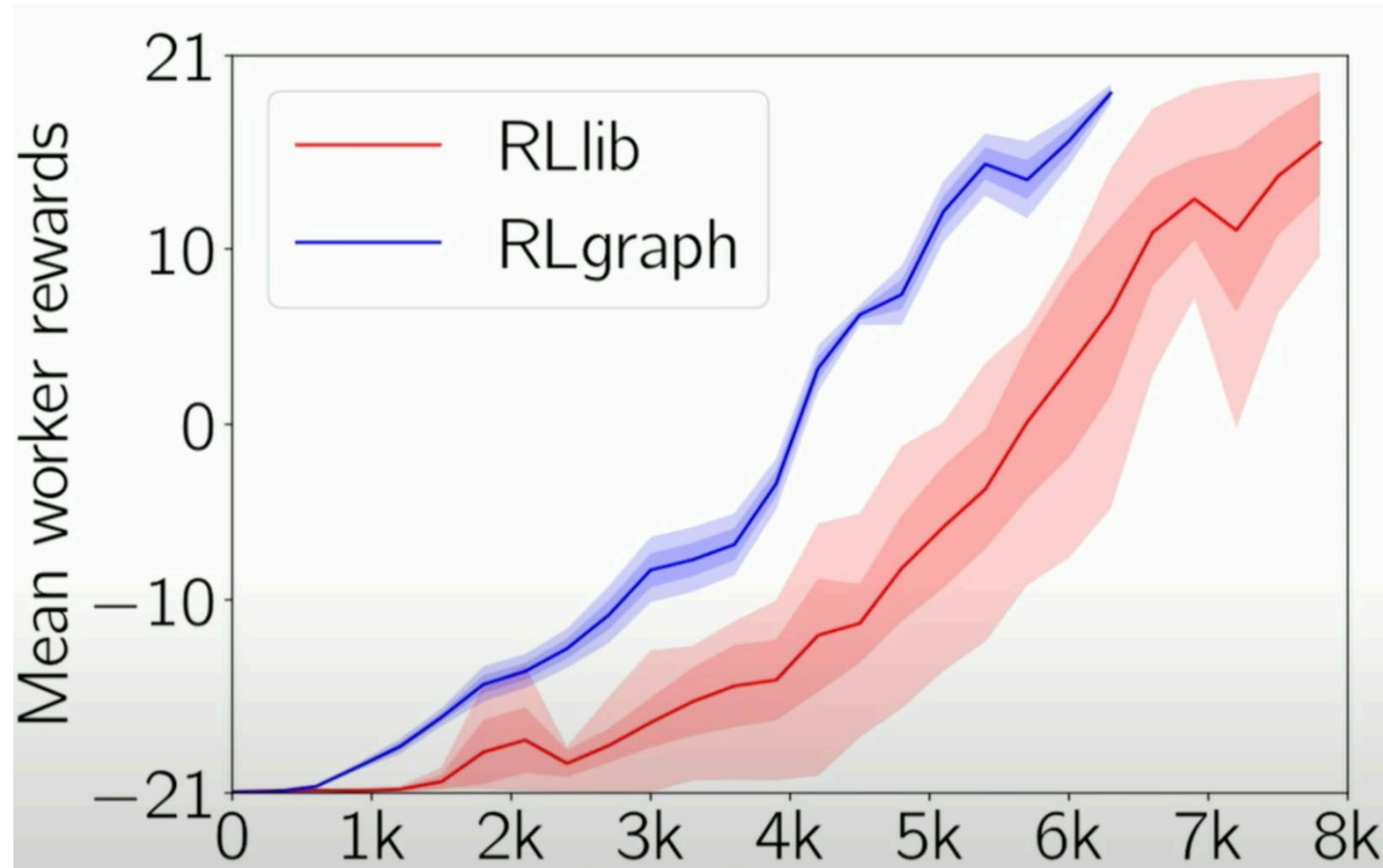
# Build Overhead



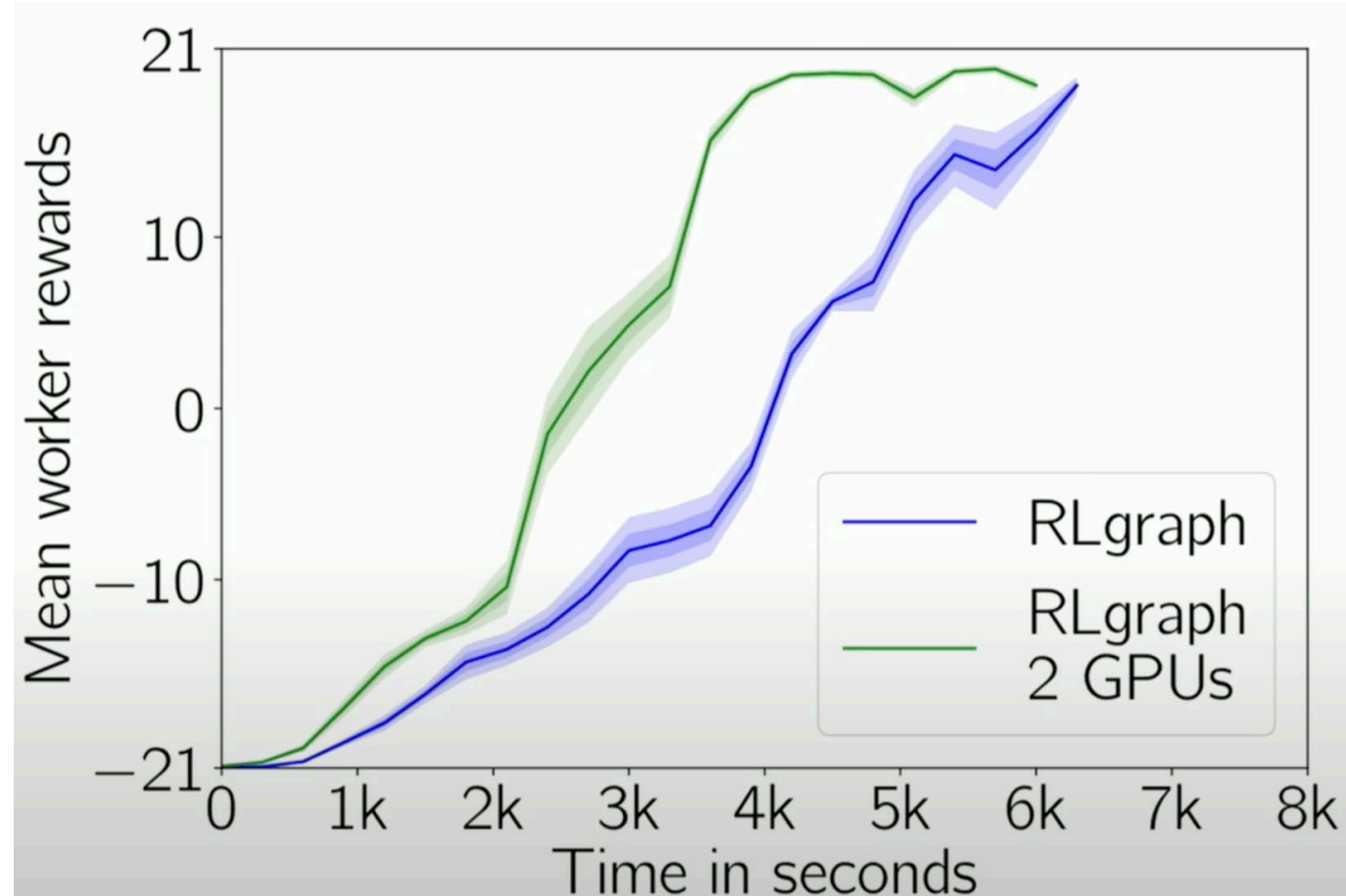
# Runtime Overhead



# RLgraph vs RLlib



# RLgraph with multi-GPUs



# Summary

- Introduce modularity to RL Tools
- Focus on dataflow design instead of backend tools
- Future work
  - Integrate AutoGraph / JIT Tracing into build process
- Reference
  - M. Schaarschmidt, S. Mika, K. Fricke, E. Yoneki: RLgraph: Flexible Computation Graphs for Deep Reinforcement Learning, SysML, 2019.
  - <https://www.youtube.com/watch?v=96cludHRSYM&t=1073s>