

# Deep Multi-Task and Meta Learning

CS 330

# Introductions



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Instructor



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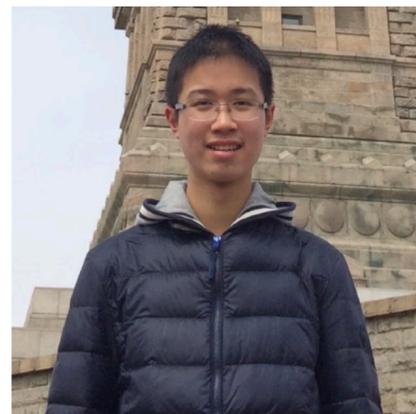
Archit Sharma  
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Course Coordinator



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TA



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TA



Kamil Ali  
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# Welcome!

First question: How are you doing?

(answer by raising hand)

# The Plan for Today

1. Course logistics
2. Why study multi-task learning and meta-learning?

# Course Logistics

# Information & Resources

**Course website:** <http://cs330.stanford.edu/>

**Ed:** Connected to Canvas

**Staff mailing list:** [cs330-aut2122-staff@lists.stanford.edu](mailto:cs330-aut2122-staff@lists.stanford.edu)

**Office hours:** Check course website & Ed, start on Weds.

# Topics

1. Multi-task learning, transfer learning basics
2. Meta-learning algorithms  
(black-box approaches, optimization-based meta-learning, metric learning)
3. Advanced meta-learning topics  
(meta-overfitting, unsupervised meta-learning, Bayesian models)
4. Multi-task RL, goal-conditioned RL
5. Meta-reinforcement learning
6. Hierarchical RL
7. Lifelong learning
8. Open problems

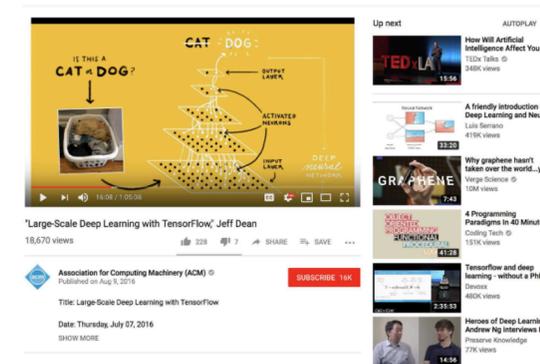
**New:** offline multi-task RL

**New:** learning optimizers  
(guest lecture)

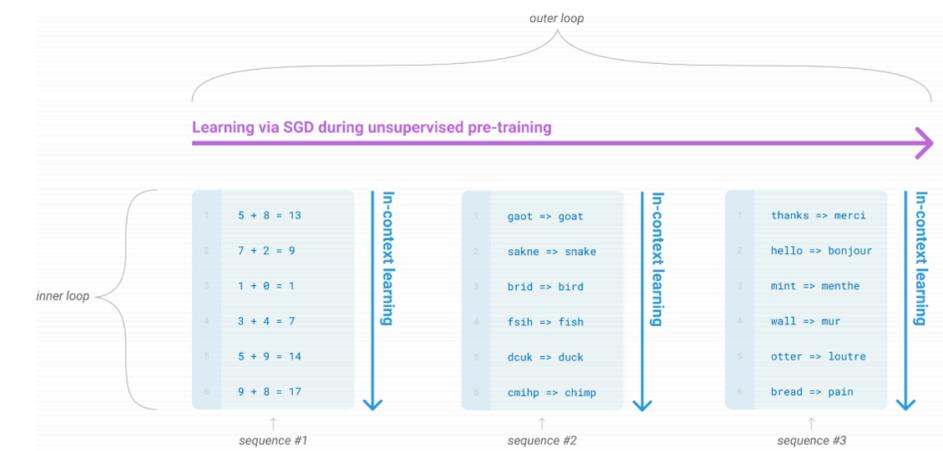
Emphasis on **deep learning** techniques.

## Case studies of important & timely applications

- Multi-task learning in recommender systems
- Meta-learning for land cover classification, education
- Few-shot learning from GPT-3



Zhao et al. Recommending What Video to Watch Next. 2019



Brown et al. Language Models are Few-Shot Learners. 2020

# Topics We Won't Cover

Won't cover some **AutoML** topics:

- architecture search
- hyperparameter optimization

Though, many of the underlying techniques will be covered.

# Lectures & Office Hours

## Lectures

- In-person, livestreamed, & recorded
- Two guest lectures (Colin Raffel, Jascha Sohl-Dickstein)

## *Ask questions!*

- by raising your hand
- by entering the question in zoom chat

## Office hours

- mix of in-person and remote  
(all TA office hours remote for first 2 weeks)
- mix of pre-scheduled and drop-in

# Pre-Requisites

**Pre-requisites:** CS229 or equivalent, previous or concurrent RL knowledge recommended.

## PyTorch:

- Assignments will require training networks in **PyTorch**.
- Kyle will hold a PyTorch review session on Thursday, Sep 23, 6 pm PT on zoom.

## Other tutorial sessions:

- Variational inference tutorial (October 7)
- RL review tutorial (October 12)

# Assignments

- Homework 0 (optional):** Multi-task learning basics (2% extra credit)
- Homework 1:** Multi-task data processing, black-box meta-learning
- Homework 2:** Gradient-based meta-learning & metric learning
- Homework 3:** Multi-task RL, goal relabeling
- Homework 4 (optional):** Meta-RL (replaces 15% of HW or project)

**Grading:** 45% homework (15% each), 55% project

**6 late days** total across: homeworks, project-related assignments  
maximum of 2 late dates per assignment

# Final Project

Research-level project of your choice

- in groups of **1-3 students**
- encouraged to **use your research!**
- can share with other classes, with slightly higher expectation
- same late day policy as HWs  
(but no late days for poster, final report)

Poster presentation on December 1st.

# Initial Steps

1. Optional Homework 0 is out
2. Start forming final project groups if you want to work in a group

# The Plan for Today

1. Course logistics

**2. Why study multi-task learning and meta-learning?**

# Some of Chelsea's Research

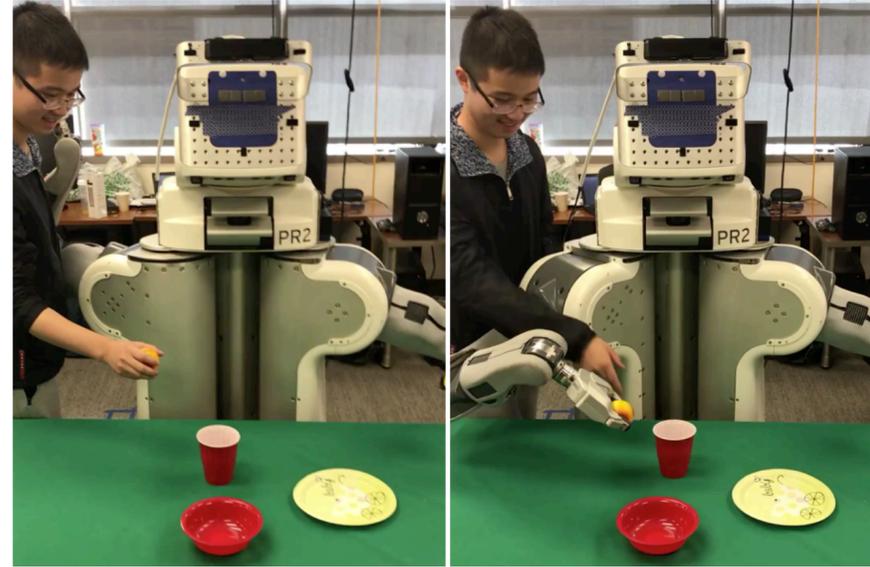
(and why I care about multi-task learning and meta-learning)

How can we enable agents to learn a breadth of skills in the real world?

Robots.



Levine\*, Finn\*, Darrell, Abbeel.  
JMLR '16



Yu\*, Finn\*, Xie, Dasari, Zhang,  
Abbeel, Levine, RSS '18



Xie, Ebert, Levine, Finn, RSS '19

**Why robots?**

Robots can teach us things about intelligence.

