

RLgraph: Modular Computation Graphs for Deep Reinforcement Learning

M. Schaarschmidt, S. Mika, K. Fricke, E. Yoneki at SysML, 2019

R244 Large-scale data processing and optimisation Presentation by Martin Graf on 19/10/2022





• Algorithmic instability



- Algorithmic instability
- Diversity of models and optimization strategies



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- Highly varied resource requirements



- Algorithmic instability
- Diversity of models and optimization strategies
- Highly varied resource requirements
- Heterogeneous distributed communication patterns





- Reference implementations on benchmark tasks
 - OpenAl baselines (Sidor & Schulman, 2017)
 - Keras-rl (Plappert, 2016)

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Problem: No separation of concerns



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Trends in Machine Learning Tooling



Trends in Machine Learning Tooling

- Towards higher level APIs and standardization
 - •Keras (Chollet et al., 2015)
 - •ONNX (Facebook Inc., 2017)

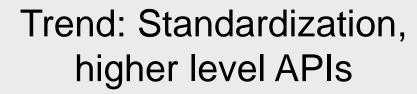


Trends in Machine Learning Tooling

- Towards higher level APIs and standardization
 - •Keras (Chollet et al., 2015)
 - •ONNX (Facebook Inc., 2017)
- Towards better performance
 - Hardware improvements
 - Software improvements
 - Weld (Palkar et al., 2017)
 - FlexFlow (Jia et al., 2018)



Value Hypothesis

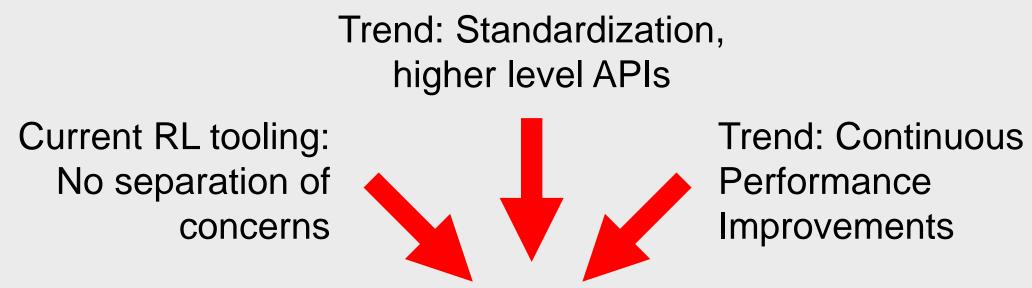


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Current RL tooling: No separation of concerns Trend: Continuous Performance Improvements



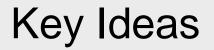
Value Hypothesis



RLgraph







• Separate execution details and user code



- Separate execution details and user code
- No-code distributed computation



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- No-code distributed computation
- Backend agnostic, high level API



- Separate execution details and user code
- No-code distributed computation
- Backend agnostic, high level API
- Testable



high-level backend-agnostic scalable graph-based testable library with a component-based modular build-system for designing and executing fast, robust, incrementally testable, and easy to extend or re-use reinforcement learning algorithms



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Multi-framework

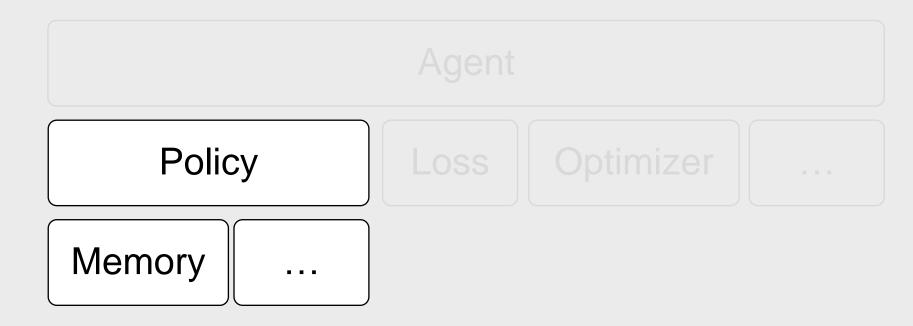
- TensorFlow
- PyTorch

Multi-paradigm

- distributed TensorFlow (Abadi et al., 2016)
- Ray (Moritz et al., 2017)

