# Robot Learning

Meta & Multi-task Learning

USC University of Southern California

LiraLab

# Project milestone report

- 5% of the overall class grade (=12.5% of the project grade)
- 2 pages
- You don't have to re-introduce the project. You can assume we already know it, unless…
  - You partially and fully changed your project after the proposal report.
  - Our feedback to your proposal included some clarification questions.

# Project milestone report

- Describe the progress since the proposal report.
  - Did you complete the mathematical formulation / solution? Share your work.
  - Did you implement something? Share any results you may have.
  - Did you read many papers? Share what you learned and how they are related to your project.

- Describe what else remains to be done.

# Today…

- Multi-task Learning
- Transfer Learning
- Meta Learning

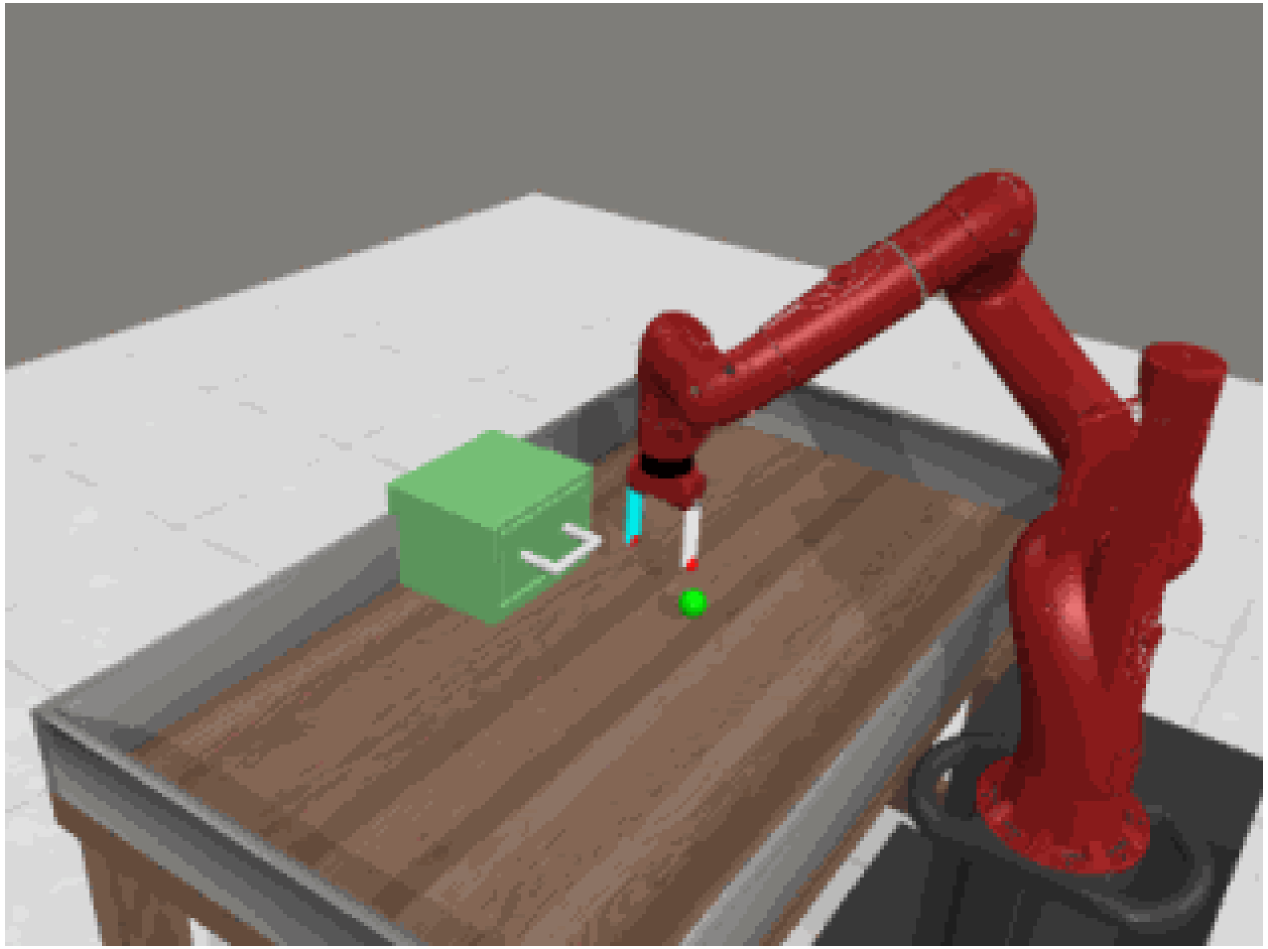
# What is a task?

$$\underset{\pi}{\text{maximize}} \quad \mathbb{E}_{\boldsymbol{w}}\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)\right]$$

