Frontiers and Open-Challenges

CS330

Logistics

Final project presentations next week

Schedule on Piazza.

Final project report

Due next Friday midnight.

This is the last lecture!

We'll leave time for course evaluations at the end.

Today: What doesn't work very well?

(and how might we fix it)

Meta-learning for addressing distribution shift

Capturing equivariances with meta-learning
Adapting to distribution shift

What does it take to run multi-task & meta-RL across distinct tasks?

what set of distinct tasks do we train on?
what challenges arise?

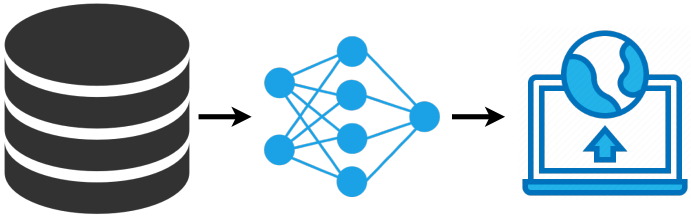
Open Challenges

Why address distribution shift?

Our current paradigm

v

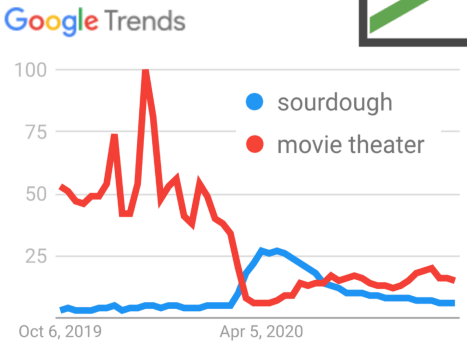
(ML research)



dataset model evaluation

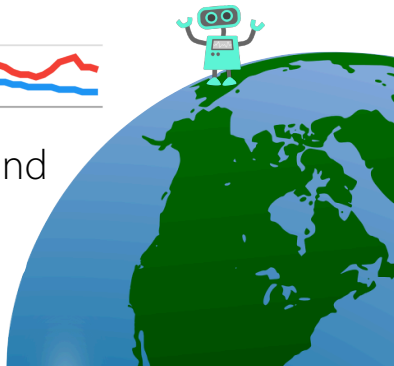
Our current reality

stocks



supply & demand

robots



Can our algorithms handle the **changing** world?

How does industry cope?

Chip Huyen on misperceptions about ML production:

Chip Huyen
@chipro

Replying to @chipro

3. If nothing happens, model performance remains the same

ML models perform best right after training. In prod, ML systems degrade quickly bc of concept drift.

Tip: train models on data generated 6 months ago & test on current data to see how much worse they get.

(4/6)

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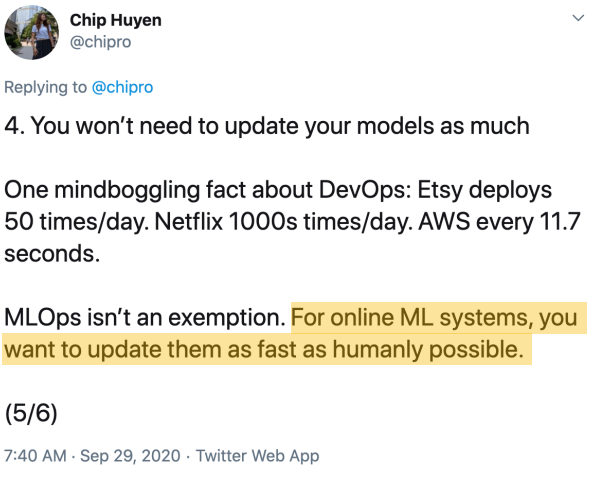

Chip Huyen
@chipro

Replying to @chipro

4. You won't need to update your models as much

One mindboggling fact about DevOps: Etsy deploys 50 times/day. Netflix 1000s times/day. AWS every 11.7 seconds.

MLOps isn't an exemption. For online ML systems, you want to update them as fast as humanly possible.

(5/6)

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the way our techniques are being *used* != the way we *intend*

One solution to distribution shift: build in structure to solve this problem.

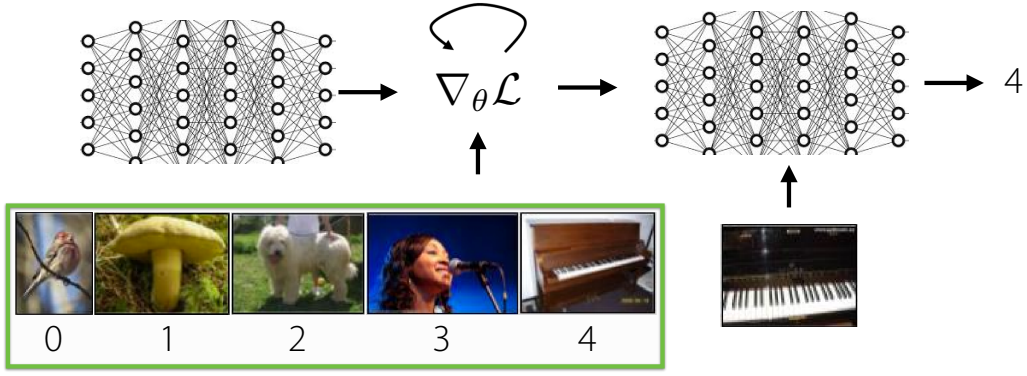
e.g. convolutions

+ Great when we know the structure & how to build it in! **—** Not great when we don't

Can we discover **equivariant** and **invariant structure** via meta-learning?

(i.e. symmetries)

Does MAML already do this?



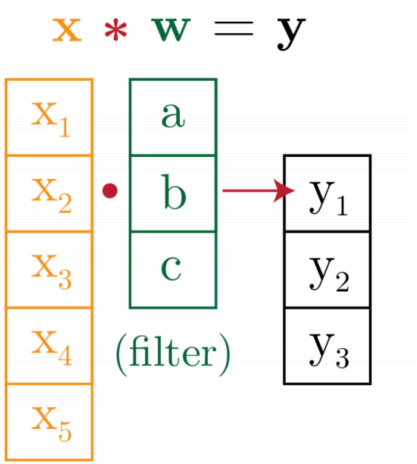
MAML can learn equivariant initial features
but equivariance may not be preserved in the gradient update!

Goal: Can we decompose weights into equivariant structure & corresponding parameters?