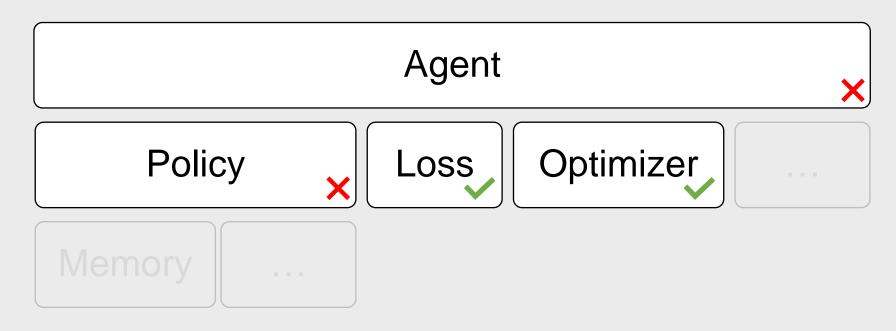


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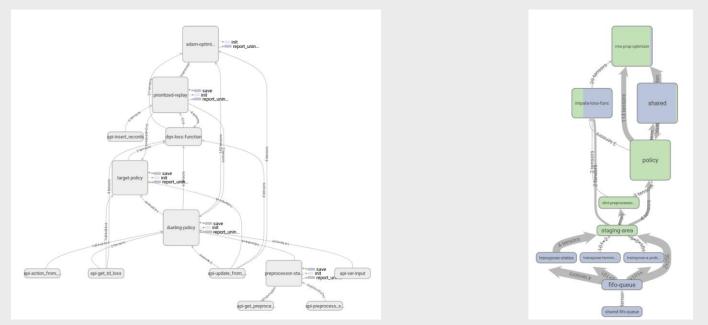


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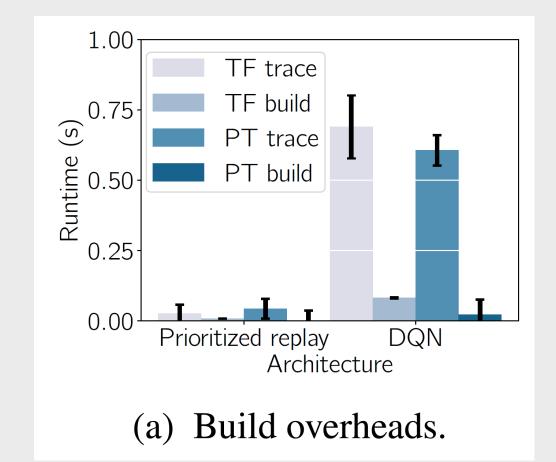




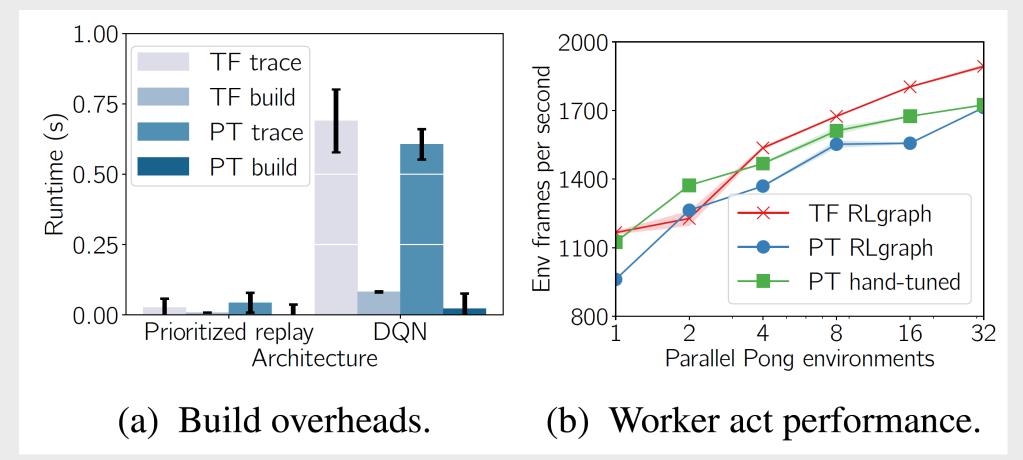
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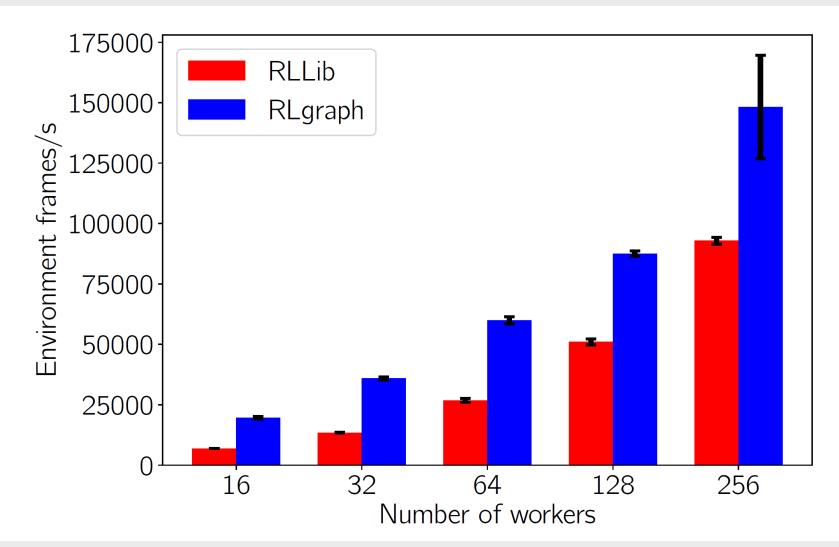