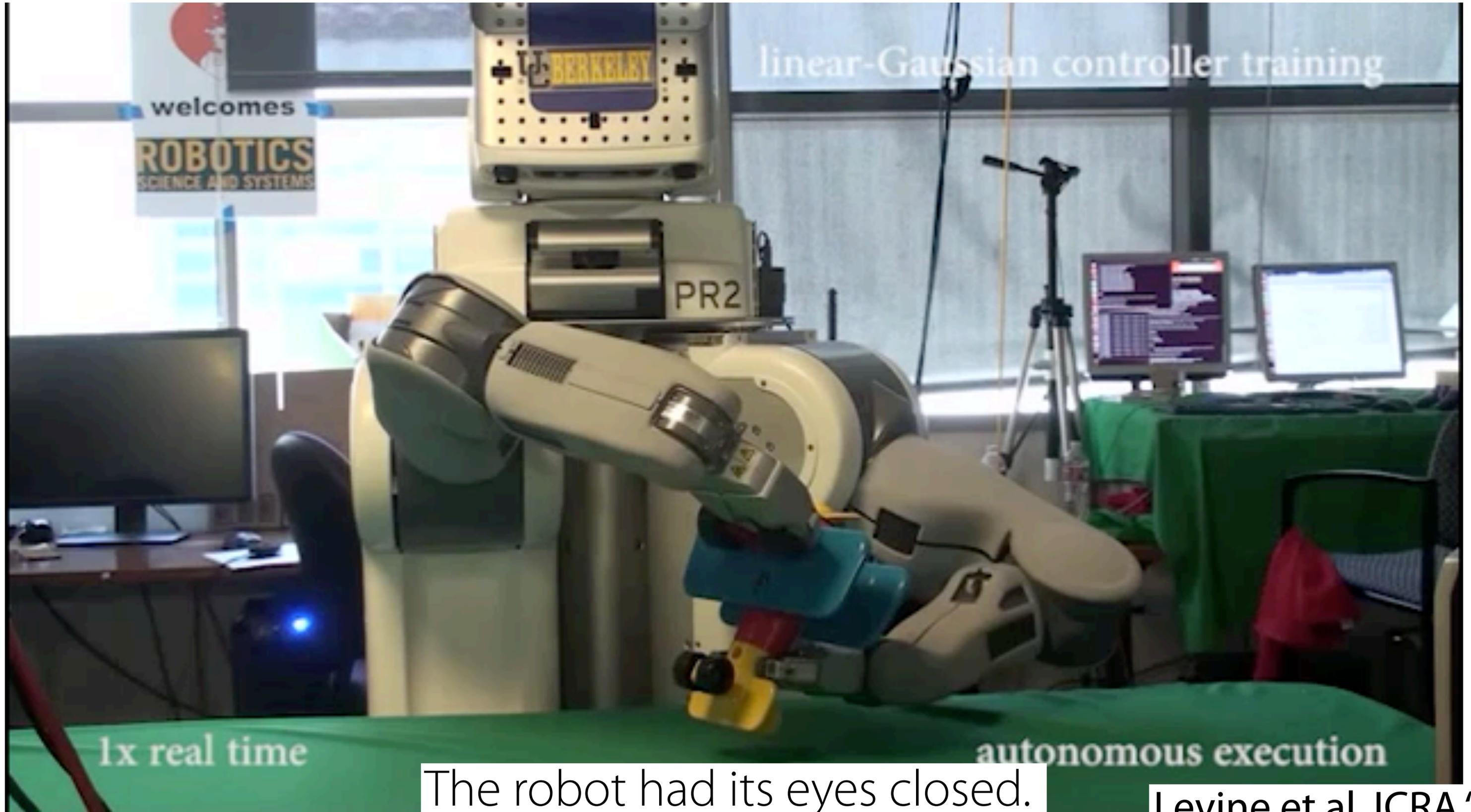
faced with the **real world**

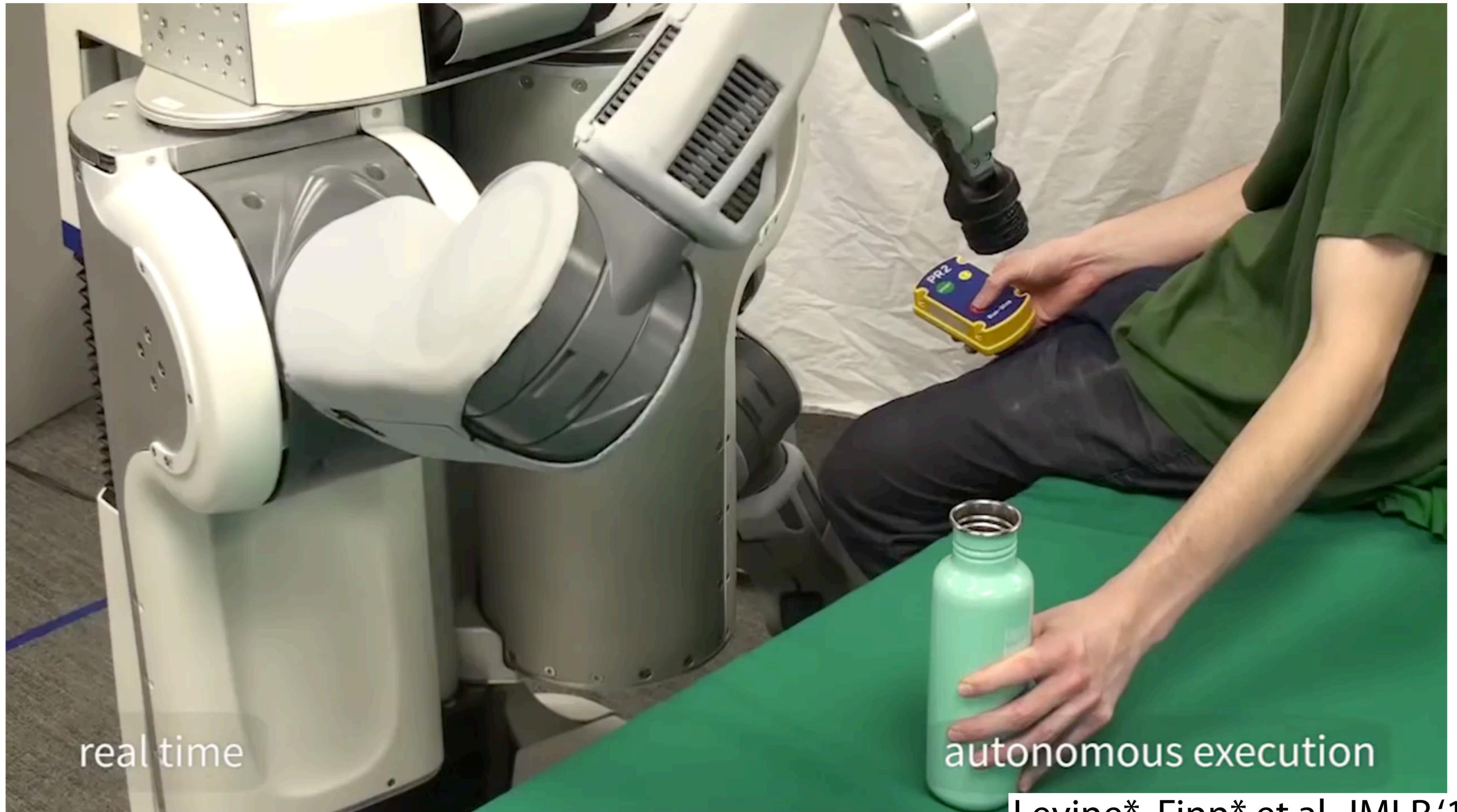
must **generalize** across tasks, objects, environments, etc

