CS 839: Foundation Models
Fine-Tuning, Specialization, Adaptation

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Announcements

- **Logistics:**
  - Homework 1 deadline pushed to Thursday.
- Class roadmap:

Tuesday Oct. 10	Fine-Tuning, Specialization, Adaptation
Thursday Oct. 12	Training
Tuesday Oct. 17	RLHF
Thursday Oct. 19	Data
Tuesday Oct. 24	Multimodal and Specialized Foundation Models

Outline

- **Fine-Tuning and Adapter Intro**
  - Fine-tuning vs. prompting, linear probing, etc. Full vs partial fine tuning vs adapting. Popular adapters
- **Cross-Modal Adaptation**
  - Frozen transformers, ORCA, aligning via optimal transport dataset distance
- **Model Editing**
  - Idea, MEND

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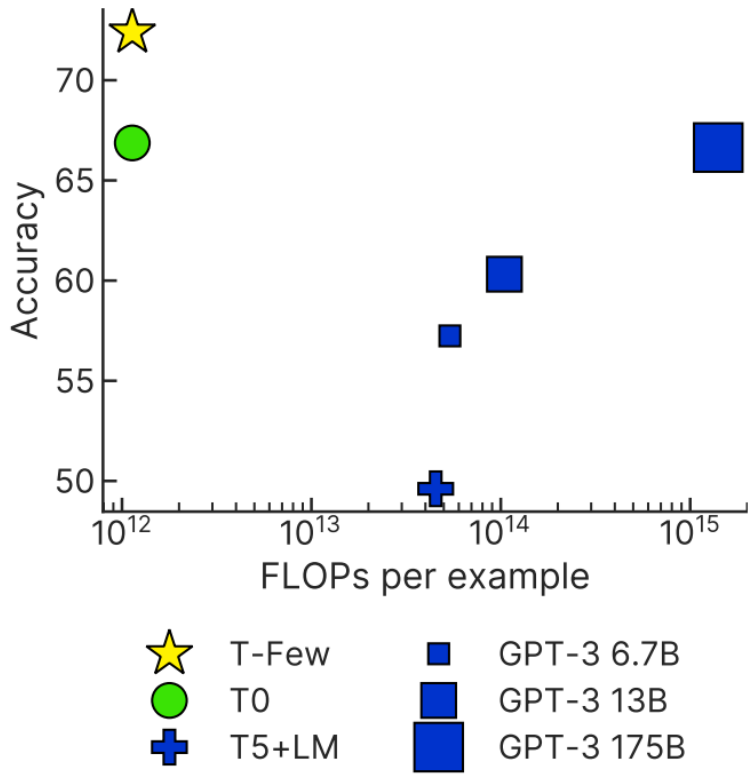
Before: **Prompting**

With prompting, we didn't change the model

- To improve performance, we used few-shot/ICL
- But, this might be **worse** than changing our model weights

Few-Shot Parameter-Efficient Fine-Tuning is Better and Cheaper than In-Context Learning