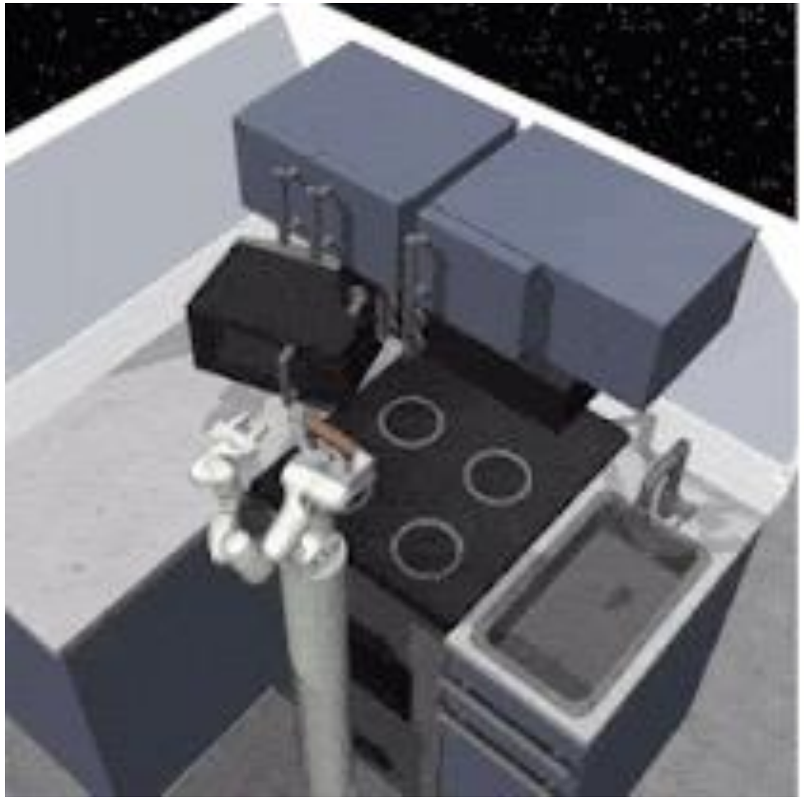
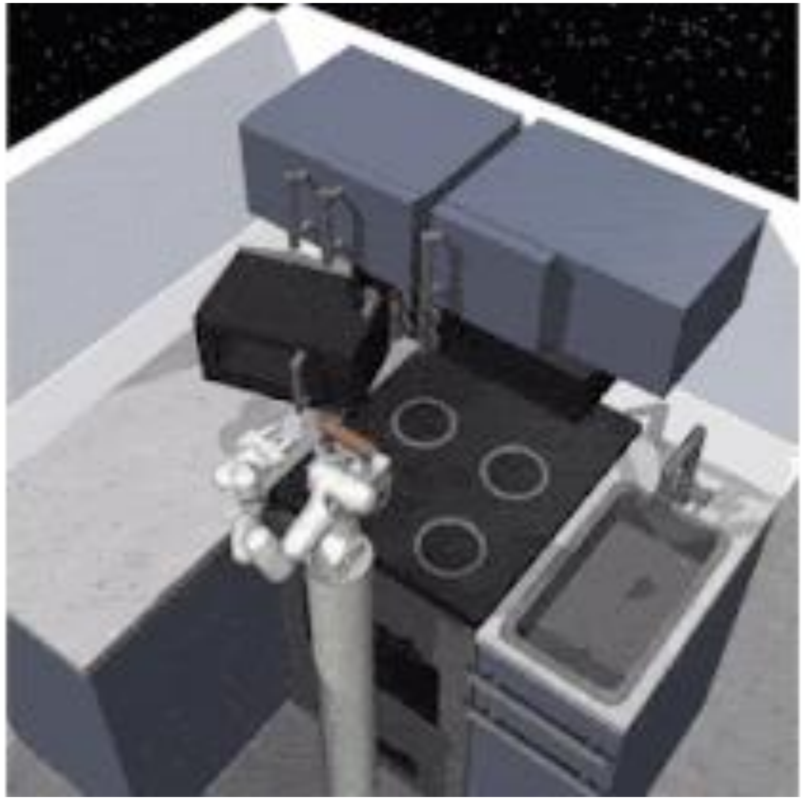
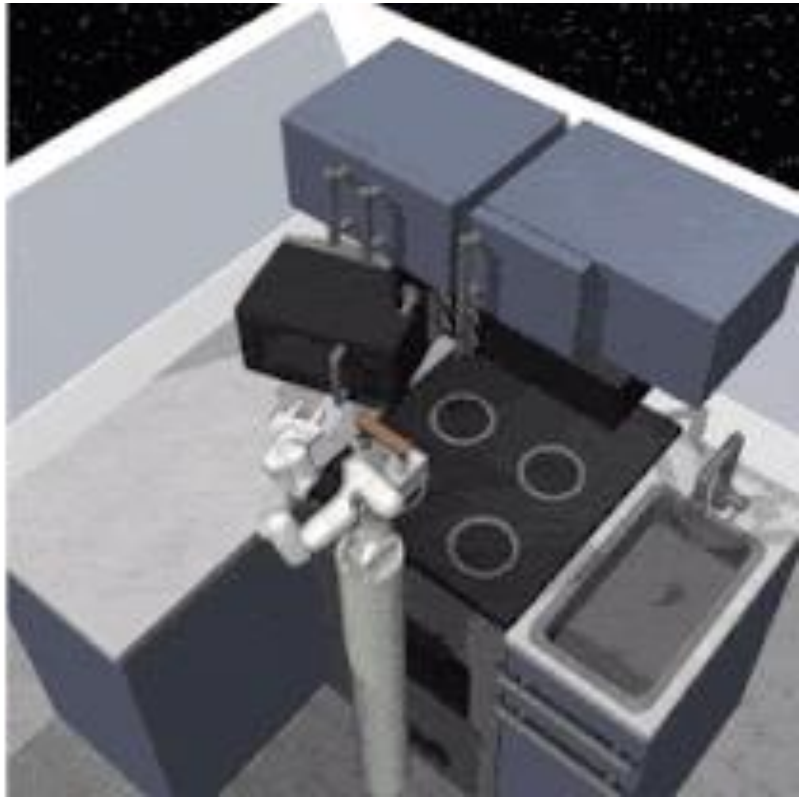
$$\text{subject to } s_{t+1} = f(s_t, a_t, w_t)$$
$$a_t = \pi(s_t)$$

More generally in machine learning, a dataset-loss function pair defines a task.

