Generalization & Self-Supervision in Deep Robotic Learning

Chelsea Finn
Impressive Feats in AI

Why are these impressive? They perform a complex task very well, sometimes even better than a human.

What is equally important: Generality: ability to perform many tasks
but not impressive (on the surface)

How can we build generalists?
It turns out — the simpler, but broader capabilities are really hard. (Moravec’s Paradox)

This talk: can we do the unimpressive things?
Collect **diverse** data in a **scalable** way.

In contrast to policy learning: no notions of progress or success!
Learning Generalizable Models through Self-Supervision

self-supervised robot learning

Pinto & Gupta ‘16
Levine, Pastor, Krizhevsky, Quillen ‘16
Nair*, Chen*, Agrawal*, Isola, Abbeel, Malik, Levine ‘17

model-based control

Petrovskaya, Park, Khatib ‘07
Arruda, Mathew, Kopicki, Mistry, Azad, Wyatt ‘17
Yu, Bauza, Fazeli, Rodriguez ‘17

our approach

acquire a general-purpose model
many objects, raw perceptual inputs, intuitive physics

learn model from video data
Learn to predict

\[ I_t, a_{t:t+H} \rightarrow I_{t:t+H} \]

Contrast to:

Models capture general purpose knowledge about the world

Use all of the available supervision signal.

Also: No assumptions about task representations.
Planning with Visual Foresight

1. Consider potential action sequences
2. Predict the future for each action sequence
3. Pick best future & execute corresponding action
4. Repeat 1-3 to replan in real time

visual model-predictive control (MPC)

Finn & Levine. Deep Visual Foresight for Planning Robot Motion. ICRA ‘17
How it works

Specify goal

Visual MPC execution

Planning with a **single model** for many tasks

Can we incorporate some supervision to learn a variety of **complex** skills?

Collect data

Learn to predict
\[ I_t, a_{t:t+H} \rightarrow I_{t:t+H} \]

Plan using model

Collect diverse, multi-task demonstrations

Fit model of \( p(a_{t:t+H} \mid I_t) \) to the demonstration data.

Example multi-task demonstrations:

Samples from action proposal model:

Xie, Ebert, Levine, Finn. Improvisation through Physical Understanding, RSS ‘19
How it works

Specify goal

Guided visual planning w.r.t. goal

Executing actions

Xie, Ebert, Levine, Finn. Improvisation through Physical Understanding, RSS ’19
Qualitative Experiments

solve new tasks
unseen tools
decide when to use a tool...

out-of-reach objects
unseen unconventional tools
...and when not to

Takeaway: Achieve greater complexity of skills while maintaining generality.

Xie, Ebert, Levine, Finn. Improvisation through Physical Understanding, RSS ‘19
Demo at NIPS 2017: Long Beach, CA

planning with visual models

one-shot imitation

Demo at AI4ALL Outreach Camp

The students were unimpressed.
(but still had fun)
Lessons that I learned during my PhD

And 3 anecdotes.

Year 1
Learn as much as you can from senior students & post-docs.

Year 2-3
Most research ideas don’t work.
Don’t be afraid to pivot.

Year 4
Good to have a rough plan, but you don’t need to have your career plan figured out.
Questions?