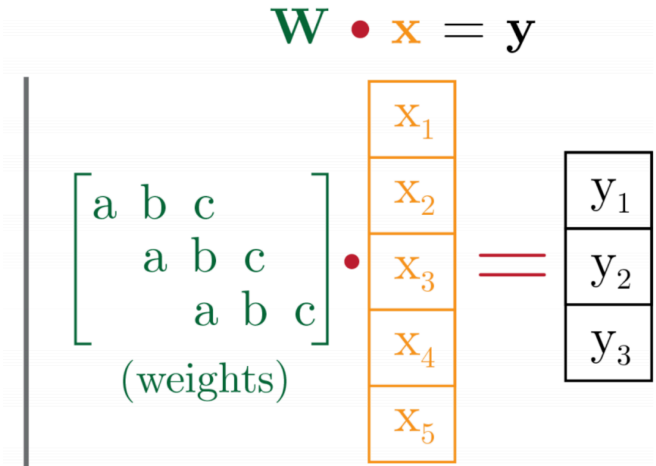
If so: update *only* parameters in the inner loop, retaining equivariance.

How are equivariances represented in neural networks?

Let's look at an example.



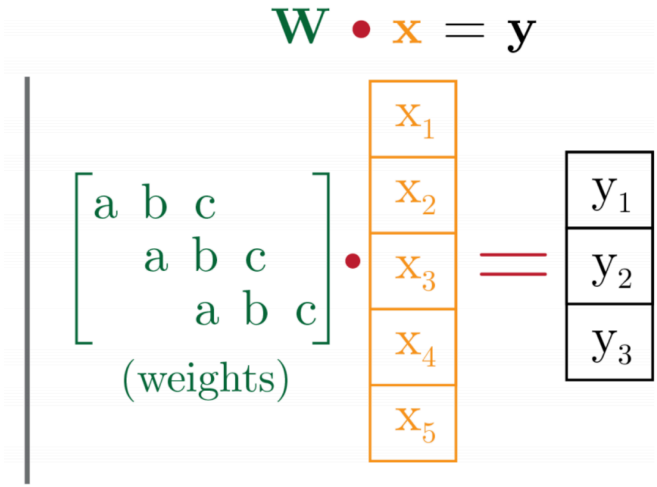
1D convolution layer



1D convolution represented as FC layer

Zhou, Knowles, Finn. *Meta-Learning Symmetries by Reparametrization*. under review '20

Representing Equivariance by Reparametrization



1D convolution represented as FC layer

Key idea: reparametrize weight matrix W

sharing matrix

$$\mathbf{U} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \\ & \vdots & \\ 0 & 0 & 1 \end{bmatrix}$$

Captures symmetries.

underlying filter parameters

$$\mathbf{v} = \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$

$$\bullet \quad = \mathrm{vec}(\mathbf{W})$$

Captures underlying shared parameters.

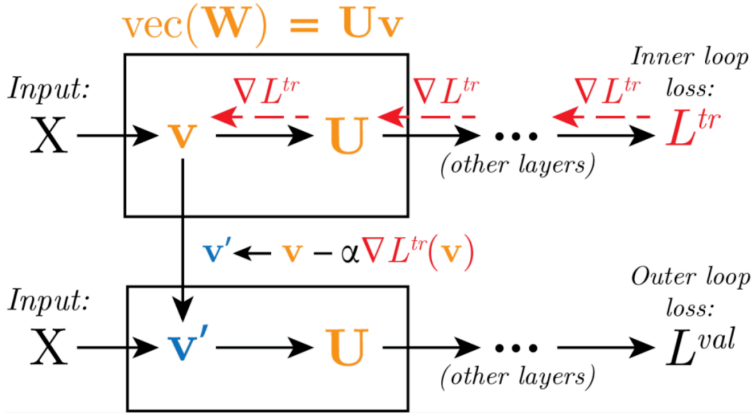
Theoretically, this can directly represent *decoupled* equivariant sharing pattern + filter parameters.

for *all* G-convolutions with finite group G

Zhou, Knowles, Finn. *Meta-Learning Symmetries by Reparametrization*. under review '20

Meta-Learning Equivariance

Inner loop: only update parameters $v \rightarrow v'$, keep equivariance U fixed
Outer loop: learn equivariance U and initial parameters v



Important assumption:
Some symmetries shared by all tasks.

meta-learning symmetries by reparametrization (MSR)

Zhou, Knowles, Finn. *Meta-Learning Symmetries by Reparametrization*. under review '20

Can we recover convolutions?

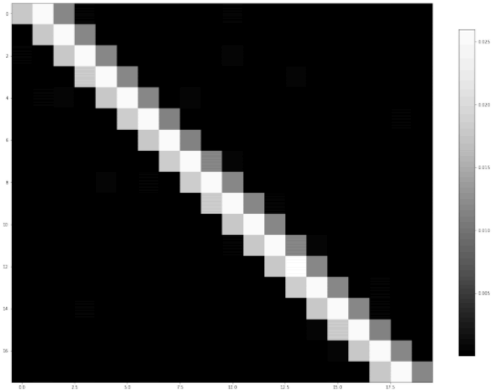
from translationally equivariant data

Mean-squared error on held-out test tasks

Method	$k = 1$
MAML-FC	$3.2 \pm .29$
MAML-LC	$2.4 \pm .23$
MAML-Conv	$\mathbf{.16 \pm .02}$
MSR-FC (Ours)	$\mathbf{.18 \pm .03}$

MAML-X: X corresponds to architecture
(fully-connected, locally-connected, convolution)

MSR-FC: fully-connected layer weights $\boldsymbol{W}$



recovered weight matrix

Zhou, Knowles, Finn. *Meta-Learning Symmetries by Reparametrization*. under review '20

Can we recover something better than convolutions?

…from data with *partial* translation symmetry

Method	$k = 1$	$k = 2$	$k = 5$
MAML-FC	$3.2 \pm .29$	$2.1 \pm .15$	$.89 \pm .05$
MAML-LC	$2.4 \pm .23$	$1.6 \pm .11$	$.81 \pm .05$
MAML-Conv	$\mathbf{.16 \pm .02}$	$.52 \pm .05$	$.44 \pm .02$
MSR-FC (Ours)	$\mathbf{.18 \pm .03}$	$\mathbf{.21 \pm .02}$	$\mathbf{.22 \pm .01}$

k: rank of a locally-connected layer

…from data with translation + rotation + reflection symmetry

Rotation/Flip Equivariance MSE		
Method	Rot	Rot+Flip
MSR-Conv (Ours)	**.004**	**.001**
MAML-Conv	.504	.507

MSR-Conv: $\boldsymbol{W}$ corresponds to convolution layer weights

Zhou, Knowles, Finn. *Meta-Learning Symmetries by Reparametrization*. under review '20

Can we learn symmetries from augmented data?