# What’s wrong with single-task learning?



# What's wrong with single-task learning?

# Still... Why multi-task learning?

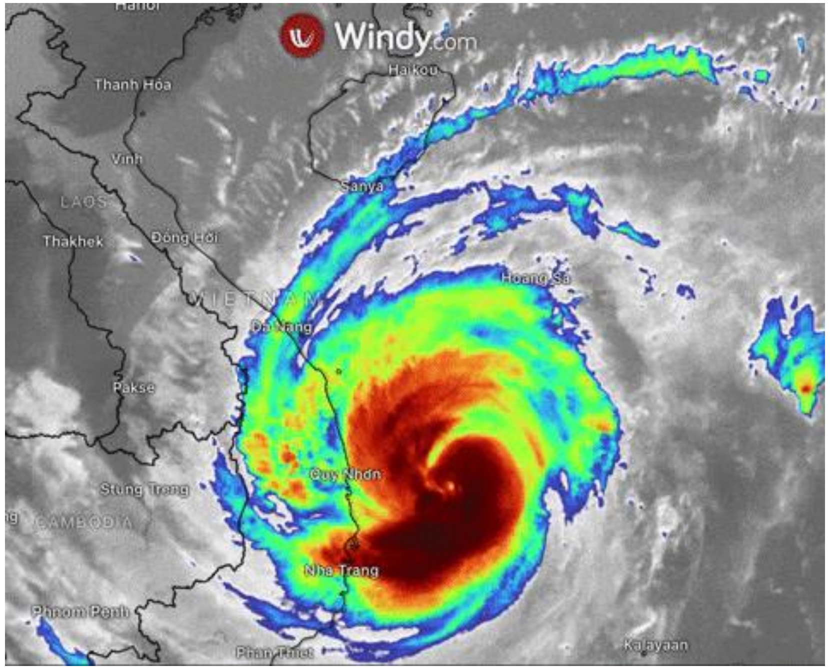
We could just learn each task independently!

- What if we have little data for some tasks?

- What if we have little time to learn some tasks?

# Still... Why multi-task learning?

You should learn each task independently if there is no shared structure between the tasks.


Left: Playing atari with deep reinforcement learning
Mnih et al., NeurIPS Deep Learning Workshop 2013
Right: Windy.com Community

# Still... Why multi-task learning?

In real life, many tasks share structure!



From: Stanford CS330

# Today…

- Multi-task Learning
- Transfer Learning
- Meta Learning

# Today…

- Multi-task Learning: Learn multiple tasks together
- Transfer Learning
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# Today…

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- Transfer Learning: Learn multiple tasks and transfer your knowledge to a new one
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# Multi-task learning

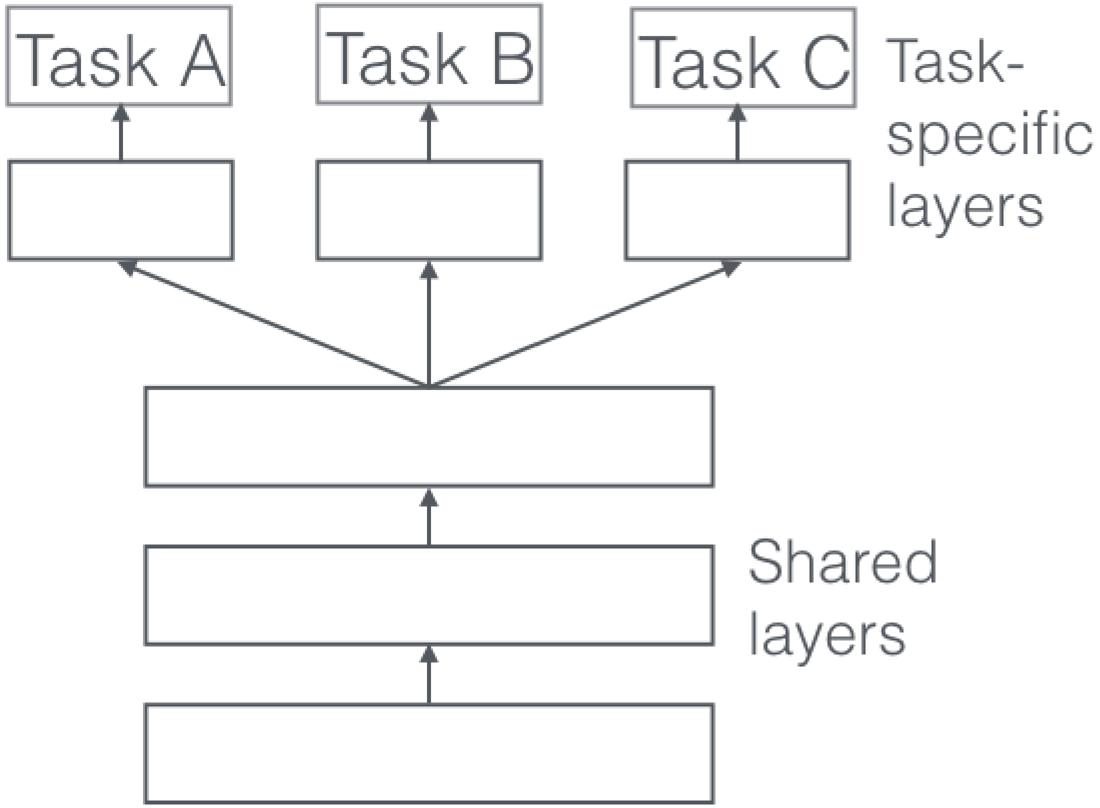
Common solution:

1. Sample tasks from the task distribution $P(\tau)$
2. Compute their losses
3. Sum the losses
4. Backpropagate
5. Go back to step 1