need some **common sense understanding** to do well

**supervision** can't be taken for granted

# Beginning of my PhD

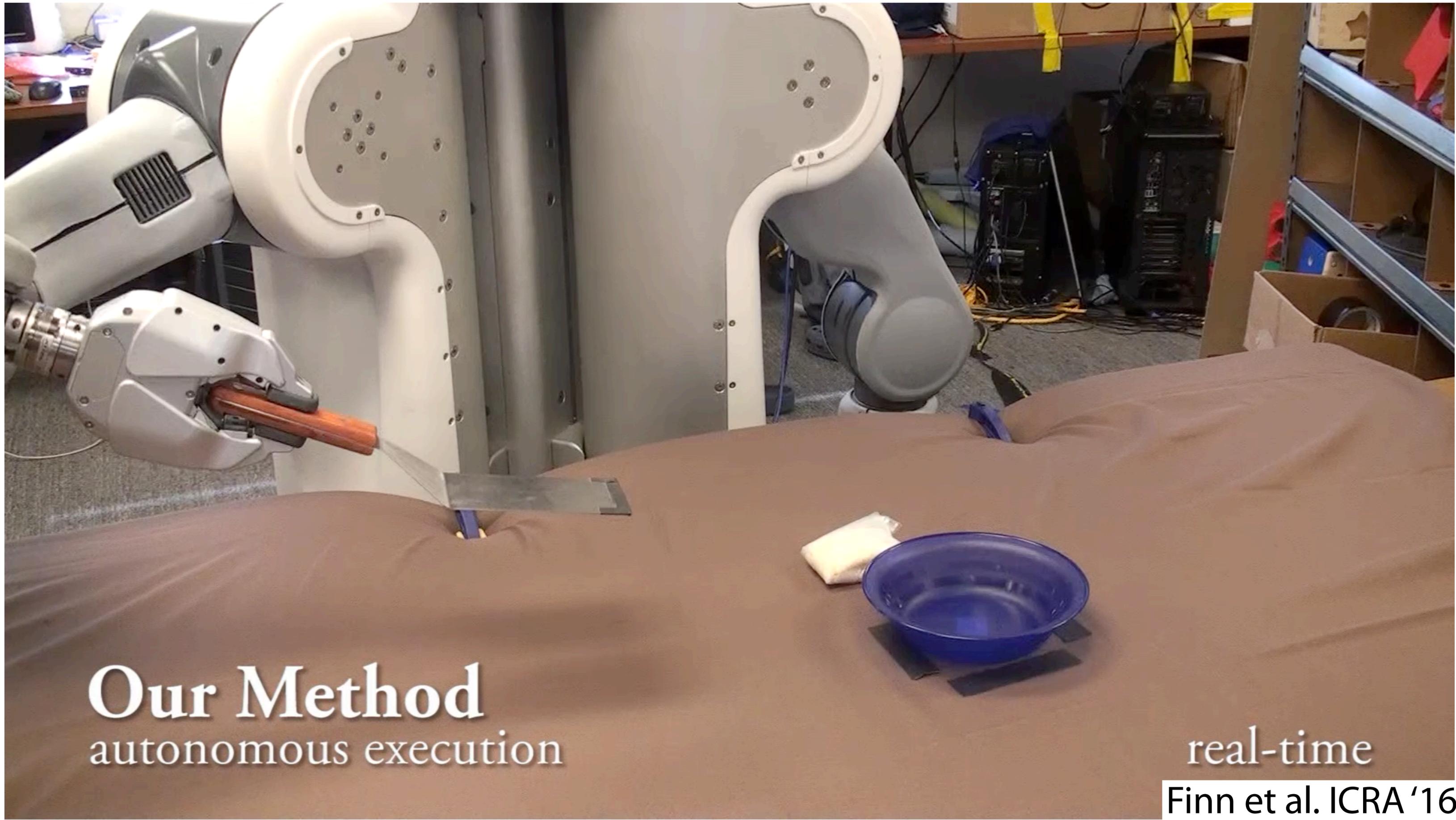




real time

autonomous execution

Levine\*, Finn\* et al. JMLR'16

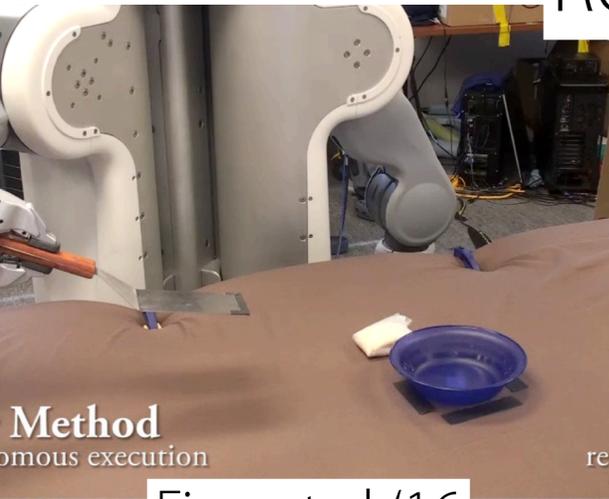


**Our Method**  
autonomous execution

real-time

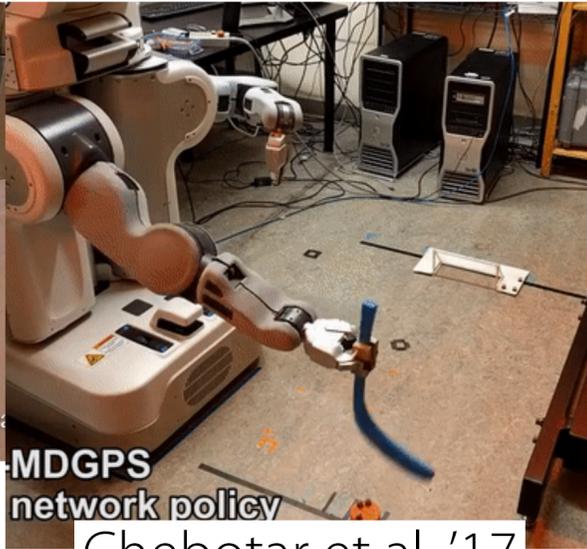
Finn et al. ICRA '16

# Robot reinforcement learning



Method  
omous execution

Finn et al. '16

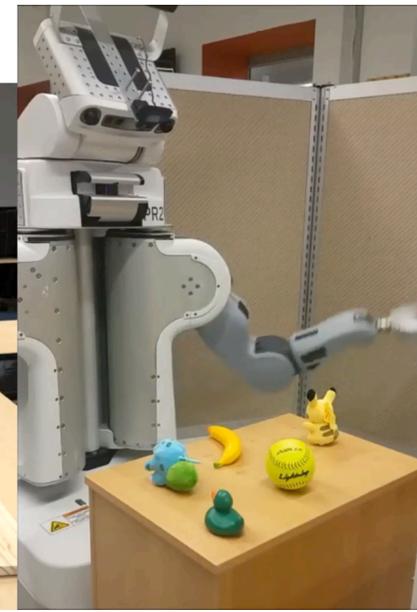


MDGPS  
network policy

Chebotar et al. '17

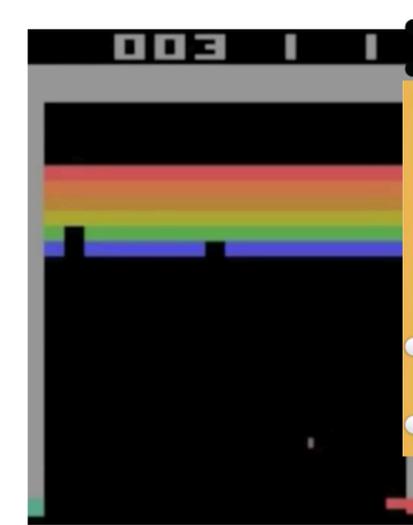


Yahya et al. '17

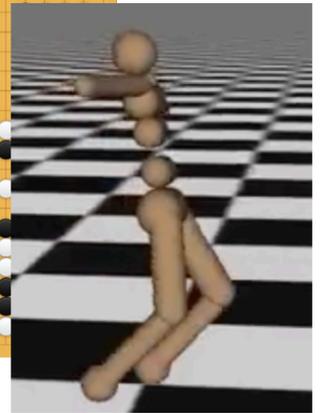


Ghadirzadeh et al. '17

# Reinforcement learning



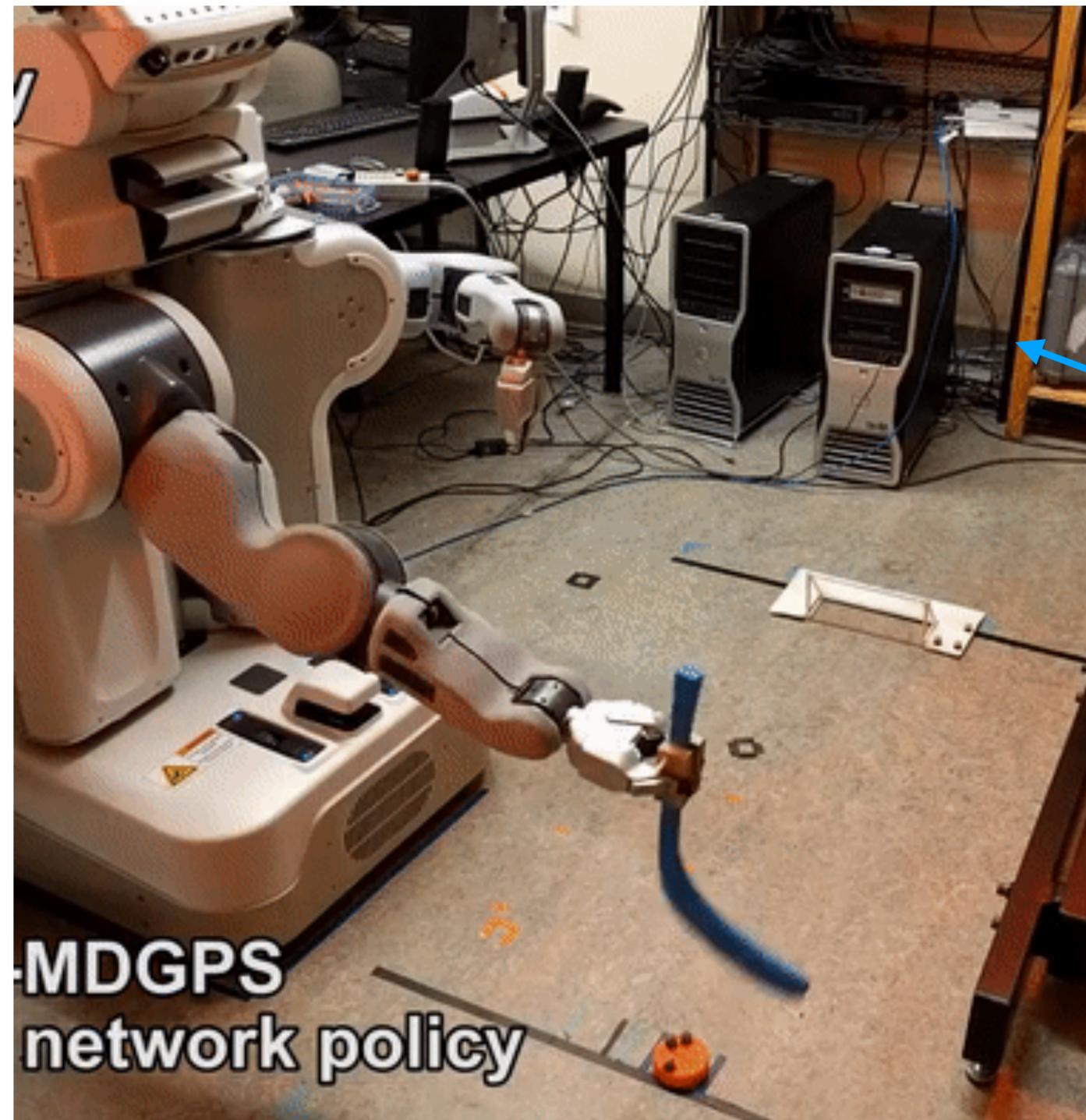
Atari



locomotion

Learn **one task** in **one environment**, starting from scratch

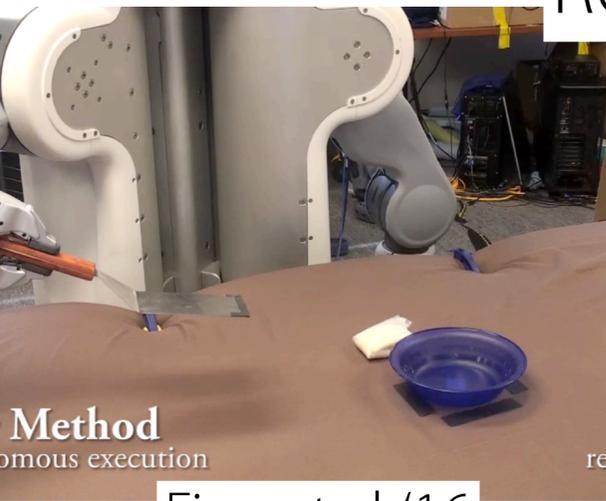
Behind the scenes...



Yevgen

