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

arXiv:1806.10293, Kalashnikov et al, 2018.

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# Motivation: Why Robotics + Reinforcement Learning

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  - **Reinforcement Learning**
    Provide ability to make decision in long-term, using previous experiences in complex and robust scenarios
- Combining two techniques
  - Able to learn policy continuously from their experience
  - No need for manual engineering, use data they collects

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$\Rightarrow$ Lots of researchers focused on reusing pervious experiences

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$\Rightarrow$ **Where this researches start!!**

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# Goal

Use Reinforcement Learning with Deep Neural Network
to **perform pre-grasp manipulation**,
**response to dynamic disturbances**,
and **learn grasping in a generic framework**
that makes minimal assumptions about the task

# Goal: Constraint/Condition + Literature Review

- **Closed-loop condition** (With feedback, *Morrison, et al.*)
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  - This paper focuses on making generalized RL algorithm
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- **Self-supervised** learning task
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  - Actions consist of end-effector **Cartesian motion** and **gripper opening/closing**
- Observation comes from **a single RGB camera** over the sholder
  - Many current grasping system utilizes depth sensing
  - Using wrist-mounted cameras

# References


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