Algorithm 2: Augmentation Meta-Training

input : $\{\mathcal{T}_i\}_{i=1}^{N}$: Meta-training tasks
input : META-TRAIN: Any meta-learner
input : AUGMENT: Data augmenter
forall $\mathcal{T}_i \in \{\mathcal{T}_i\}_{i=1}^{N}$ **do**
  $\{\mathcal{D}_i^{tr}, \mathcal{D}_i^{val}\} \leftarrow \mathcal{T}_i$; `// task data split`
  $\hat{\mathcal{D}}_i^{val} \leftarrow \text{AUGMENT}\left(\mathcal{D}^{val}\right)$;
  $\hat{\mathcal{T}}_i \leftarrow \{\mathcal{D}^{tr}, \hat{\mathcal{D}}_i^{val}\}$
META-TRAIN$\left(\{\hat{\mathcal{T}}_i\}_{i=1}^{N}\right)$

—> baking data augmentation into the architecture / update rule

Method	Aug-Omniglot 5 way 1-shot	Aug-Omniglot 5 way 5-shot	Aug-Omniglot 20 way 1-shot	Aug-Omniglot 20 way 5-shot	Aug-MiniImagenet 5 way 1-shot	Aug-MiniImagenet 5 way 5-shot
MAML	87.3 ± 0.5	93.6 ± 0.3	67.0 ± 0.4	79.9 ± 0.3	42.5 ± 1.1	61.5 ± 1.0
MAML (Big)	89.3 ± 0.4	94.8 ± 0.3	69.6 ± 0.4	83.2 ± 0.3	37.2 ± 1.1	63.2 ± 1.0
ANIL	86.4 ± 0.5	93.2 ± 0.3	67.5 ± 3.5	79.8 ± 0.3	43.0 ± 1.1	62.3 ± 1.0
ProtoNets	92.9 ± 0.4	$\mathbf{97.4 \pm 0.2}$	$\mathbf{85.1 \pm 0.3}$	$\mathbf{94.3 \pm 0.2}$	34.6 ± 0.5	54.5 ± 0.6
MSR (Ours)	$\mathbf{95.3 \pm 0.3}$	$\mathbf{97.7 \pm 0.2}$	84.3 ± 0.2	92.6 ± 0.2	$\mathbf{45.5 \pm 1.1}$	$\mathbf{65.2 \pm 1.0}$

Zhou, Knowles, Finn. *Meta-Learning Symmetries by Reparametrization*. under review '20

MSR provides a framework for understanding the interplay of features & structure in meta-learning

Zhou, Knowles, Finn. *Meta-Learning Symmetries by Reparametrization*. under review '20

Today: What doesn't work very well?

(and how might we fix it)

Meta-learning for addressing distribution shift

Capturing equivariances with meta-learning
Adapting to distribution shift

What does it take to run multi-task & meta-RL across distinct tasks?

what set of distinct tasks do we train on?
what challenges arise?

Open Challenges

What kind of distribution shift to adapt to?

We'll now focus on: ***group shift***

categorical group variable z

e.g. user, location, time of day

(can be derived from meta-data)

Training data from $p(x, y \mid z)p_{\text{tr}}(z)$

Test data from $p(x, y \mid z)p_{\text{ts}}(z)$

can capture label shift, most covariate shift

captures problems like federated learning

Group DRO (*distributionally robust optimization*):

(Ben-Tal et al. '13, Duchi et al '16)

Form adversarial distribution $q(z)$: $\min_{\theta} \sup_{q \in \mathcal{Q}} \mathbb{E}_{q_z} \left[\mathbb{E}_{p_{xy|z}} [\ell(g(x; \theta), y)] \right]$

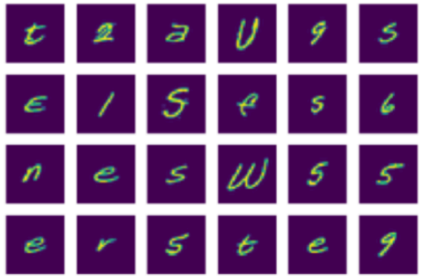
+ can enable robust solutions - often sacrifices average/empirical group performance

+ less pessimistic than adversarial robustness

Can we aim to *adapt* instead of aiming for robustness?

Test time

unlabeled data from test sub-distribution
(e.g. new user, different time-of-day, new place)



adapt model & infer labels

Assumption: test inputs from one group available in a batch or streaming.

Adaptive risk minimization (ARM)

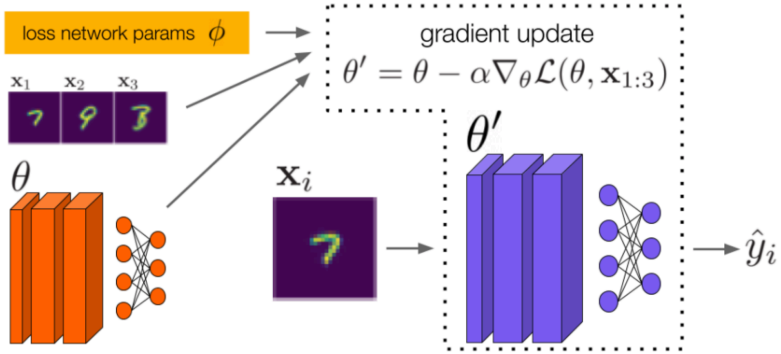
Zhang*, Marklund*, Dhawan, Gupta, Levine, Finn. *Adaptive Risk Minimization: A Meta-Learning Approach for Tackling Group Shift*. '20

Adaptive risk minimization (ARM)

1. Construct sub-distributions of training data
2. Train for adaptation to sub-distributions.

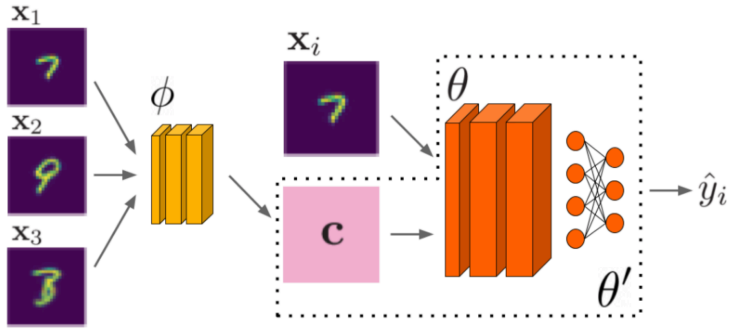
How to adapt with unlabeled data?