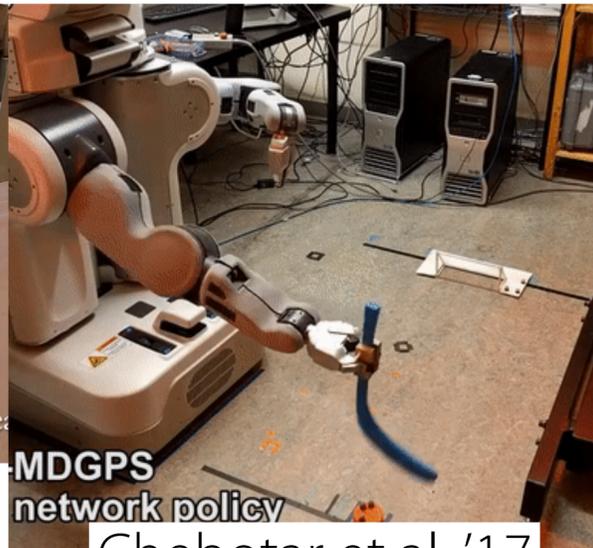
Yevgen is doing more work than the robot!  
It's not practical to collect a lot of data this way.

# Robot reinforcement learning



Method  
omous execution

Finn et al. '16



MDGPS  
network policy

Chebatar et al. '17

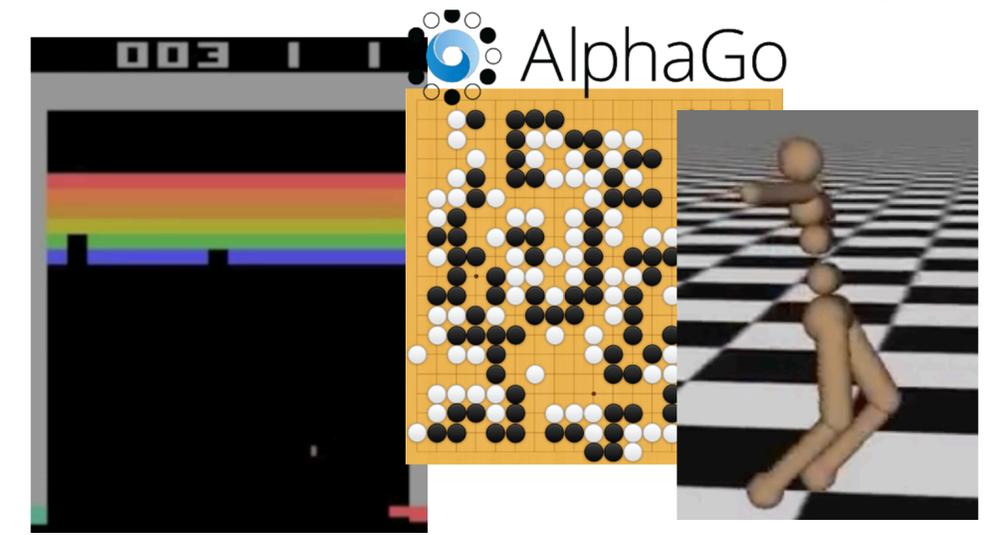


Yahya et al. '17



Ghadirzadeh et al. '17

# Reinforcement learning



AlphaGo

Atari

locomotion

Learn **one task** in **one environment**, starting from scratch using **detailed supervision**

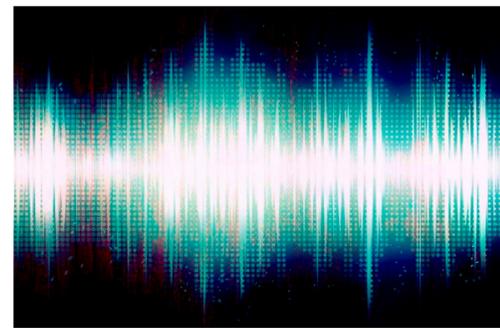
Not just a problem with reinforcement learning & robotics.

*specialists*

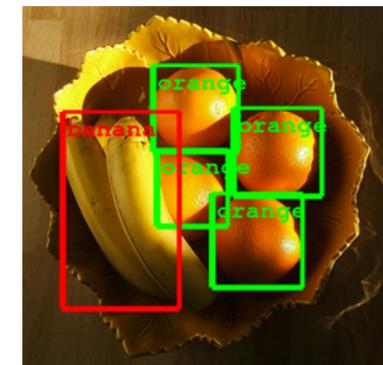
[single task]



machine translation



speech recognition

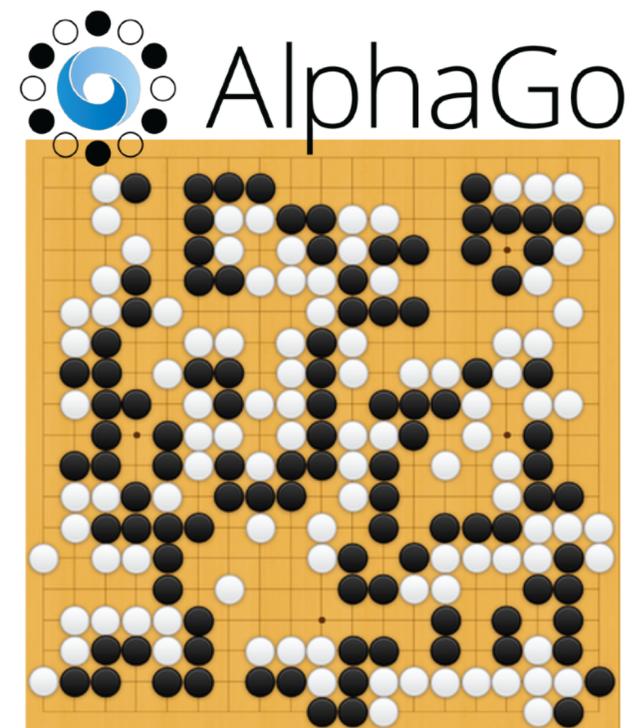


object detection

More diverse, yet still **one task**, from scratch, with **detailed supervision**



Humans are *generalists*.



vs.