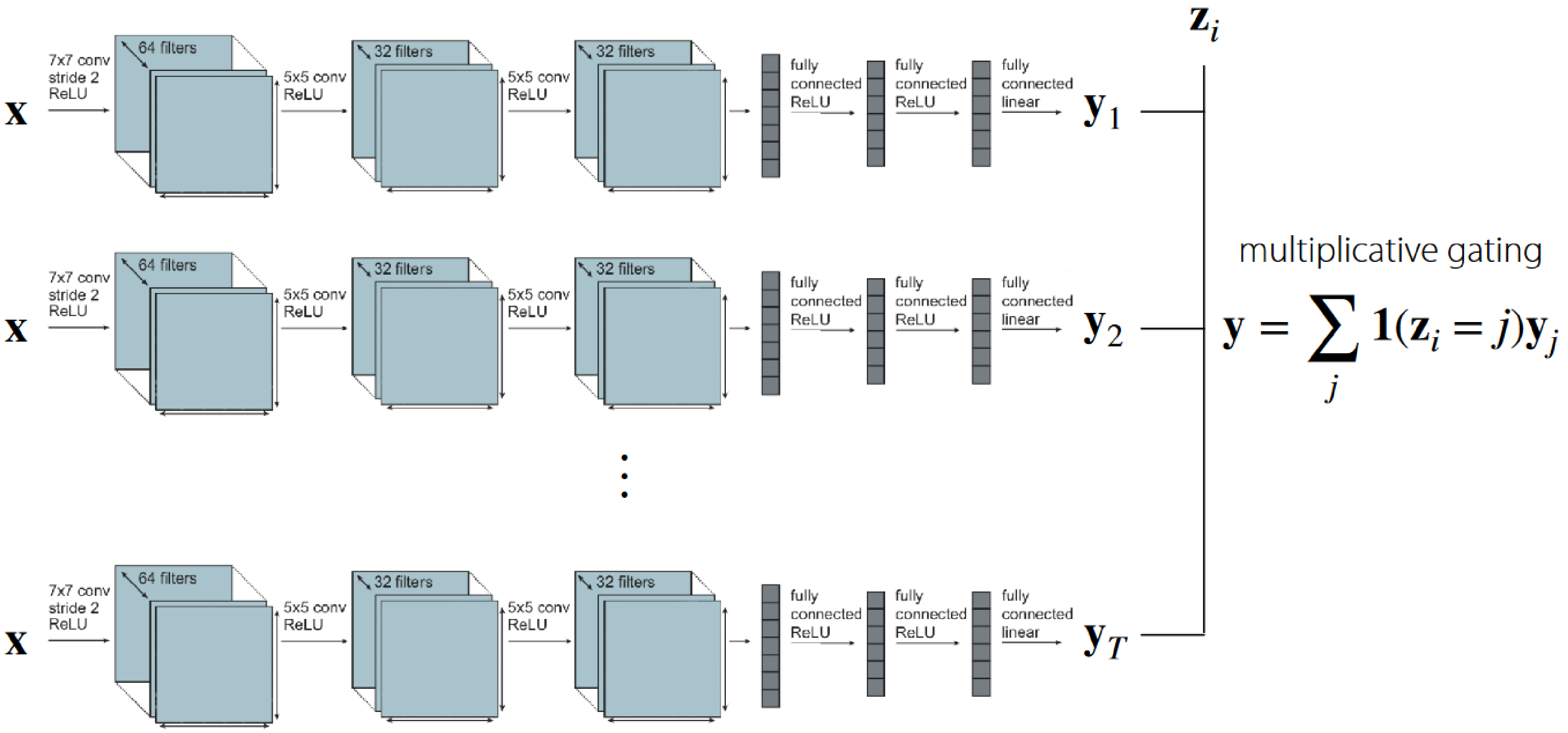
How will the model know which task to do?

What if the sum of losses is not a good loss?

# Parameter sharing



# Extreme case: no parameter sharing

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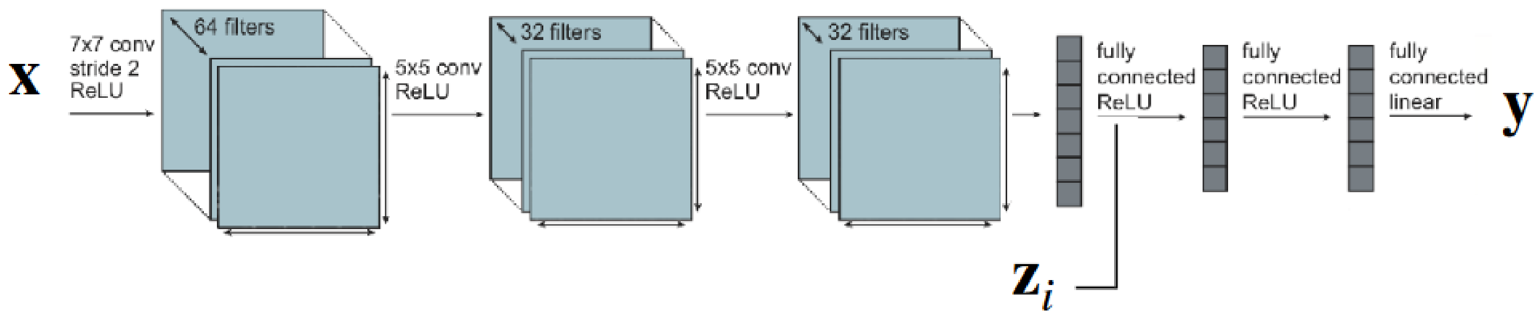
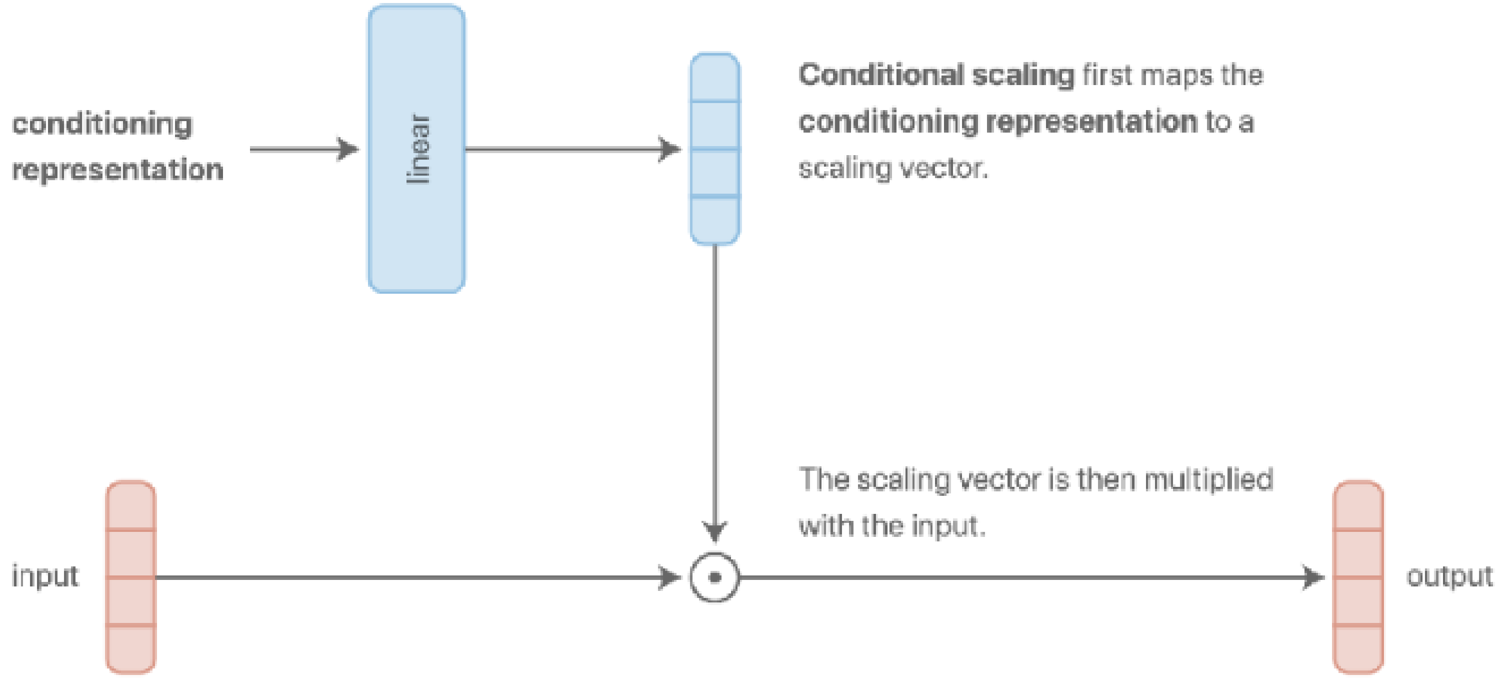
# Extreme case: full parameter sharing