MAML with learned loss



or

meta-learning with context variable



Simplest setting: context = BN statistics

Zhang*, Marklund*, Dhawan, Gupta, Levine, Finn. *Adaptive Risk Minimization: A Meta-Learning Approach for Tackling Group Shift*. '20

Experimental Comparisons

ERM - standard deep network training

DRNN - distributional robustness
(Sagawa, Koh et al. ICLR '20)

UW - ERM but upweight groups to
the uniform distribution

ARM - adaptive risk minimization

- ARM-CML - adapt with context variable
- ARM-BN - adapt using batch norm stats
- ARM-LL - adapt with learned loss

Experiment 1. Federated Extended MNIST (Cohen et al. 2017, Caldas et al. 2019)

Distribution shift: adapt to *new* users with only unlabeled data

	FEMNIST	
Method	**WC**	**Avg**
ERM	62.9 ± 1.9	80.1 ± 0.9
UW*	61.8 ± 0.9	80.1 ± 0.3
DRNN	58.1 ± 0.7	74.4 ± 0.8
q-FedAvg [37]	58.2 ± 1.0	80.8 ± 0.3
ARM-CML	67.8 ± 1.3	$\mathbf{85.7 \pm 0.3}$
ARM-BN	$\mathbf{72.6 \pm 0.3}$	$\mathbf{85.7 \pm 0.1}$
ARM-LL	69.6 ± 2.1	$\mathbf{85.6 \pm 0.5}$

+ 5% improvement in average accuracy

+ 10% improvement in worst-case accuracy

ARM - adaptive risk minimization

ERM - standard deep network training

DRNN - distributional robustness (Sagawa, Koh et al. ICLR '20)

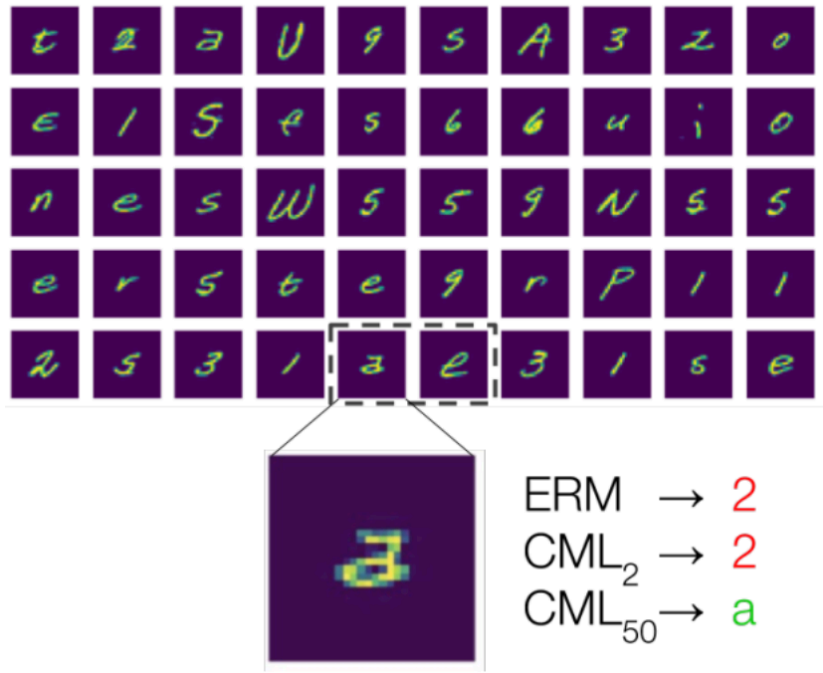
UW - ERM but upweight groups to the uniform distribution

q-FedAvg (Li et al. 2020) - federated learning method

Zhang*, Marklund*, Dhawan, Gupta, Levine, Finn. *Adaptive Risk Minimization: A Meta-Learning Approach for Tackling Group Shift*. '20

Experiment 1. Federated Extended MNIST (Cohen et al. 2017, Caldas et al. 2019)

Distribution shift: adapt to *new* users with only unlabeled data



Zhang*, Marklund*, Dhawan, Gupta, Levine, Finn. *Adaptive Risk Minimization: A Meta-Learning Approach for Tackling Group Shift*. '20

Experiment 2. CIFAR-C, TinyImageNet-C (Hendrycks & Dietterich, 2019)

Distribution shift: adapt to *new* image corruptions

(train using 56 corruptions, test using 22 disjoint corruptions)

	CIFAR-10-C		Tiny ImageNet-C	
Method	**WC**	**Avg**	**WC**	**Avg**
ERM	49.6 ± 0.1	69.8 ± 0.4	19.3 ± 0.5	41.4 ± 0.2
UW*	—	—	—	—
DRNN	44.5 ± 0.5	70.7 ± 0.6	19.9 ± 0.3	41.6 ± 0.2
ARM-CML	67.7 ± 0.5	79.2 ± 0.3	21.4 ± 0.2	43.3 ± 0.4
ARM-BN	$\mathbf{71.1 \pm 0.1}$	$\mathbf{80.9 \pm 0.2}$	$\mathbf{27.7 \pm 0.2}$	$\mathbf{44.9 \pm 0.2}$
ARM-LL	66.9 ± 0.2	75.7 ± 0.3	27.1 ± 0.3	44.2 ± 0.4

+ 3-10% improvement in average accuracy

+ 8-21% improvement in worst-case accuracy

ARM - adaptive risk minimization

ERM - standard deep network training

DRNN - distributional robustness (Sagawa, Koh et al. ICLR '20)

UW - ERM but upweight groups to the uniform distribution

Today: What doesn't work very well?

(and how might we fix it)

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Capturing equivariances with meta-learning

Adapting to distribution shift

Takeaways

Preliminary evidence that meta-learning can capture *equivariances*
via reparametrized weight matrices

Allow adaptation / fine-tuning *without* labeled target data
via adaptive risk minimization

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(and how might we fix it)

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What does it take to run multi-task & meta-RL across distinct tasks?

what set of distinct tasks do we train on?

what challenges arise?

Open Challenges

Have MAML, RL^2, PEARL, DREAM accomplished our goal of making policy adaptation fast?

