

QT-Opt: Scalable Deep Reinforcement Learning for Vision-Based Robotic Manipulation

arXiv:1806.10293, Kalashnikov et al, 2018.

Summarized by Hyecheol (Jerry) Jang

Department of Computer Sciences
University of Wisconsin–Madison

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1 Motivation

2 Goal

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- Combining two techniques
 - Able to learn policy continuously from their experience
 - No need for manual engineering, use data they collects



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 - ⇒ Lots of researchers focused on reusing previous experiences



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 - opening door
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⇒ **Where this researches start!!**



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