Concatenate $\mathbf{z}_i$ with input and/or activations

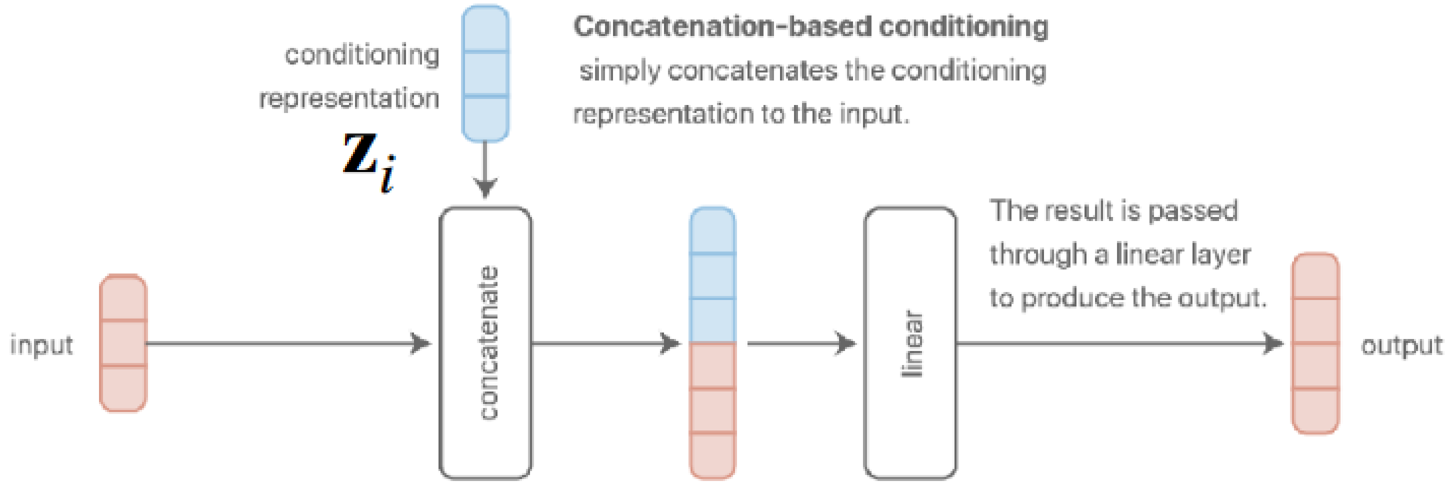
From: Stanford CS330

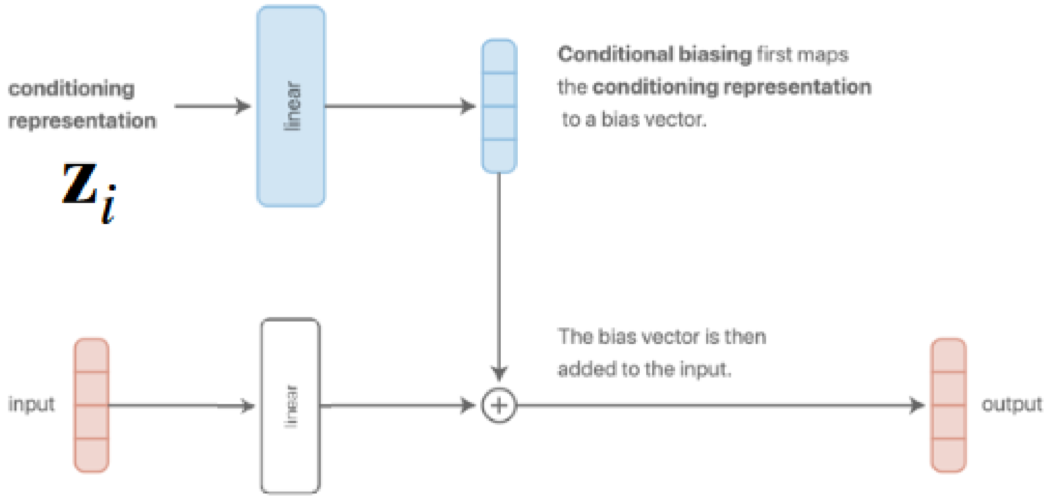
# Multiplicative coding




Feature-wise transformations
Dumoulin et al., Distill 2018

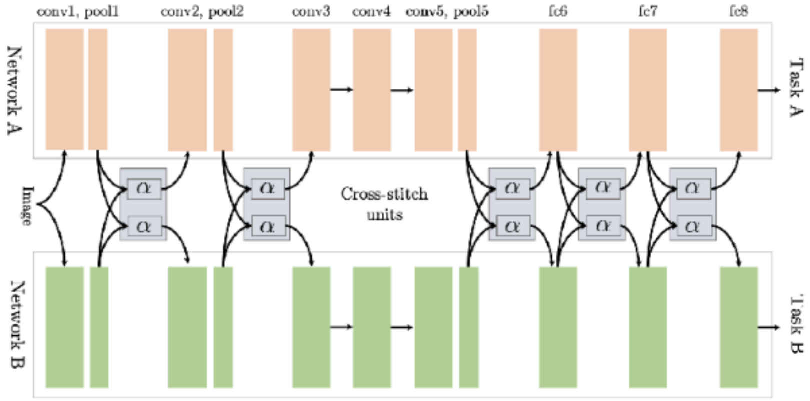
# Concatenation-based coding



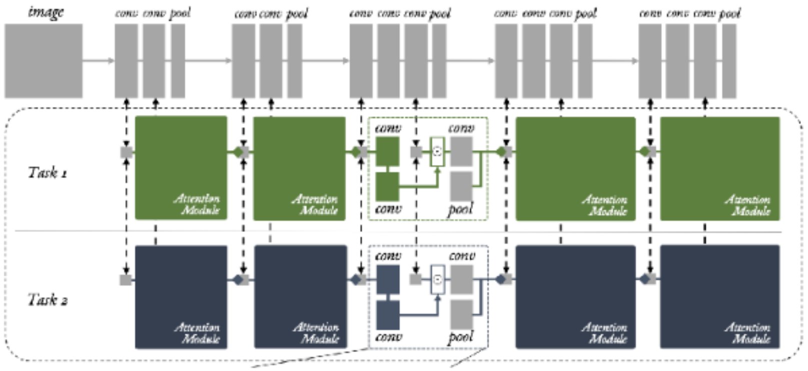




These are the same!

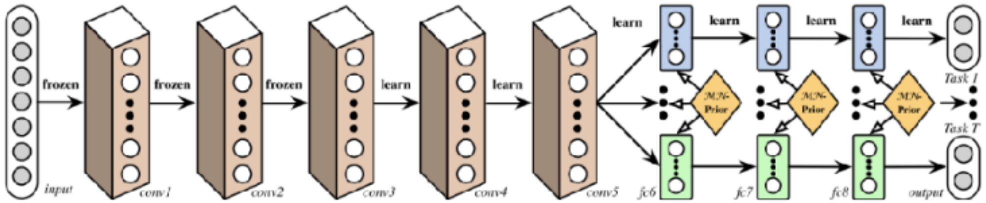
# There is no right way



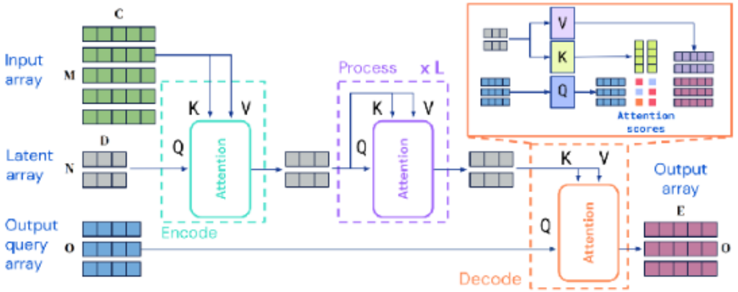

*Cross-Stitch Networks*. Misra, Shrivastava, Gupta, Hebert '16




*Multi-Task Attention Network*. Liu, Johns, Davison '18




*Deep Relation Networks*. Long, Wang '15




*Perceiver IO*. Jaegle et al. '21

From: Stanford CS330

# Multi-task learning

Common solution:

1. Sample tasks from the task distribution $P(\tau)$
2. Compute their losses
3. Sum the losses
4. Backpropagate