Sort of…

Can we adapt to *entirely new tasks*?

meta-train task distribution

=

meta-test task distribution

—> Need broad distribution of tasks for meta-training

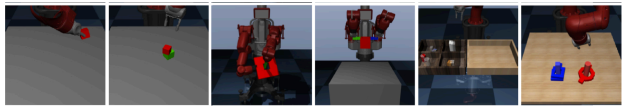
& not sparse

^

A few options:

Brockman et al. *OpenAI Gym*. 2016

Bellemare et al. *Atari Learning Environment*. 2016



Fan et al. *SURREAL: Open-Source Reinforcement Learning Framework and Robot Manipulation Benchmark*. CoRL 2018

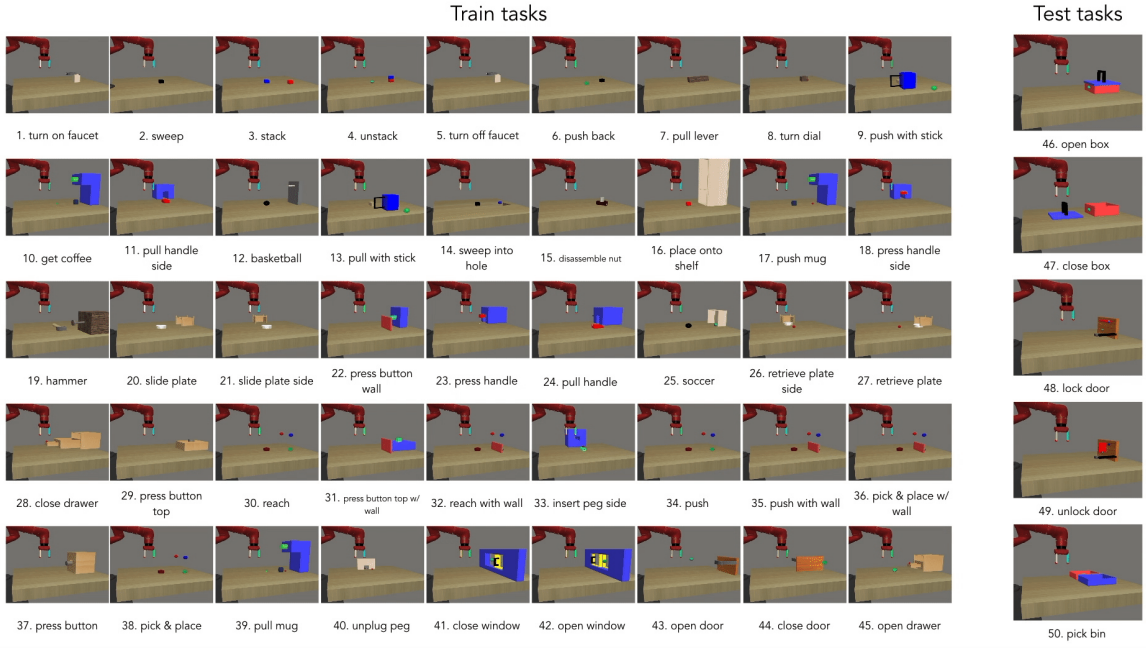
Our desiderata

50+ qualitatively distinct tasks

shaped reward function & success metrics

All tasks individually solvable (to allow us to focus on multi-task / meta-RL component)

Unified state & action space, environment (to facilitate transfer)



Meta-World Benchmark

T Yu, D Quillen, Z He, R Julian, K Hausman, C Finn, S Levine. *Meta-World*. CoRL '19

Results: Meta-learning algorithms seem to struggle…

Methods	ML45	
	meta-train	meta-test
MAML		
RL^2		
PEARL		

…even on the 45 meta-training tasks!

Multi-task RL algorithms also struggle…

Methods	MT50
Multi-task PPO	8.98%
Multi-task TRPO	22.86%
Task embeddings	15.31%
Multi-task SAC	28.83%
Multi-task multi-head SAC	**35.85%**

T Yu, D Quillen, Z He, R Julian, K Hausman, C Finn, S Levine. *Meta-World*. CoRL '19

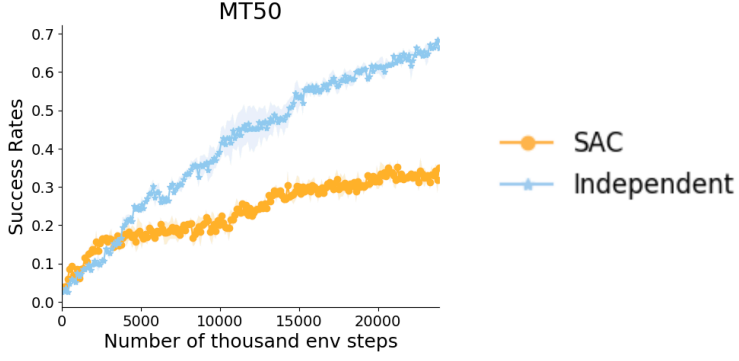
Why the poor results?

Exploration challenge? All tasks individually solvable.

Data scarcity? All methods given budget with plenty of samples.

Limited model capacity? All methods plenty of capacity.

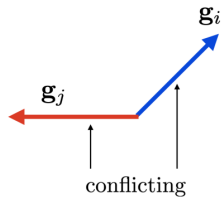
Training models ***independently*** performs the best.



Our conclusion: must be a multi-task *optimization* challenge.

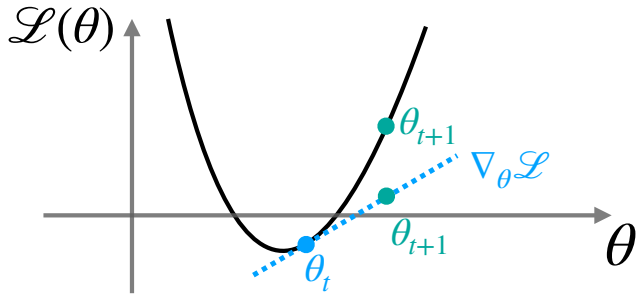
Hypothesis 1: Gradients from different tasks often conflict

If so: would see negative inner product of gradients.



Hypothesis 2: When they do conflict, they cause more damage than expected.

i.e. due to high curvature

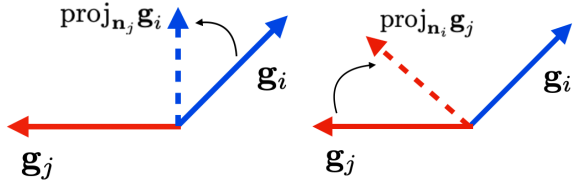


T Yu, S Kumar, A Gupta, S Levine, K Hausman, C Finn. ***Gradient Surgery for Multi-Task Learning***. NeurIPS '20

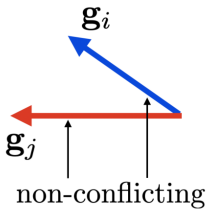
Our solution: try to avoid making other tasks worse, when taking gradient step.