Why Karol cares about multi-task and meta learning

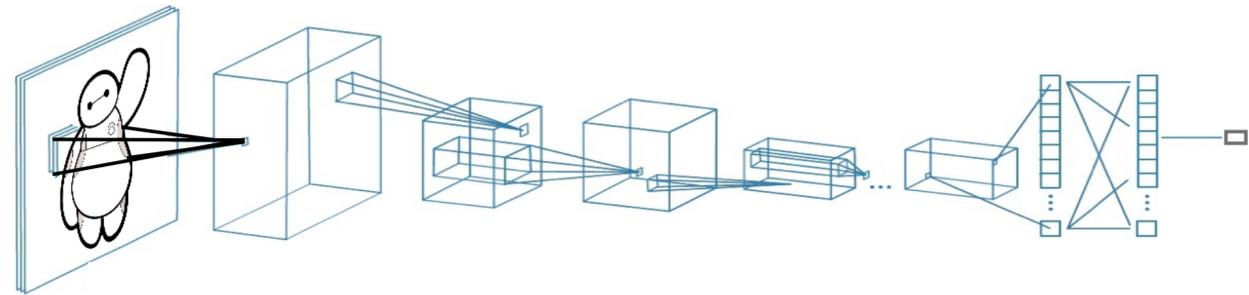


# Can we use the same recipe for robotics?

A lot of data

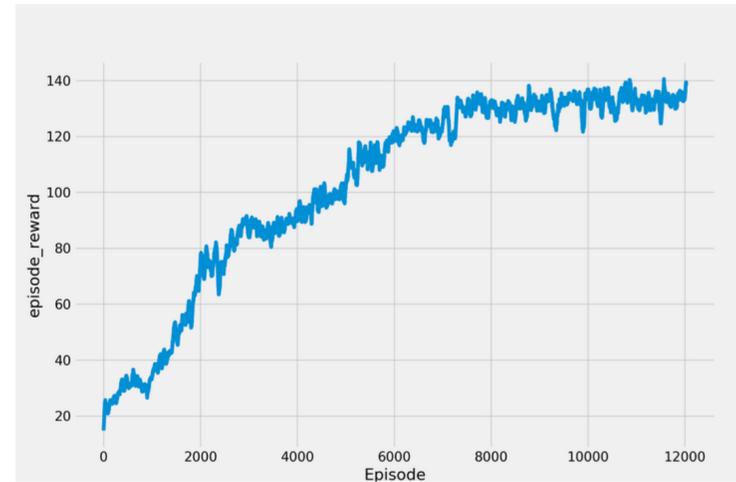
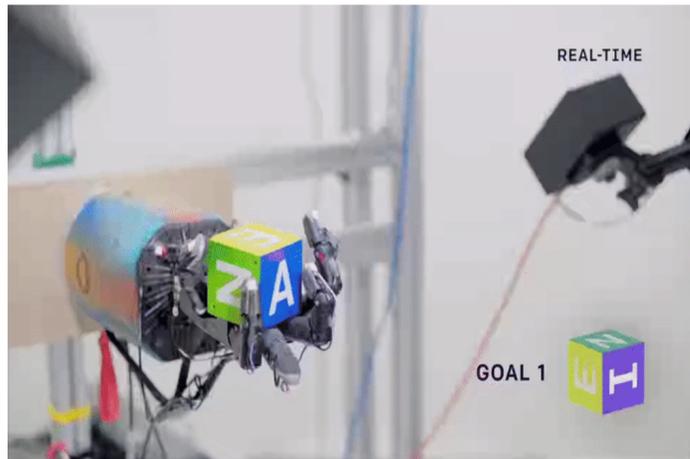
Expressive, capable models

?



# A lot of data?!

## Reinforcement Learning



~100 years of experience

[Learning Dexterous In-Hand Manipulation,  
OpenAI et al. 2018]

## Supervised Learning



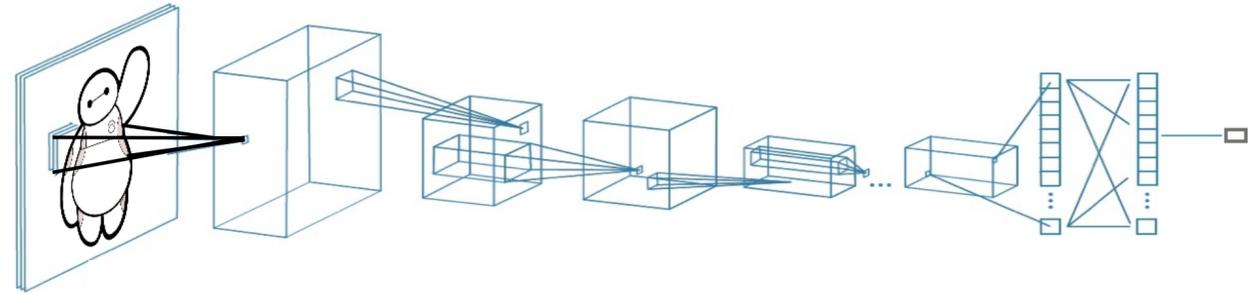
ImageNet

# Can we use the same recipe for robotics?

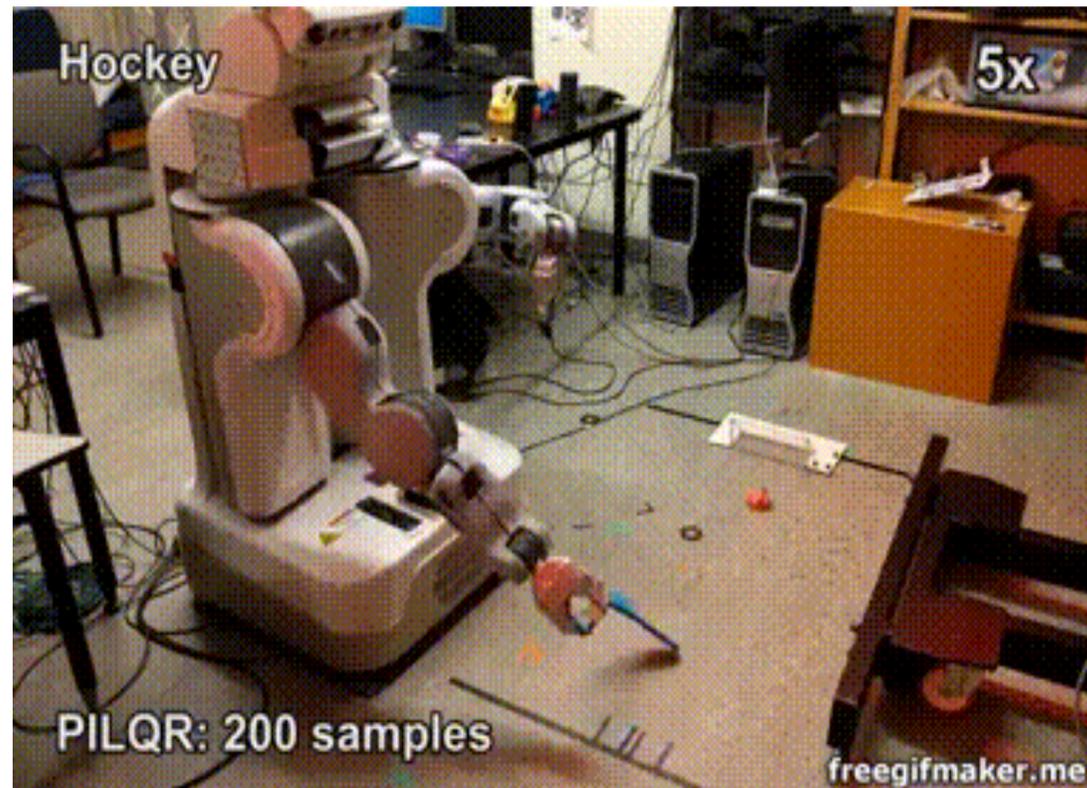
A lot of **diverse, multi-task** data

Expressive, capable models

?



# Multi-task RL: the real reason



Why should we care about multi-task & meta-learning?

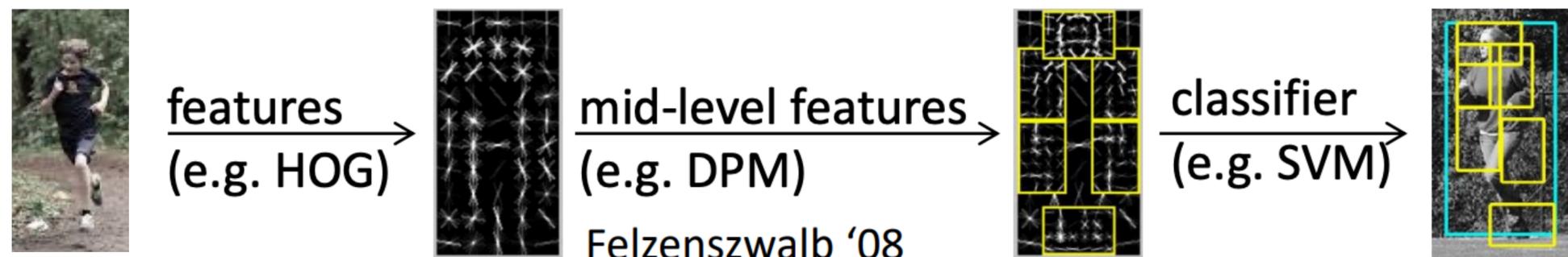
...beyond the robots and general-purpose ML systems