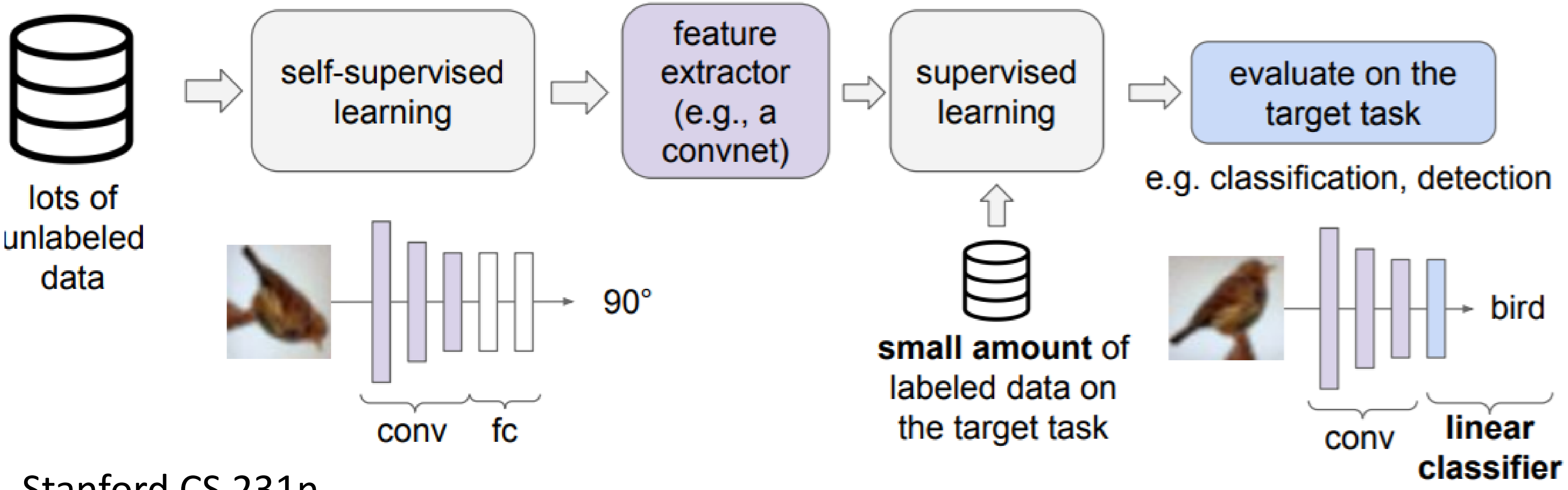
Liu et al '22



Before: **Frozen Models/Linear Probing**

We previously discussed freezing our model, and using just some trainable heads

- E.g., a linear model on top (called **linear probing**)
- Our self-supervised learning example



Stanford CS 231n

Full Fine-Tuning

Performance might still be bottlenecked,

- Frozen representations might not be suitable for task
- Might need lots of capacity on top to adapt
- **Change all the weights!**

```
>>> from transformers import AutoModelForSequenceClassification

>>> model = AutoModelForSequenceClassification.from_pretrained("bert-base-cased", num_labels=5)
```

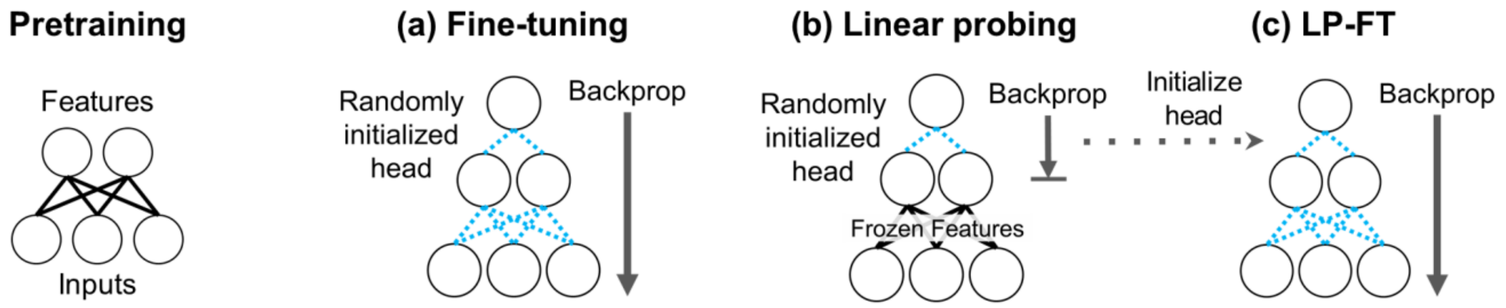
```
>>> trainer.train()
```

https://huggingface.co/docs/transformers/training

Full Fine-Tuning: **Downsides**

Fine-tuning all parameters is tough:

1. **Expensive:** just like training a full model
2. **Known to cause issues on OOD data…**
   - Fine-Tuning can Distort Pretrained Features and Underperform Out-of-Distribution



	(a) Fine-tuning	(b) Linear probing	(c) LP-FT
ID test	85.1%	82.9%	**85.7%**
OOD test	59.3%	66.2%	**68.9%**

