## Welcome


https://www.youtube.com/watch?v=1EpJv34gQ88\&t=183s

https://www.youtube.com/watch?v=kVmpOuGtShk\&t=55s

## Solving a Rubik's cube with a robotic hand (Learning dexterous manipulations)

## Outline

- Why you should care
- How to train your robotic hand
- Learning dexterous manipulations


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## Why you should care

- Human hands are awesome
- Custom robot for every task
- Learning to use a humanoid hand would give more freedom


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## How to train your robotic hand

- Imitation Learning

https://vcresearch.berkeley.edu/news/berkeley-startup-train-robots-puppets
- Simulation


Andrychowicz, Marcin, et al. "Learning dexterous in-hand manipulation." arXiv preprint arXiv:1808.00177 (2018)., Figure 3 left

## Simulations

- Simulate everything
- Collect a lot of data for training
- Train policy in Sim


Akkaya, Ilge, et al. "Solving Rubik's Cube with a Robot Hand.", Figure 7

## Reinforcement learning

- Learning from mistakes
- Agenct, action, states and reward
- Goal is represented through a function



## Deep Reinforcement learning

- Combine ANNs and RF
- Policy is learned by ANN
- Second ANN for state values



## Memory

- Long-short-term-memory (LSTM)
- Well suited for clasification based on time series
- Store important information
- Can retrieve it ater arbitrary time


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## Domain Randomizations (DR)

- Randomize physical properties of sim environments
- Hand-picked randomizations
- Uniform distribution
- Problem:
- What is important?
- Not that robust

Automatic Domain Randomization (ADR)

- Basic Idea:
- Automatically change domain randomizations with progress


Automatic Domain Randomization (ADR)

- Changes can be made in:
- Cube size
- Friction of the hand
- Gravity
- Brightness
- Action delay
- Motor backlash



## Learning dexterous manipulations

- Using ADR
- Train for several months (~13 Thausand years of sim)
- Two networks during training
- One to predict value function
- One for agent policy


## Learning dexterous manipulations



## The robotic hand



- The cage with 3 cameras from different angles
- Hand with tactile sensors
- Used CNN for vision


## Comparisson

| Policy | Training Time | ADR Entropy | Successes (Sim) |  | Successes (Real) |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  | Mean | Median | Mean | Median |
| Baseline (data from [77]) | - | - | $43.4 \pm 0.6$ | 50 | $18.8 \pm 5.4$ | 13.0 |
| Baseline (re-run of [77]) | - | - | $33.8 \pm 0.9$ | 50 | $4.0 \pm 1.7$ | 2.0 |
| Manual DR | 13.78 days | $-0.348^{*} \mathrm{npd}$ | $42.5 \pm 0.7$ | 50 | $2.7 \pm 1.1$ | 1.0 |
| ADR (Small) | 0.64 days | $-0.881 \mathrm{npd}$ | $21.0 \pm 0.8$ | 15 | $1.4 \pm 0.9$ | 0.5 |
| ADR (Medium) | 4.37 days | $-0.135 \mathrm{npd}$ | $34.4 \pm 0.9$ | 50 | $3.2 \pm 1.2$ | 2.0 |
| ADR (Large) | 13.76 days | 0.126 npd | $40.5 \pm 0.7$ | 50 | $13.3 \pm 3.6$ | 11.5 |
| ADR (XL) | - | 0.305 npd | $45.0 \pm 0.6$ | 50 | $16.0 \pm 4.0$ | 12.5 |
| ADR (XXL) | - | 0.393 npd | $46.7 \pm 0.5$ | 50 | $32.0 \pm 6.4$ | 42.0 |

## How robust is the outcome?


(a) Unperturbed (for reference).

(d) Blanket occlusion and perturbation.

(b) Rubber glove.

(e) Plush giraffe perturbation ${ }^{17}$

(c) Tied fingers.

(f) Pen perturbation.

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## Comparisson

| Policy | Sensing |  | ADR Entropy | Successes (Real) |  | Success Rate |  |
| :--- | :--- | :--- | ---: | ---: | ---: | ---: | ---: |
|  | Pose | Face Angles |  | Mean | Median | Half | Full |
| Manual DR | Vision | Giiker | $-0.569^{*} \mathrm{npd}$ | $1.8 \pm 0.4$ | 2.0 | $0 \%$ | $0 \%$ |
| ADR | Vision | Giiker | -0.084 npd | $3.8 \pm 1.0$ | 3.0 | $0 \%$ | $0 \%$ |
| ADR (XL) | Vision | Giiker | 0.467 npd | $17.8 \pm 4.2$ | 12.5 | $30 \%$ | $10 \%$ |
| ADR (XXL) | Vision | Giiker | $\mathbf{0 . 4 7 9} \mathbf{n p d}$ | $\mathbf{2 6 . 8} \pm \mathbf{4 . 9}$ | $\mathbf{2 2 . 0}$ | $\mathbf{6 0 \%}$ | $\mathbf{2 0} \%$ |
| ADR (XXL) | Vision | Vision | $\mathbf{0 . 4 7 9} \mathbf{n p d}$ | $12.8 \pm 3.4$ | 10.5 | $20 \%$ | $0 \%$ |

Akkaya, Ilge, et al. "Solving Rubik's Cube with a Robot Hand.", Table 6
npd $=$ nats per dimension, where nat is the natural unit of information

## But ...

- Not a Rubik‘s Cube but Giiker‘s Cube
- Policy only solved 20\% with a ,fair scramble‘
- Other robotic hands can solve rubik's cube faster
- Solution steps were generated before



## Thank you


https://www.youtube.com/watch?v=QyJGXc9WeNo

## Questions?

## Feedback

## Source

- https://skymind.ai/wiki/deep-reinforcement-learning
- https://towardsdatascience.com/welcome-to-deep-reinforcement-learning-part-1-dqn-c3cab4d41b6b
- Akkaya, Ilge, et al. "Solving Rubik's Cube with a Robot Hand."
- Andrychowicz, Marcin, et al. "Learning dexterous in-hand manipulation." arXiv preprint arXiv:1808.00177 (2018).
- https://openai.com/blog/solving-rubiks-cube/


[^0]:    Akkaya, Ilge, et al. "Solving Rubik's Cube with a Robot Hand.", Figure 17