**deep**  
v

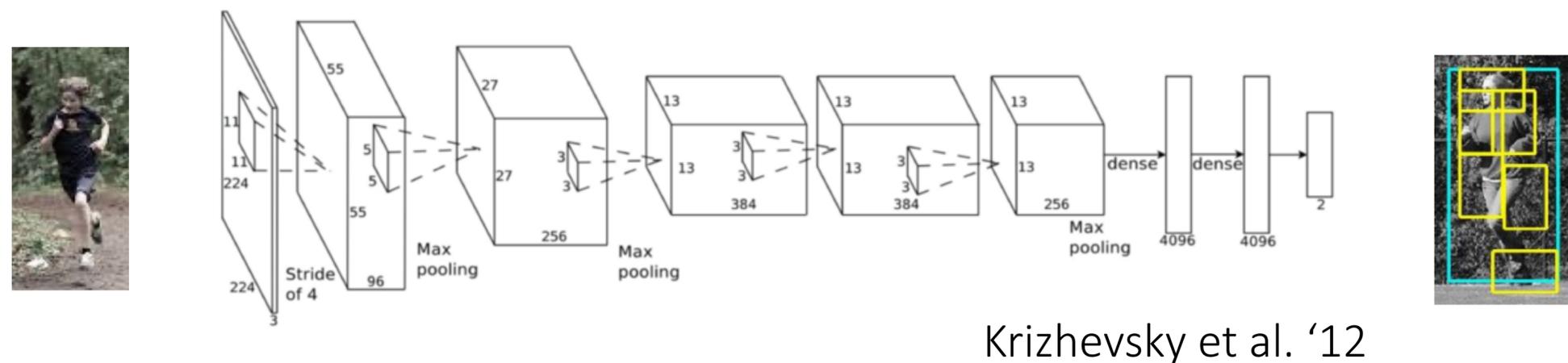
Why should we care about multi-task & meta-learning?

...beyond the robots and general-purpose ML systems

**Standard computer vision:**  
hand-designed features

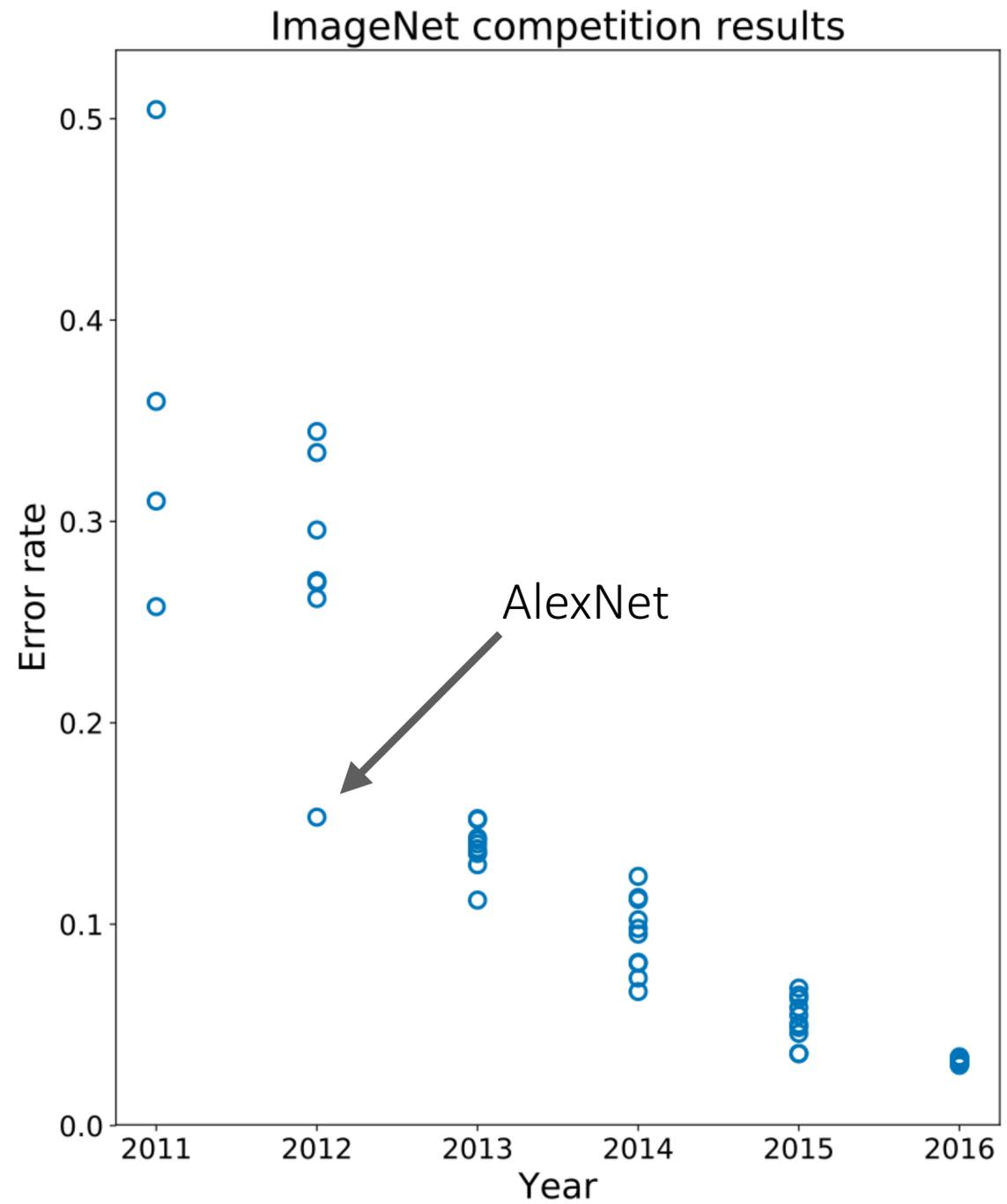


**Modern computer vision:**  
end-to-end training



Deep learning allows us to handle *unstructured inputs* (pixels, language, sensor readings, etc.)  
without hand-engineering features, with less domain knowledge

## Deep learning for object classification



## Deep learning for machine translation

Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi  
 yonghui,schuster,zhifengc,qvl,mnorouzi@google.com

Table 10: Mean of side-by-side scores on production data

	PBMT	GNMT	Human	Relative Improvement
English → Spanish	4.885	5.428	5.504	87%
English → French	4.932	5.295	5.496	64%
English → Chinese	4.035	4.594	4.987	58%
Spanish → English	4.872	5.187	5.372	63%
French → English	5.046	5.343	5.404	83%
Chinese → English	3.694	4.263	4.636	60%

Human evaluation scores on scale of 0 to 6

PBMT: Phrase-based machine translation

GNMT: Google's neural machine translation (in 2016)

Why deep **multi-task** and **meta-learning**?

Large, diverse data (+ large models)  $\xrightarrow{\text{deep learning}}$  Broad generalization