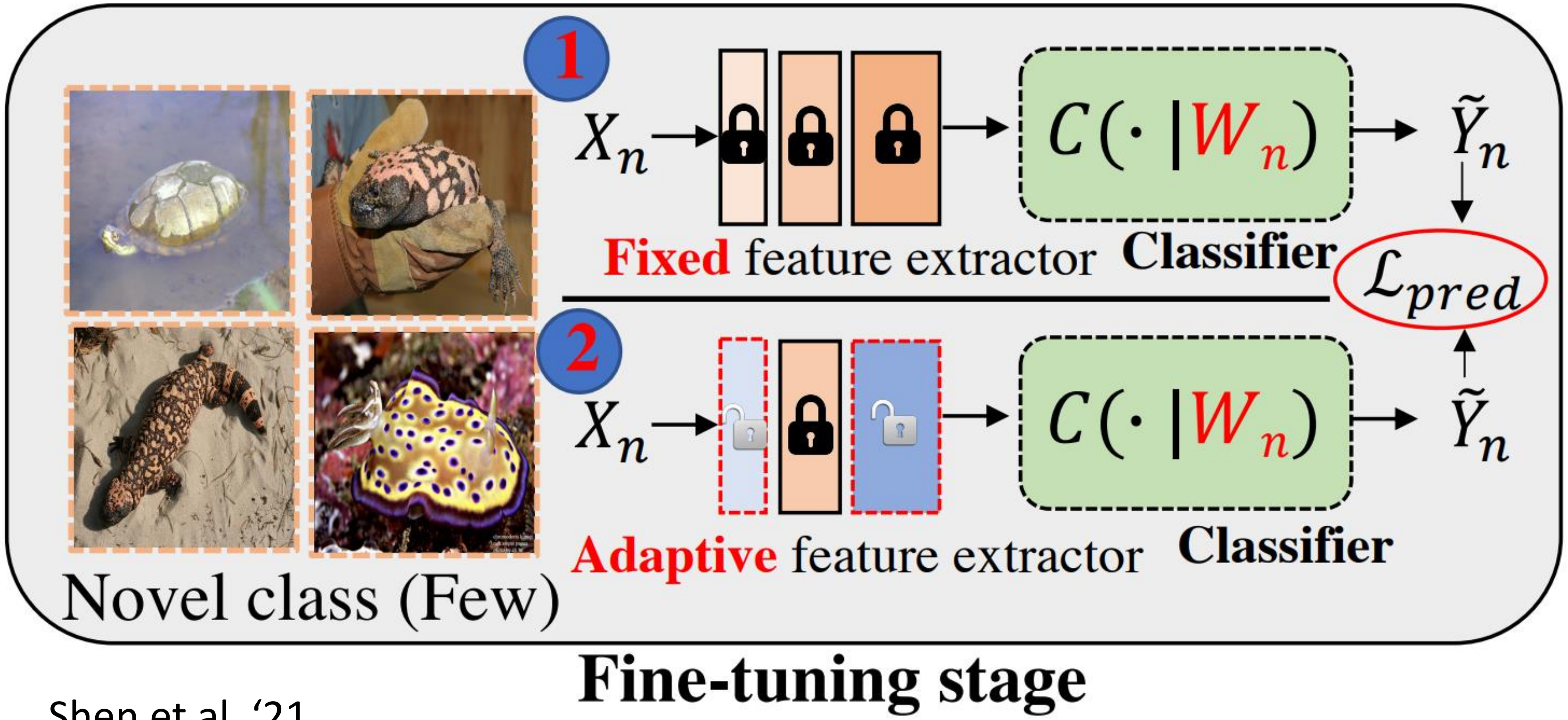
Average accuracies (10 distribution shifts)

Kumar et al '22

Partial Fine-Tuning

Full fine-tuning might be expensive

- Partial fine-tuning might be a good choice
- Only some layers change

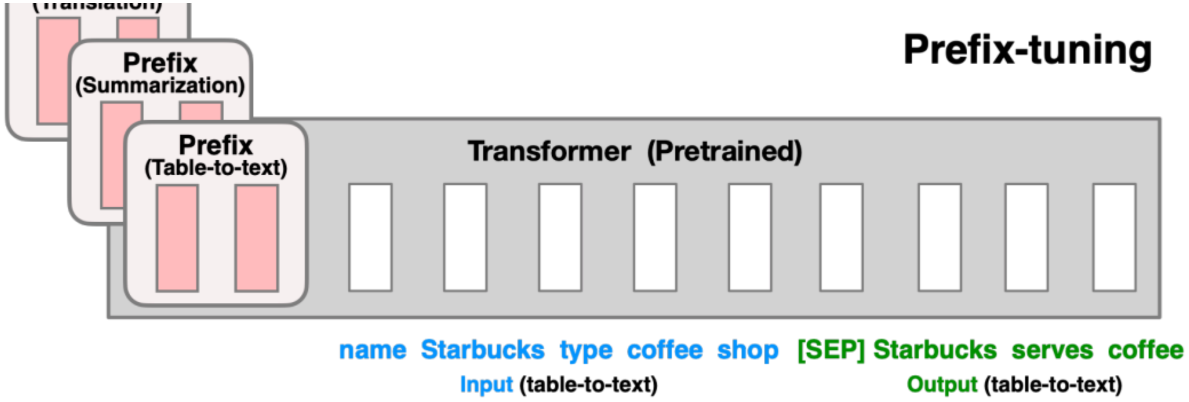


Shen et al, ‘21

Prefix-Tuning

Recall this *soft prompting* method.