5. Go back to step 1

How will the model know which task to do?

What if the sum of losses is not a good loss?

# Multi-task learning

Common solution:

Popular heuristic: try to make gradients have similar magnitude

1. Sample tasks from the task distribution $P(\tau)$
2. Compute their losses
3. Sum the losses w/ some weights
4. Backpropagate
5. Go back to step 1

How will the model know which task to do?

What if the sum of losses is not a good loss?

# Multi-task learning

Common solution:

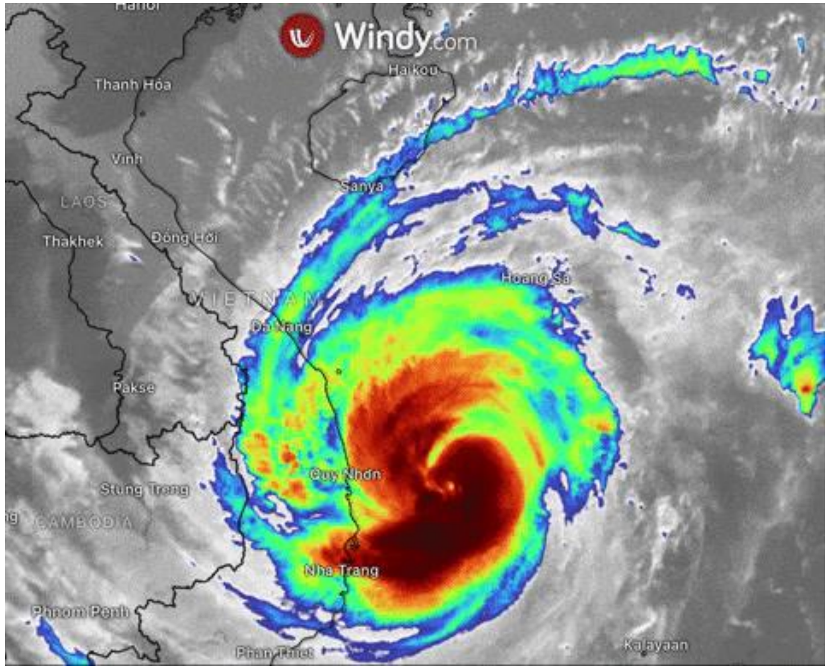
1. Sample tasks from the task distribution $P(\tau)$
2. Compute their losses
3. Take the maximum of the losses
4. Backpropagate
5. Go back to step 1

How will the model know which task to do? ✅

What if the sum of losses is not a good loss? ❓

# Common problems

- Negative transfer


You should share less between the tasks.