Algorithm:

If two gradients conflict:
project each onto the normal plane of the other



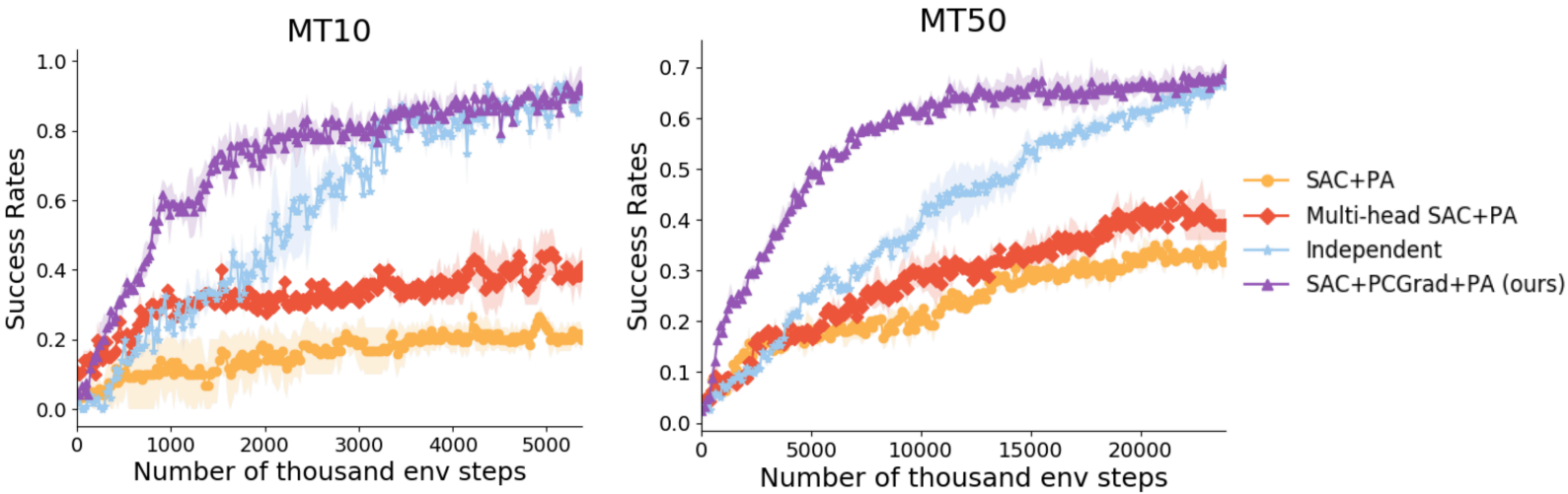
Else:
leave them alone



i.e. project conflicting gradients
"PCGrad"

T Yu, S Kumar, A Gupta, S Levine, K Hausman, C Finn. ***Gradient Surgery for Multi-Task Learning***. NeurIPS '20

Multi-Task RL on Meta-World:



T Yu, S Kumar, A Gupta, S Levine, K Hausman, C Finn. ***Gradient Surgery for Multi-Task Learning***. NeurIPS '20

Multi-Task CIFAR-100

	% accuracy
task specific-1-fc (Rosenbaum et al., 2018)	42
task specific-all-fc (Rosenbaum et al., 2018)	49
cross stitch-all-fc (Misra et al., 2016b)	53
routing-all-fc + WPL (Rosenbaum et al., 2019)	74.7
independent	67.7
PCGrad (ours)	71
routing-all-fc + WPL + PCGrad (ours)	**77.5**

Multi-Task NYUv2

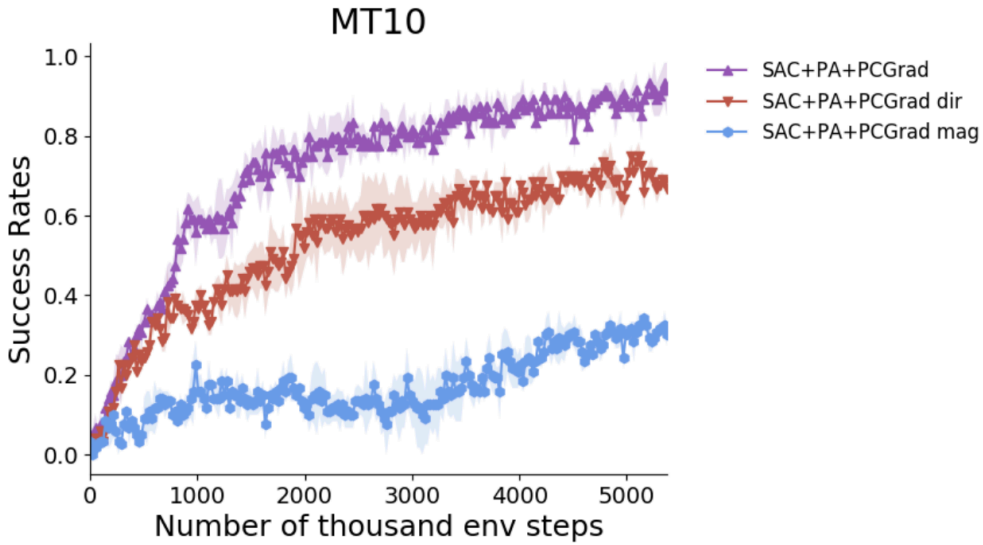
#P.	Architecture	Weighting	Segmentation (Higher Better)		Depth (Lower Better)		Surface Normal: Angle Distance (Lower Better)		Surface Normal: Within t° (Higher Better)		
			mIoU	Pix Acc	Abs Err	Rel Err	Mean	Median	11.25	22.5	30
≈3	Cross-Stitch‡	Equal Weights	14.71	50.23	0.6481	0.2871	33.56	28.58	20.08	40.54	51.97
		Uncert. Weights*	15.69	52.60	0.6277	0.2702	32.69	27.26	21.63	42.84	54.45
		DWA†, $T = 2$	**16.11**	**53.19**	**0.5922**	**0.2611**	**32.34**	**26.91**	**21.81**	**43.14**	**54.92**
1.77	MTAN†	Equal Weights	**17.72**	55.32	**0.5906**	0.2577	31.44	**25.37**	**23.17**	45.65	57.48
		Uncert. Weights*	17.67	**55.61**	0.5927	0.2592	**31.25**	25.57	22.99	**45.83**	**57.67**
		DWA†, $T = 2$	17.15	54.97	0.5956	**0.2569**	31.60	25.46	22.48	44.86	57.24
1.77	MTAN† + PCGrad (ours)	Uncert. Weights*	**20.17**	**56.65**	**0.5904**	**0.2467**	**30.01**	**24.83**	22.28	**46.12**	**58.77**

also helps multi-task supervised learning, complementary to multi-task architectures

T Yu, S Kumar, A Gupta, S Levine, K Hausman, C Finn. ***Gradient Surgery for Multi-Task Learning***. NeurIPS '20

Why does it work?