Russakovsky et al. '14



Wu et al. '16

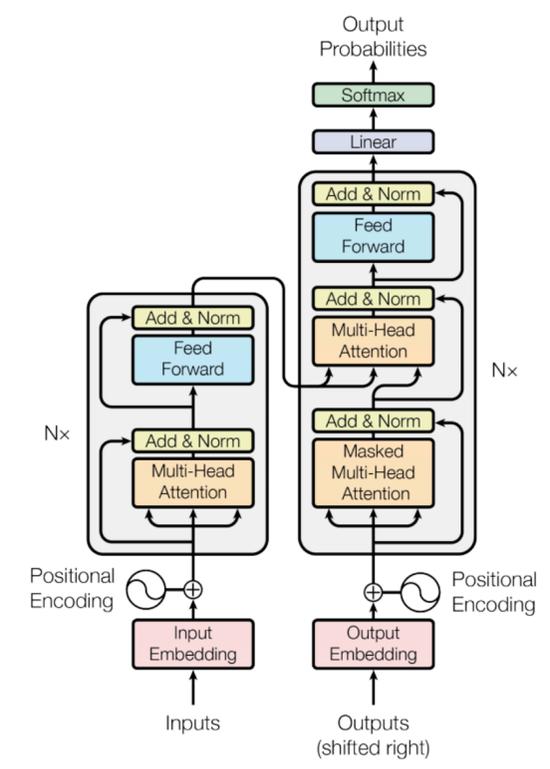


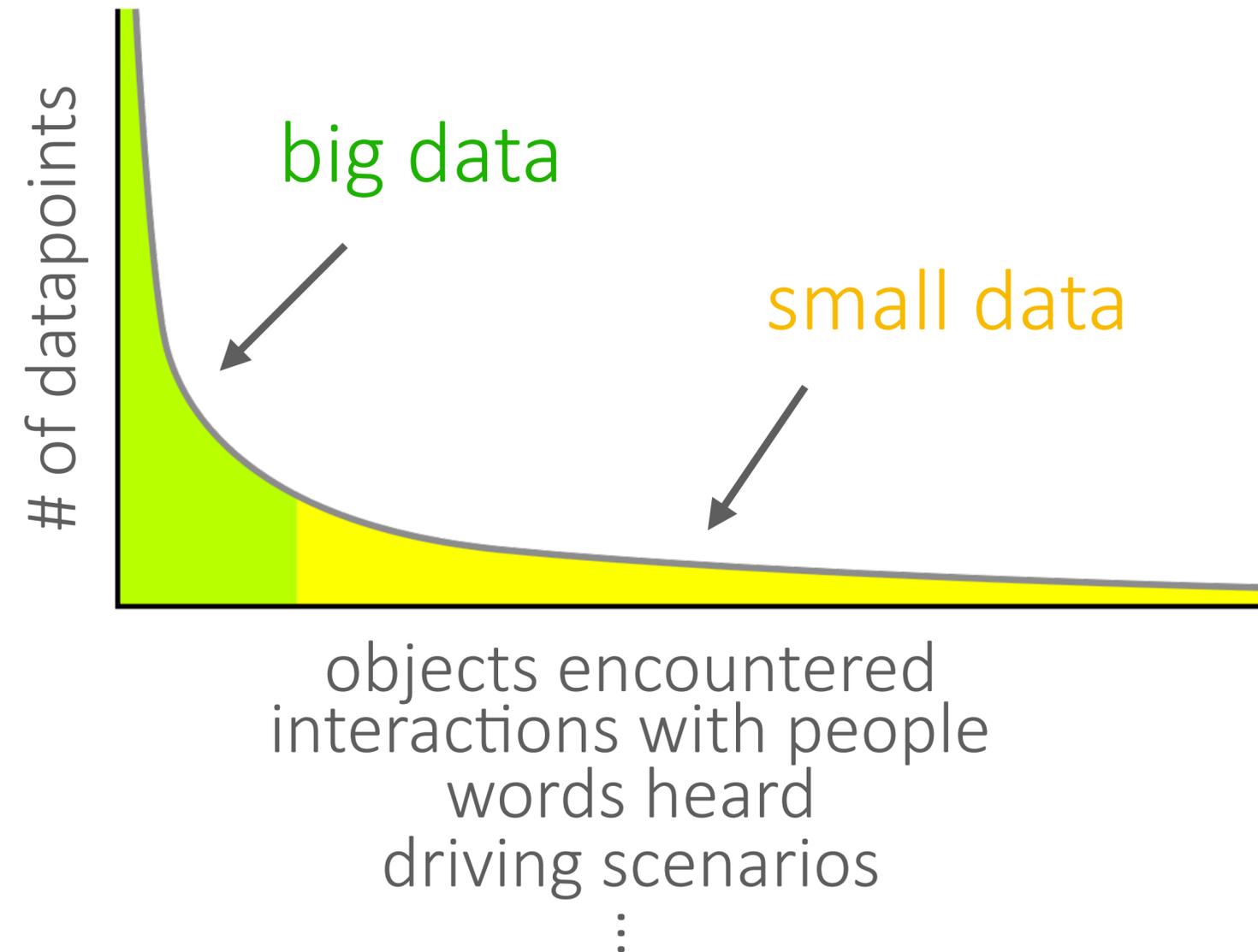
Figure 1: The Transformer - model architecture.

Vaswani et al. '18

## What if you don't have a large dataset?

medical imaging, robotics, personalized education, translations  
tr  
 Impractical to learn from scratch for each disease, each robot, each person, each language, each **task**

# What if your data has a long tail?



This setting breaks standard machine learning paradigms.

# What if you need to quickly learn something new?

about a new person, for a new task, about a new environment, etc.

# training data

Braque

Cezanne



# test datapoint



By Braque or Cezanne?

# What if you need to quickly learn something new?

about a new person, for a new task, about a new environment, etc.

“few-shot learning”



How did you accomplish this?

by leveraging prior experience!

# What if you want a more general-purpose AI system?

Learning each task from scratch won't cut it.

## What if you don't have a large dataset?

medical imaging

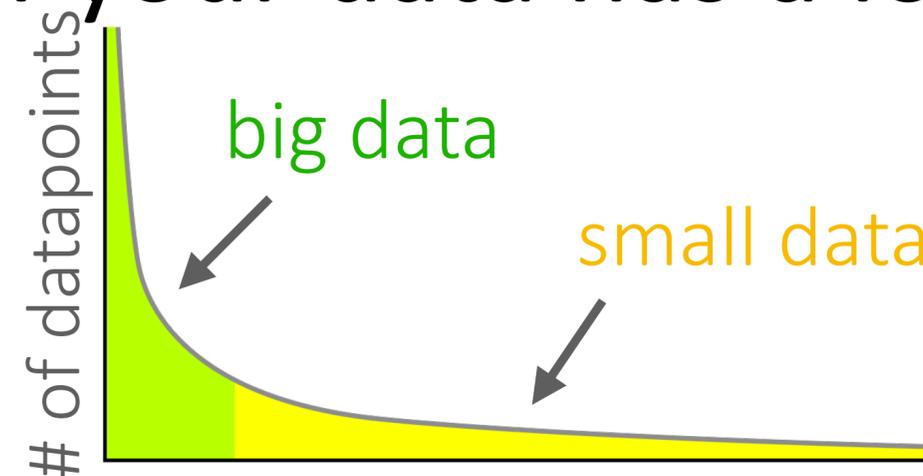
robotics

personalized education,

translation for rare languages

medicine, recommendations

## What if your data has a long tail?



## What if you need to quickly learn something new?

about a new person, for a new task, about a new environment, etc.

**This is where elements of multi-task learning can come into play.**

What is a task?

# What is a task?

For now: dataset  $\mathcal{D}$  → model  $f_\theta$   
loss function  $\mathcal{L}$

Different tasks can vary based on:

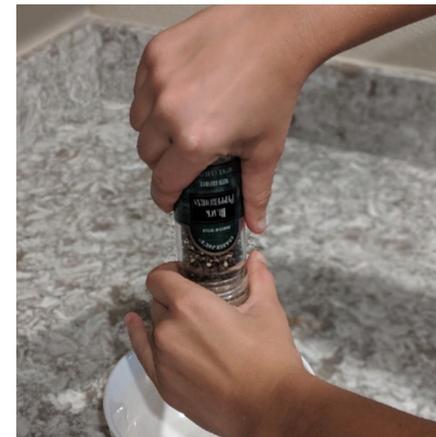
- different objects
- different people
- different objectives
- different lighting conditions
- different words
- different languages
- ...

**Not *just* different “tasks”**

# Critical Assumption

**The bad news:** Different tasks need to share some structure.  
If this doesn't hold, you are better off using single-task learning.

**The good news:** There are many tasks with shared structure!



Even if the tasks are seemingly unrelated:

- The laws of physics underly real data.
- People are all organisms with intentions.
- The rules of English underly English language data.
- Languages all develop for similar purposes.

This leads to far greater structure than random tasks.

# Informal Problem Definitions

We'll define these more formally next time.

**The multi-task learning problem:** Learn all of the tasks more quickly or more proficiently than learning them independently.

**The meta-learning problem:** Given data on previous tasks, learn a new task more quickly and/or more proficiently.

**This course:** anything that solves these problem statements.

Doesn't multi-task learning reduce to single-task learning?

$$\mathcal{D} = \bigcup \mathcal{D}_i \quad \mathcal{L} = \sum \mathcal{L}_i$$

Are we done with the course?

Doesn't multi-task learning reduce to single-task learning?

Yes, it can!

Aggregating the data across tasks & learning a single model is one approach to multi-task learning.

But, we can often do better!

Exploit the fact that we know that data is coming from different tasks.

# Why now?

Why should we study deep multi-task & meta-learning now?

# Multitask Learning\*

RICH CARUANA

Multitask Learning (MTL) is an inductive transfer mechanism whose principle goal is to improve generalization performance. MTL improves generalization by leveraging the domain-specific information contained in the training signals of *related* tasks. It does this by **training tasks in parallel while using a shared representation**. In effect, the training signals for the extra tasks serve as an inductive bias. Section 1.2 argues that inductive transfer is important if we wish to scale tabula rasa learning to complex, real-world tasks. Section 1.3 presents the simplest method we know for doing **multitask inductive transfer, adding extra tasks (i.e., extra outputs) to a backpropagation net**. Because the MTL net uses a shared hidden layer trained in parallel on all the tasks, what is learned for each task can help other tasks be learned better. Section 1.4 argues that it is reasonable to view training signals as an inductive bias when they are used this way.

Caruana, 1997

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## Is Learning The $n$ -th Thing Any Easier Than Learning The First?

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Sebastian Thrun<sup>1</sup>

They are often able to **generalize correctly even from a single training example [2, 10]**. One of the key aspects of the learning problem faced by humans, which differs from the vast majority of problems studied in the field of neural network learning, is the fact that humans encounter a whole stream of learning problems over their entire lifetime. **When faced with a new thing to learn, humans can usually exploit an enormous amount of training data and experiences that stem from other, related learning tasks**. For example, when learning to drive a car, years of learning experience with basic motor skills, typical traffic patterns, logical reasoning, language and much more precede and influence this learning task. The transfer of knowledge across learning tasks seems to play an essential role for generalizing accurately, particularly when training data is scarce.