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Source: https://github.com/rlgraph/rlgraph, accessed on 18/10/2022

RLgraph still relevant? 2022...

• Ray RLlib incorporates concepts of RLgraph

Source: <u>https://docs.ray.io/en/latest/rllib/index.html</u>, accessed 18/10/2022



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• Autograph far more capable



Critique

- Is being backend agnostic really beneficial?
 - Constant updates with new backend versions necessary
 - Increased maintenance effort



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- Problems in one specific backend should be addressed in that backend



Critique

- Is being backend agnostic really beneficial?
 - Constant updates with new backend versions necessary
 - Increased maintenance effort
- Problems in one specific backend should be addressed in that backend
- Is mixing Python control flow with machine learning framework code really bad?
 - Autograph



- Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M., et al. Tensorflow: A system for large-scale machine learning. In OSDI, volume 15, pp. 265–283, 2016.
- Chollet, F. et al. Keras. https://keras.io, 2014.
- Facebook Inc. ONNX- Open Neural Network Exchange Format. https://onnx.ai, 2016.



- Jia, Z., Zaharia, M., and Aiken, A. Beyond data and model parallelism for deep neural networks. http://arxiv.org/pdf/1806.05358v1, 2018.
- Liang, E., Liaw, R., Nishihara, R., Moritz, P., Fox, R., Goldberg, K., Gonzalez, J., Jordan, M., and Stoica, I. Rllib: Abstractions for distributed reinforcement learning. In International Conference on Machine Learning, pp. 3058–3068, 2018.



- Moritz, P., Nishihara, R., Wang, S., Tumanov, A., Liaw, R., Liang, E., Paul, W., Jordan, M. I., and Stoica, I. Ray: A distributed framework for emerging AI applications. CoRR, abs/1711.05889, 2017. URL http://arxiv.org/abs/1712.05889.
- Palkar, S., Thomas, J. J., Shanbhag, A., Narayanan, D., Pirk, H., Schwarzkopf, M., Amarasinghe, S., Zaharia, M., and InfoLab, S. Weld: A common runtime for high performance data analytics. In Conference on Innovative Data Systems Research (CIDR), 2016.



- Plappert, M. keras-rl. https://github.com/matthiasplappert/keras-rl, 2015.
- Schaarschmidt, M., Kuhnle, A., Ellis, B., Fricke, K., Gessert, F., and Yoneki, E. Lift: Reinforcement learning in computer systems by learning from demonstrations. CoRR, abs/1807.07903, 2018. URL http://arxiv.org/abs/1707.06347.
- Sidor, S. and Schulman, J. Openai baselines. website, 2016. URL https://blog.openai.com/ openai-baselines-dqn/.





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