(Part 1)



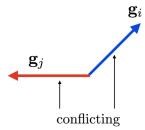
T Yu, S Kumar, A Gupta, S Levine, K Hausman, C Finn. ***Gradient Surgery for Multi-Task Learning***. NeurIPS '20

Why does it work?

(Part 2)

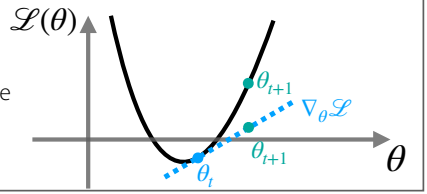
Hypothesis 1: Gradients from different tasks often conflict

If so: would see negative inner product of gradients



Hypothesis 2: When they do conflict, they cause more damage than expected.

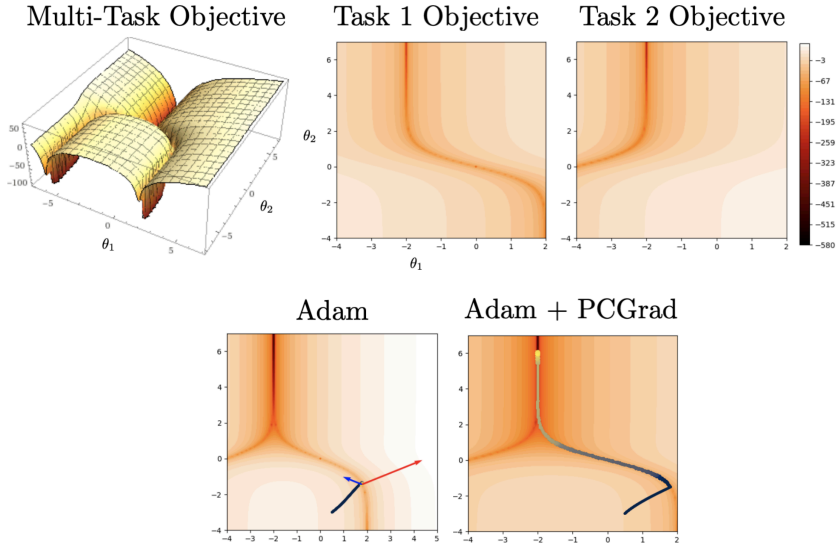
i.e. due to high curvature & difference in grad magnitude



1. conflicting gradients
2. large positive curvature
3. difference in gradient magnitude

"tragic triad"

Is PCGrad ***provably*** better under these three conditions?



Are these three conditions actually ***why*** we see improvements on large-scale problems?

T Yu, S Kumar, A Gupta, S Levine, K Hausman, C Finn. ***Gradient Surgery for Multi-Task Learning***. NeurIPS '20

"tragic triad"

Why does it work?

(Part 2)

1. conflicting gradients
2. large positive curvature
3. difference in gradient magnitude

Is PCGrad ***provably*** better under these three conditions?

short answer: yes, if large enough conflict, curvature, gradient magnitude difference

(for two tasks)

long answer:

Theorem 2. *Suppose $\mathcal{L}$ is differentiable and the gradient of $\mathcal{L}$ is Lipschitz continuous with constant $L > 0$. Let θ^{MT} and θ^{PCGrad} be the parameters after applying one update to θ with $\mathbf{g}$ and PCGrad-modified gradient $\mathbf{g}^{PC}$ respectively, with step size $t > 0$. Moreover, assume $\mathbf{H}(\mathcal{L}; \theta, \theta^{MT}) \geq \ell \|\mathbf{g}\|_2^2$ for some constant $\ell \leq L$, i.e. the multi-task curvature is lower-bounded. Then $\mathcal{L}(\theta^{PCGrad}) \leq \mathcal{L}(\theta^{MT})$ if*

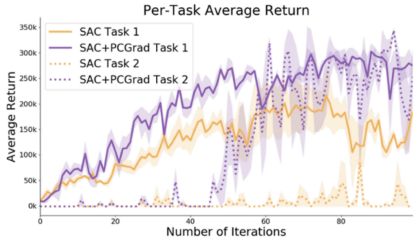
(a) $\cos \phi_{12} \leq -\Phi(\mathbf{g}_1, \mathbf{g}_2)$,

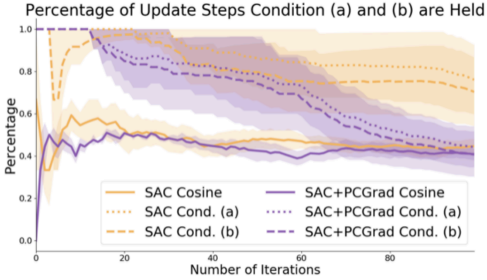
(b) $\ell \geq \xi(\mathbf{g}_1, \mathbf{g}_2) L$, *and*

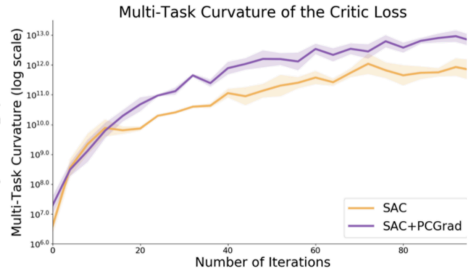
(c) $t \geq \frac{2}{\ell - \xi(\mathbf{g}_1, \mathbf{g}_2) L}$.

Proof. See Appendix B. □

Are these three conditions actually ***why*** we see improvements on large-scale problems?







T Yu, S Kumar, A Gupta, S Levine, K Hausman, C Finn. ***Gradient Surgery for Multi-Task Learning***. NeurIPS '20

Today: What doesn't work very well?

(and how might we fix it)

What does it take to run multi-task & meta-RL across distinct tasks?

what set of distinct tasks do we train on?
what challenges arise?

Takeaways

Scaling to broad task distributions is hard,
can't be taken for granted:

- Train on broad, dense task distributions
- Avoid conflicting gradients

Today: What doesn't work very well?

(and how might we fix it)

Meta-learning for addressing distribution shift

Capturing equivariances with meta-learning
Adapting to distribution shift

What does it take to run multi-task & meta-RL across distinct tasks?

what set of distinct tasks do we train on?
what challenges arise?