How?

- Fewer parameters
- Soft-sharing

Left: Playing atari with deep reinforcement learning
Mnih et al., NeurIPS Deep Learning Workshop 2013
Right: Windy.com Community

# Soft-sharing

Do not constrain the model to have the same parameters for different tasks.

Instead, penalize the model based on how different their parameters are.

# Common problems

- Overfitting

Perhaps, you have little data for some of the tasks.

You should share more between the tasks.

# Can we share based on task similarity!

Yes!

But what is task similarity?

# Today…

- Multi-task Learning: Learn multiple tasks together
- Transfer Learning: Learn multiple tasks and transfer your knowledge to a new one
- Meta Learning: Learn multiple tasks such that adapting to a new task will be easy

# Transfer learning

**Training:** Have access to tasks $\tau_1, \tau_2, \dots, \tau_n$, but not $\tau_{n+1}$.

**Transfer:** Have access to task $\tau_{n+1}$, but not $\tau_1, \tau_2, \dots, \tau_n$.

# Transfer learning

Common solution:

**Training:**

1. Run your favorite (multi-task) learning algorithm on $\tau_1, \tau_2, \dots, \tau_n$

**Transfer:**

2. Fine-tune the model on $\tau_{n+1}$

This is the idea behind using ImageNet features or BERT embeddings!

# Transfer learning

Common solution:

**Training:**

1. Run your favorite (multi-task) learning algorithm on $\tau_1, \tau_2, \dots, \tau_n$

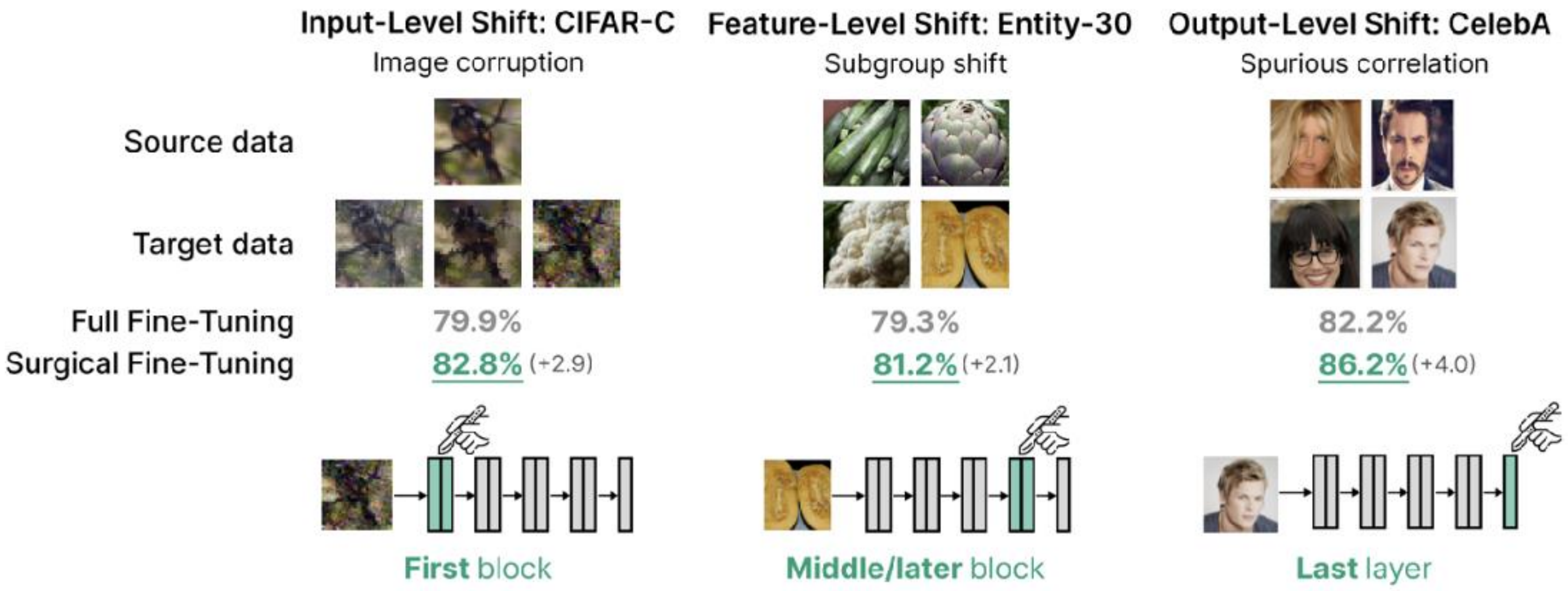
**Transfer:**

2. Fine-tune the model on $\tau_{n+1}$

Fine-tune what?

# Fine-tune what?

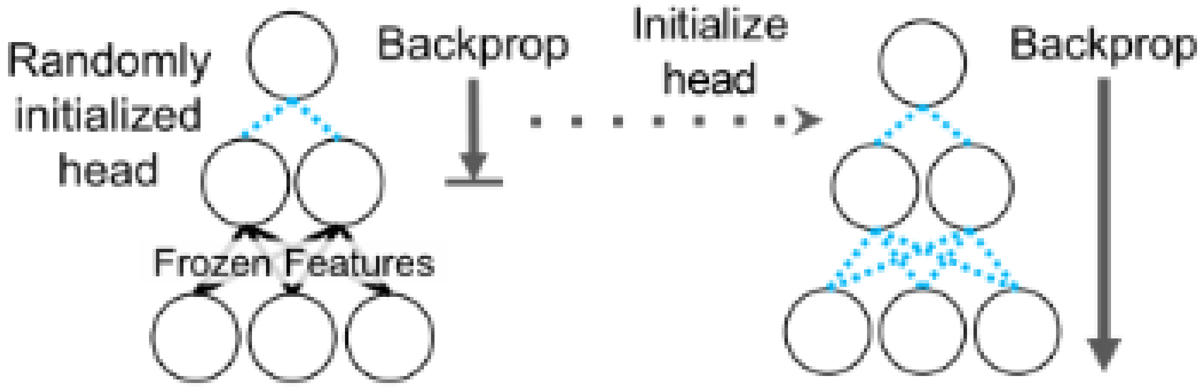
It depends.




