An agent that can do many things
(by modeling the world)
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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: but not impressive (on the surface)
Generality: ability to perform many tasks

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?
Can we build an agent that can do **many tasks**?

- learning a policy in a closed universe

- learn **general-purpose** model + plan with model for many tasks

- model-based control

- from **pixel observations**, with **limited supervision**, in the **physical world**
Can we build an agent that can do many tasks?

- learning a policy in a closed universe
- learn general-purpose model + plan with model for many tasks
- structured latent space model for long-horizon tasks
- modeling diverse, open-world environments
- from pixel observations, with limited supervision, in the physical world
1. **Collect diverse** interactions  
Greater diversity —> more general-purpose model

2. **Learn structured** representation & model  
Structure —> long-horizon reasoning

3. **Plan using model**  
Online planning —> many tasks

Goal: be able to build any tower of blocks

Janner, Levine, Freeman, Tenenbaum, Finn, Wu ’18
Learn **structured** representation & model

*object-centric* model

Assume: object segmentation masks for individual frames

- Eslami et al. ‘16, Kosiorek et al. ‘18
- Wu et al. ‘17

Full supervision of object properties

Simple, 2D scenes

Janner, Levine, Freeman, Tenenbaum, Finn, Wu ‘18
Learn **structured** representation & model

*object-centric* model

**Assume:** object segmentation masks for individual frames

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**Eslami et al. ’16, Kosiorek et al.’18**

Full supervision of object properties

**Wu et al.’17**

Simple, 2D scenes

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Object representations:

- Perception

Segment pixels:

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Janner, Levine, Freeman, Tenenbaum, Finn, Wu ’18
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simple, 2D scenes

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**object representations**

**Physics**

**Rendering**

**segment pixels**
Learn **structured** representation & model

*object-centric* model

Assume: object segmentation masks for individual frames

All modules trained with **reconstruction loss** ($L_2 + L_{VGG}$)

Eslami et al. ‘16, Kosiorek et al. ‘18

Wu et al. ‘17

full supervision of object properties

Janner, Levine, Freeman, Tenenbaum, Finn, Wu ‘18
Plan using model

**goal space**: image of object configuration

**action space**: which object & where to drop

- **sampling-based, beam search** to plan action sequence
- evaluate action sequence based on **distance** in latent space & pixel space
- **replan** after each action
Takeaways

Learning model on diverse interactions $\rightarrow$ achieve many tasks
Structured latent space $\rightarrow$ achieve complex, long-horizon tasks

Janner, Levine, Freeman, Tenenbaum, Finn, Wu '18
Can we build an agent that can do many tasks?

Learn general-purpose model + plan with model for many tasks

Learning a policy in a closed universe

Structured latent space model for long-horizon tasks

Modeling diverse, open-world environments from pixel observations, with limited supervision, in the physical world
Diverse Open-World Environments

self-supervised robot learning

Our goal: generalize to novel objects and, also to many tasks
(by learning a general-purpose model)

Overall approach: Collect data, learn model, plan to achieve many tasks
Collect *diverse* data in a *scalable* way

In contrast to policy learning: no notions of progress or success!
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**.
Are these models useful?
How can we use these models to plan?
(to achieve many human-specified goals)
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)
How to predict video?

- deep recurrent network
- multi-frame prediction
- action-conditioned
- explicitly model motion

Finn, Goodfellow, Levine NIPS ’16
Finn & Levine ICRA ’17
Which future is the best one?

Human specifies a goal by:

Selecting where pixels should move.
Providing an image of the goal.
Providing a few examples of success.

Finn & Levine ICRA ’17
Ebert, Lee, Levine, Finn CoRL ’18
Xie, Singh, Levine, Finn CoRL’18
Specify goal

Visual MPC w.r.t. goal

Visual MPC execution

How it works
How it works

Specify goal
(covering an object)

Visual MPC execution

How it works

Given 5 examples of success

Visual MPC with learned objective

infer goal classifier

visual MPC w.r.t. goal classifier

Xie, Singh, Levine, Finn. Few-Shot Goal Inference for Visuomotor Learning and Planning, CoRL 2018
Planning with a single model for many tasks
Demo at NIPS 2017: Long Beach, CA

planning with visual models

The students were unimpressed.
(but still had fun)

Demo at AI4ALL Outreach Camp

one-shot imitation
Can we build an agent that can do **many tasks**?

from **pixel observations**, with **limited supervision**, in the **physical world**

- complex, **long-horizon tasks**

**Structured latent space**

model for long-horizon tasks

+ **significant object diversity**

+ **minimal supervision**

**Future work**: best of both worlds?
Future work: How can we build better, more useful models of the world?

Can we model **uncertainty** over future observations?
More and more uncertainty over time.

Can we **adapt the model** with a small amount of experience?
Physical properties unknown until interaction.

How should we **model the reward**?
Agents need internal representation of the goal in the real world.

Stochastic adversarial video prediction
Lee, Zhang, Ebert, Abbeel, Finn, Levine. 2018

Few-shot, online model adaptation
Nagabandi*, Clavera*, Liu, Fearing, Abbeel, Levine, Finn. 2018

Goal inference from images
Xie, Singh, Levine, Finn. CoRL 2018
Collaborators

Frederik Ebert  Sudeep Dasari  Annie Xie  Avi Singh  Michael Janner

Sergey Levine  Pieter Abbeel  Bill Freeman  Josh Tenenbaum  Jiajun Wu

Papers, data, and code linked at: people.eecs.berkeley.edu/~cbfinn

Questions?