Open Challenges

Open Challenges in Multi-Task and Meta Learning

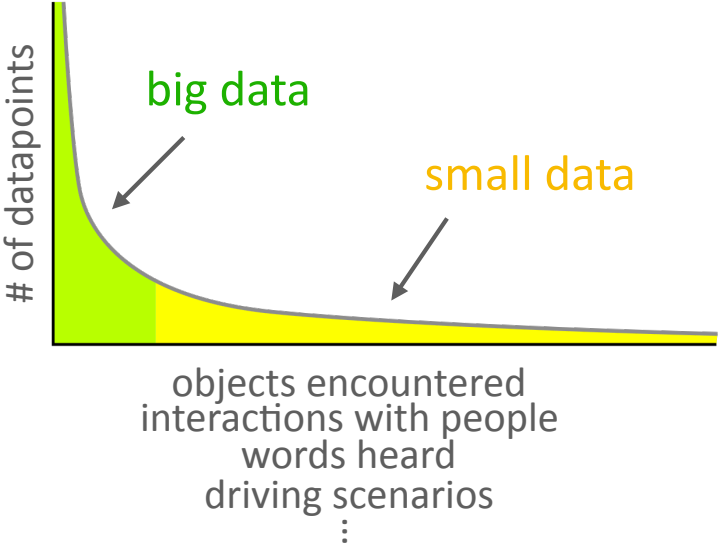
(that we haven't previously covered)

Open Challenges in Multi-Task and Meta Learning

Addressing fundamental problem assumptions

- Generalization: Out-of-distribution tasks, long-tailed task distributions

The problem with long-tailed distributions.



We've seen some generalization to the tail:

- prototypical clustering networks for dermatological diseases
- adaptive risk minimization

Further hints might come from domain adaptation, robustness literature.

We learned how to do few-shot learning

…but these few-shot tasks may be from a different distribution

Open Challenges in Multi-Task and Meta Learning

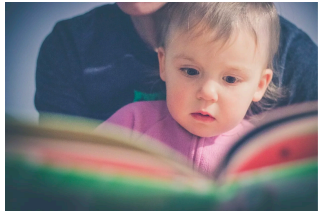
Addressing fundamental problem assumptions

- Generalization: Out-of-distribution tasks, long-tailed task distributions
- Multimodality: Can you learn priors from multiple modalities of data?

Rich sources of prior experiences.

visual imagery

tactile feedback



language

social cues

Can we learn priors across multiple data modalities?

Varying dimensionalities, units

Carry different, complementary forms of information

Some hints might come from multimodal learning literature.

One initial paper: Liang, Wu, Ziyin, Morency, Salakhutdinov. Learning in Low-resource Modalities via Cross-modal Generalization. 2020.

Open Challenges in Multi-Task and Meta Learning

Addressing fundamental problem assumptions

- Generalization: Out-of-distribution tasks, long-tailed task distributions
- Multimodality: Can you learn priors from multiple modalities of data?
- Algorithm, Model Selection: When will multi-task learning help you?

Benchmarks

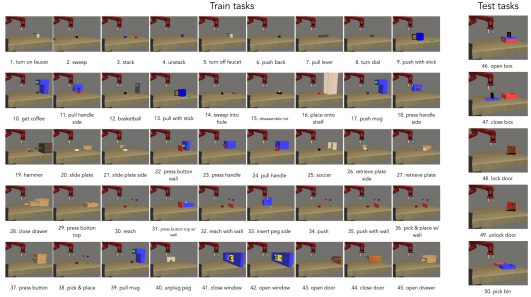
- Breadth: That challenge current algorithms to find common structure
- Realistic: That reflect real-world problems

Some steps towards good benchmarks

ILSVRC
Omniglot
Aircraft
Birds
Textures
Quick Draw
Fungi
VGG Flower
Traffic Signs
MSCOCO

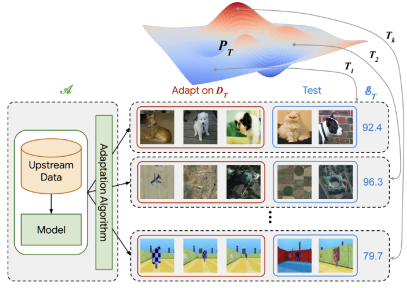
Meta-Dataset

Triantafillou et al.'19



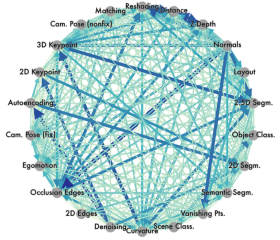
Meta-World Benchmark

Yu et al.'19



Visual Task Adaptation Benchmark

Zhai et al.'19



Taskonomy Dataset

Zamir et al.'18

Goal: reflection of real world problems + appropriate level of difficulty + ease of use

Open Challenges in Multi-Task and Meta Learning

Addressing fundamental problem assumptions

- Generalization: Out-of-distribution tasks, long-tailed task distributions
- Multimodality: Can you learn priors from multiple modalities of data?
- Algorithm, Model Selection: When will multi-task learning help you?

Benchmarks

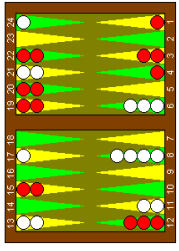
- Breadth: That challenge current algorithms to find common structure
- Realistic: That reflect real-world problems

Improving core algorithms

- Computation & Memory: Making large-scale bi-level optimization practical
- Theory: Develop a theoretical understanding of the performance of these algorithms
- Multi-Step Problems: Performing tasks in sequence presents challenges.

+ the challenges you discovered in your homework & final projects!

The Bigger Picture

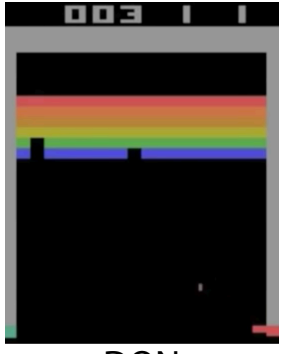


TD Gammon

Watson

helicopter acrobatics

machine translation



DQN

Machines are *specialists*.

Source: https://youtu.be/8vNxjwt2AqY

A Step Towards Generalists

Some of what we covered in CS330:

- learn multiple tasks (multi-task learning)
- leverage prior experience when learning new things (meta-learning)
- learn general-purpose models (model-based RL)
- prepare for tasks before you know what they are (exploration, skill discovery, unsupervised meta-learning)
- perform tasks in sequence (hierarchical RL)
- learn continuously (lifelong learning)

What's missing?

Reminders

Final project presentations next week

Schedule on Piazza.

Final project report

Due next Friday midnight.

This is the last lecture!

We'll leave time for course evaluations at the end.