Surgical fine-tuning improves adaptation to distribution shifts
Lee et al., ICLR 2023

# Fine-tune what?

A good default:




Slide: Chelsea Finn (Stanford)
Image: Fine-Tuning can distort pretrained features and underperform out-of-distribution
Kumar et al., ICLR 2022

# Transfer learning

What if our dataset on the target set is so small that even transfer learning does not help?

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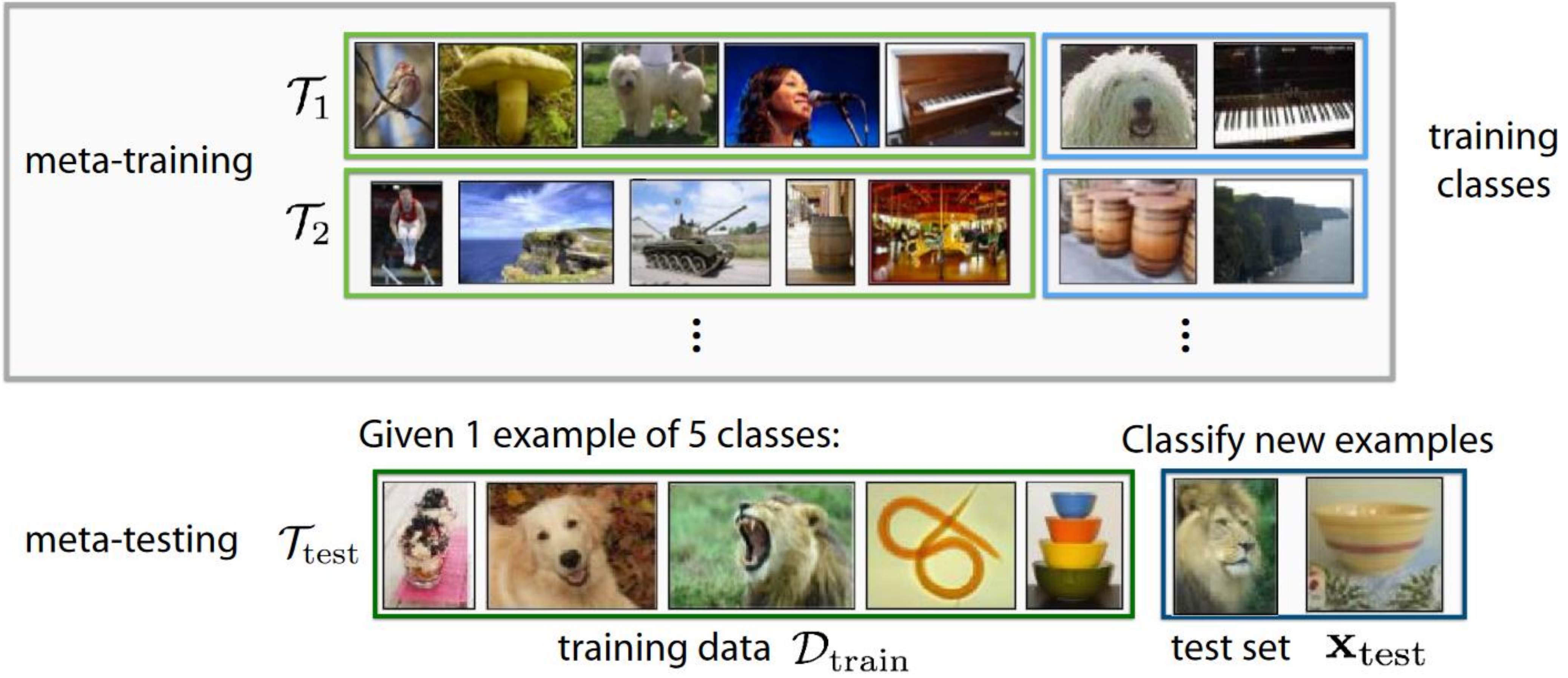
# Meta-learning




From: Stanford CS330

# Meta-learning

**Training:** Have access to tasks $\tau_1, \tau_2, \dots, \tau_n$, but not $\tau_{n+1}$.

**Transfer:** Have access to task $\tau_{n+1}$, but not $\tau_1, \tau_2, \dots, \tau_n$.

**Assumption:**

$\tau_{n+1}$ comes from the same task distribution as $\tau_1, \tau_2, \dots, \tau_n$.

# Black-box adaptation

- Design a giant neural network that takes the datasets as the input and outputs the parameters of a smaller network.

Yes, I really said this.

But sometimes we can get away with lower dimensional vectors.

- The smaller network performs the task $\tau_{n+1}$.

# Optimization-based adaptation

Learn a model such that when we take one (or some) gradient step in task $\tau_{n+1}$, it will perform good.

$$\underset{\theta}{\text{minimize}} \sum_{i=1}^{n} L\left(\theta - \alpha \nabla_\theta L\left(\theta, \tau_i^{tr}\right), \tau_i^{ts}\right)$$

# Optimization-based adaptation

1. Sample task $\tau_i$
2. Compute $\phi \leftarrow \theta - \nabla_\theta L(\theta, \tau_i^{tr})$
3. Update $\theta$ using $\nabla_\theta L(\phi, \tau_i^{ts})$

Note we will need the second gradient!

From: Stanford CS330

# Next time…

| | | | |
|---|---|---|---|
| **Week 11** | *Guest Lecture* | Prof. Heather Culbertson | TBD |
| Fri, Nov 8 | *Guest Lecture* | Dr. Aaquib Tabrez | Multimodal Explanation-based Reward Coaching and Decision Support to Improve Human-Robot Teaming |