Thrun, 1998

## On the Optimization of a Synaptic Learning Rule

Samy Bengio   Yoshua Bengio   Jocelyn Cloutier   Jan Gecsei

Université de Montréal, Département IRO

This paper presents a new approach to neural modeling based on the idea of using an automated method to optimize the parameters of a synaptic learning rule. The synaptic modification rule is considered as a parametric function. This function has *local* inputs and is the same in many neurons. We can use standard optimization methods to select appropriate parameters for a given type of task. We also present a theoretical analysis permitting to study the *generalization* property of such parametric learning rules. By generalization, we mean **the possibility for the learning rule to learn to solve *new* tasks**. Experiments were performed on three types of problems: a

Bengio et al. 1992

# These algorithms are continuing to play a fundamental role in machine learning research.

## Multilingual machine translation

### Massively Multilingual Neural Machine Translation

**Roe Aharoni\***  
Bar Ilan University  
Ramat-Gan  
Israel  
roee.aharoni@gmail.com

**Melvin Johnson and Orhan Firat**  
Google AI  
Mountain View  
California  
melvinp,orhanf@google.com

while supporting up to 59 languages. Our experiments on a large-scale dataset with 102 languages to and from English and up to one million examples per direction also show promising results, surpassing strong bilingual baselines and encouraging future work on massively multilingual NMT.

NAACL, 2019

## One-shot imitation learning from humans

### DAML Yu et al. RSS 2018



## YouTube recommendations

### Recommending What Video to Watch Next: A Multitask Ranking System

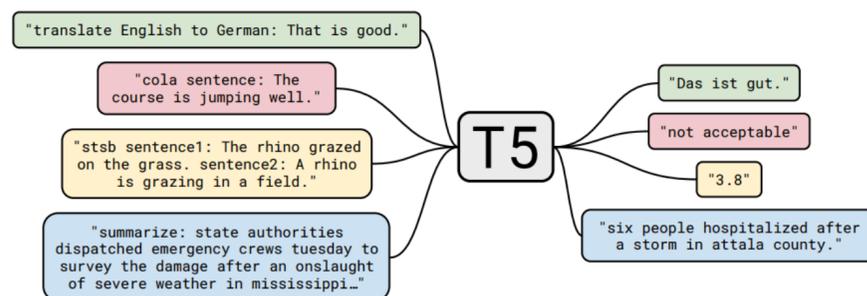
Zhe Zhao, Lichan Hong, Li Wei, Jilin Chen, Aniruddh Nath, Shawn Andrews, Aditee Kumthekar, Maheswaran Sathiamoorthy, Xinyang Yi, Ed Chi  
Google, Inc.  
{zhezhaol,lichan,liweil,jilinc,aniruddhnath,shawnandrews,aditeek,nlogn,xinyang,edchi}@google.com

In this paper, we introduce a large scale multi-objective ranking system for recommending what video to watch next on an industrial video sharing platform. The system faces many real-world challenges, including the presence of multiple competing ranking objectives, as well as implicit selection biases in user feedback. To

RecSys 2019

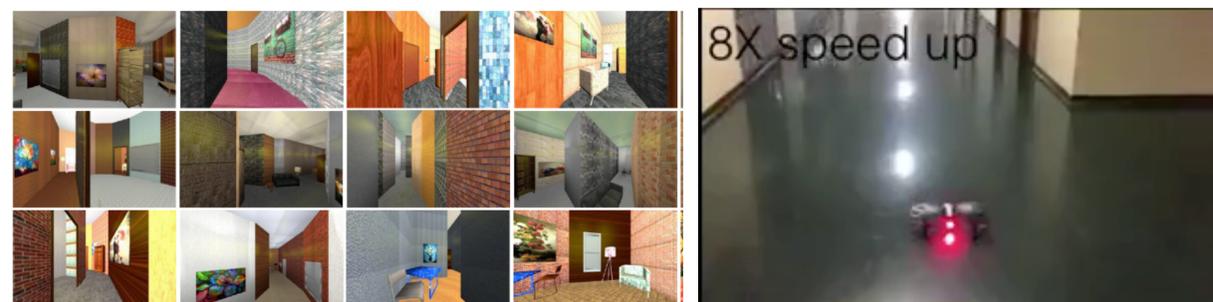
## Text-to-Text Transformer

Raffel et al. JMLR 2020



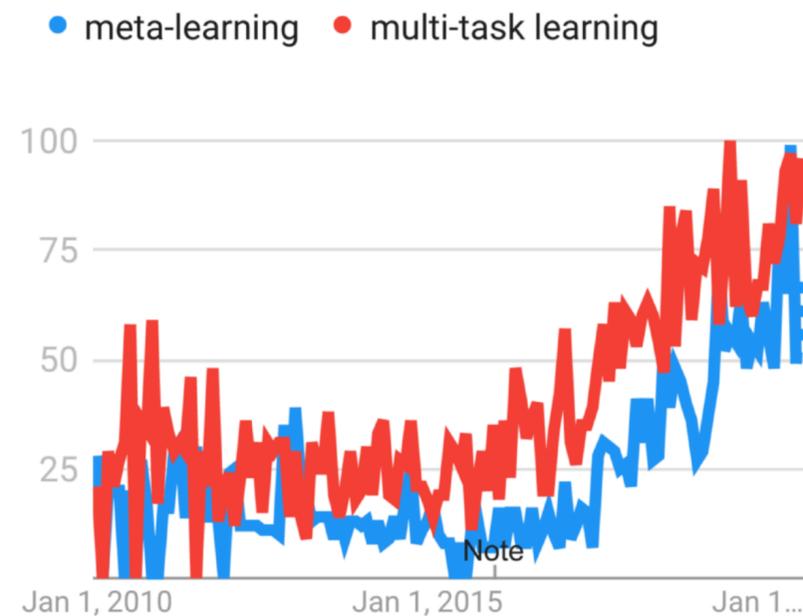
## Multi-domain learning for sim2real transfer

### CAD<sup>2</sup>RL Sadeghi & Levine, RSS 2017

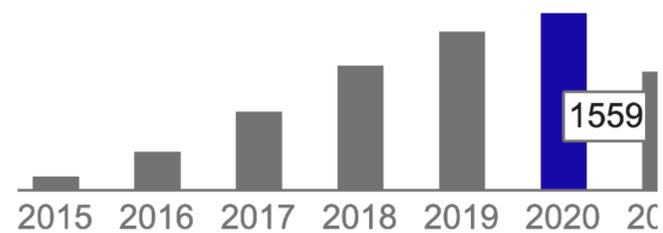


These algorithms are playing a fundamental, and **increasing** role in machine learning research.

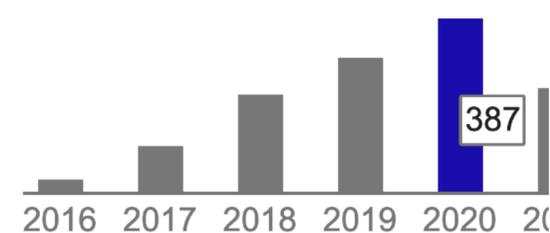
Interest level via Google search queries



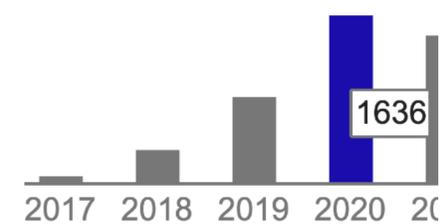
How transferable are features in a deep neural network?  
Yosinski et al. '15



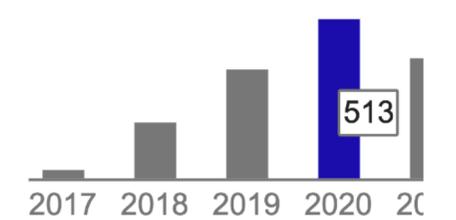
Learning to learn by gradient descent by gradient descent  
Andrychowicz et al. '15



Model-agnostic meta-learning for fast adaptation of deep networks  
Finn et al. '17



An overview of multi-task learning in neural networks  
Ruder '17



Its success will be critical for the **democratization** of deep learning.

ImageNet

1.2 million images and labels

WMT '14 English - French

40.8 million paired sentences

Switchboard Speech Dataset

300 hours of labeled data

Kaggle's Diabetic Retinopathy Detection dataset

35K labeled images

Adaptive epilepsy treatment with RL

< 1 hour of data

Guez et al. '08

Learning for robotic manipulation

< 15 min of data

Finn et al. '16

*But*, we still have many open questions and challenges!

# Reminders

1. Optional Homework 0 is out
2. Start forming final project groups if you want to work in a group

**Next time (Weds):** Multi-Task Learning & Transfer Learning Basics