- Prefixes are trainable parameters
- Train one for each goal task, only store these new parameters
- Enables cheap **adaptation** of frozen language model

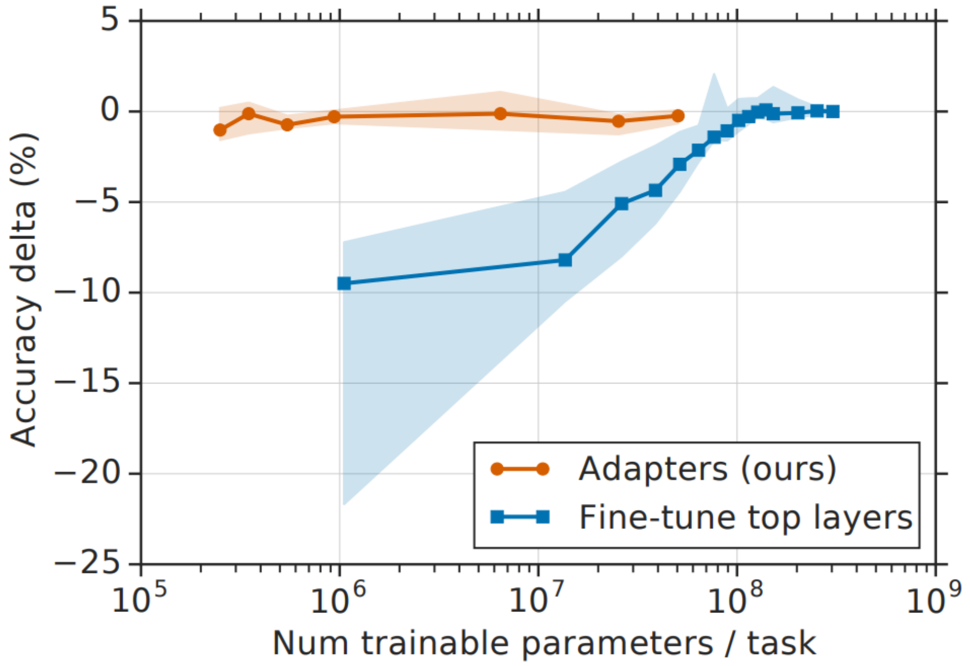


Li and Liang ‘21

Parameter-Efficient Fine-Tuning (PEFT)

None of these methods were full satisfying

- Have to figure out what layers to train, have to interpolate with prompts, etc.
  - Lots of choices!
- If we fine-tune too many parameters, that gets expensive…
  - But top only, performance isn't **great**
- Houlsby et al '19:



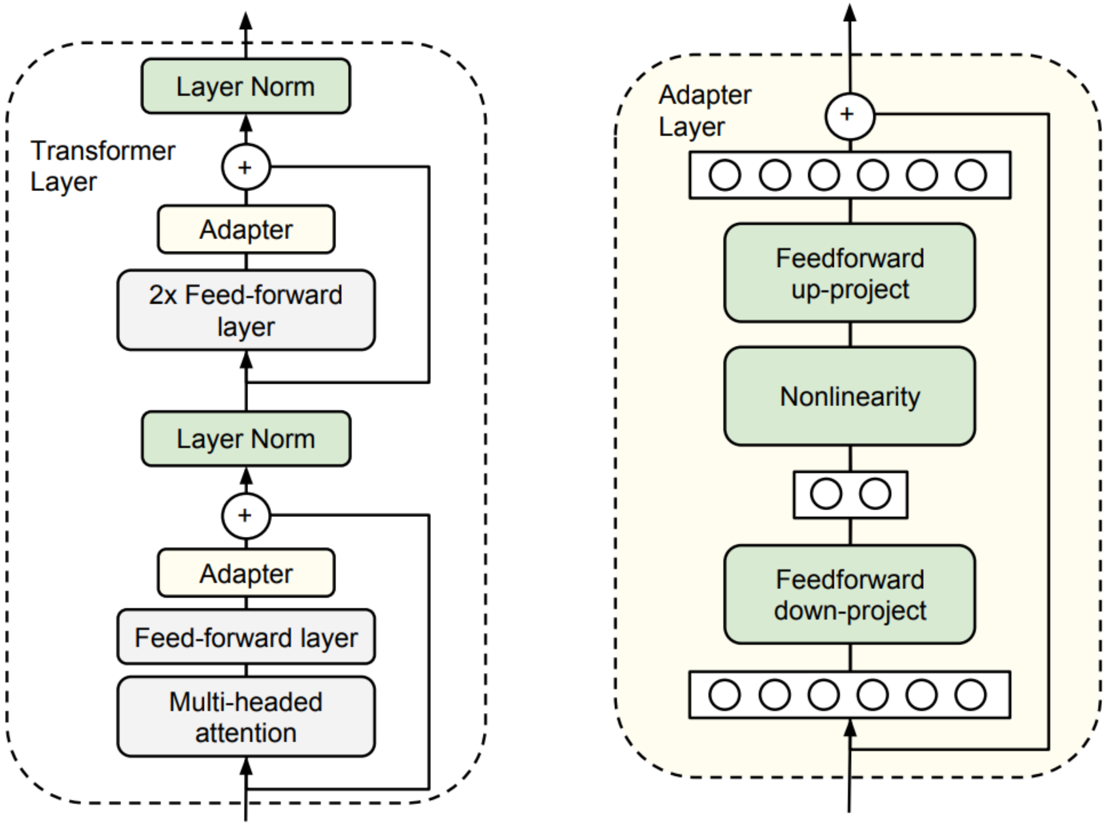
PEFT: **Adapters**

Want two things in PEFT

- Good performance (accuracy, etc.)
- Parameter efficiency

- Solution: **Adapters**
  - Small modules, inserted in between model and trained

Another **advantage:** no change to model, new modules for tasks



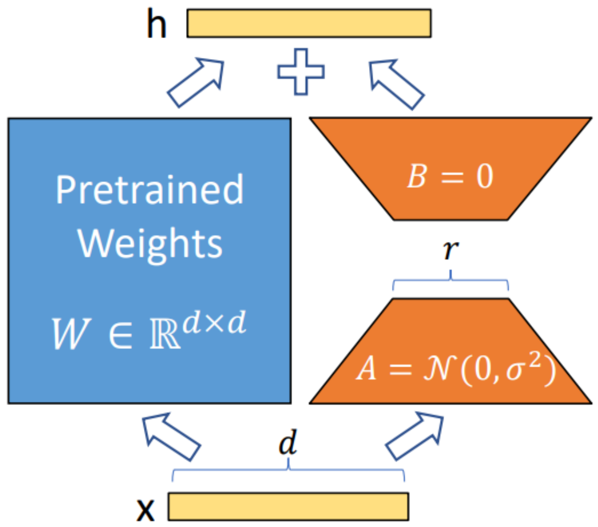
Houlsby et al '19

PEFT: **Low-Rank Adapters (LoRA)**

Perhaps the most popular variant

- LoRA makes an assumption on adapter layer structure
  - Specifically, should be low-rank
  - Intuition: the weight matrices already live close to a low-rank manifold

- Transformers, apply only to attention weight matrices



Hu et al '22

Break & Questions

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What About Other Modalities?

So far, mostly talked about language models.

- Suppose we want tasks that are not directly language-based
- Could just train a new model… but harder

Can we adapt language models? Lots of c**hallenges:**

- Must change data types
- How do we know modalities are usable together?

Cross-Modal: **FPTs**

Frozen language-pretrained transformers (Lu et al ‘21)

Basic idea:

- Change the **input/output layers** (here, linear)
- Layer norm parameters
- Everything else frozen

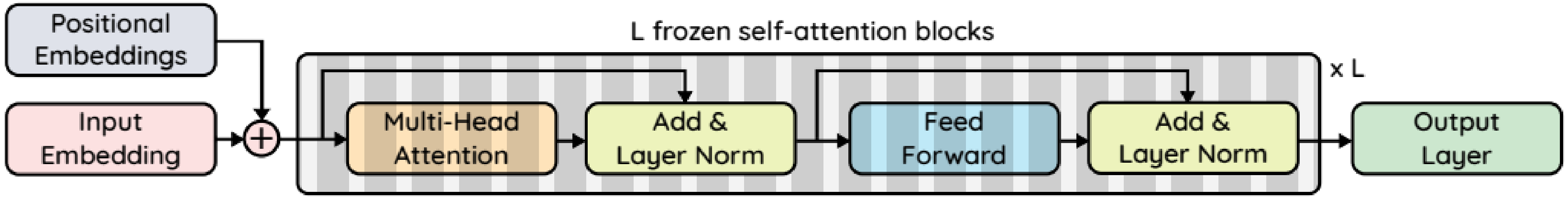


Figure 2: Frozen Pretrained Transformer (FPT). The self-attention & feedforward layers are frozen.

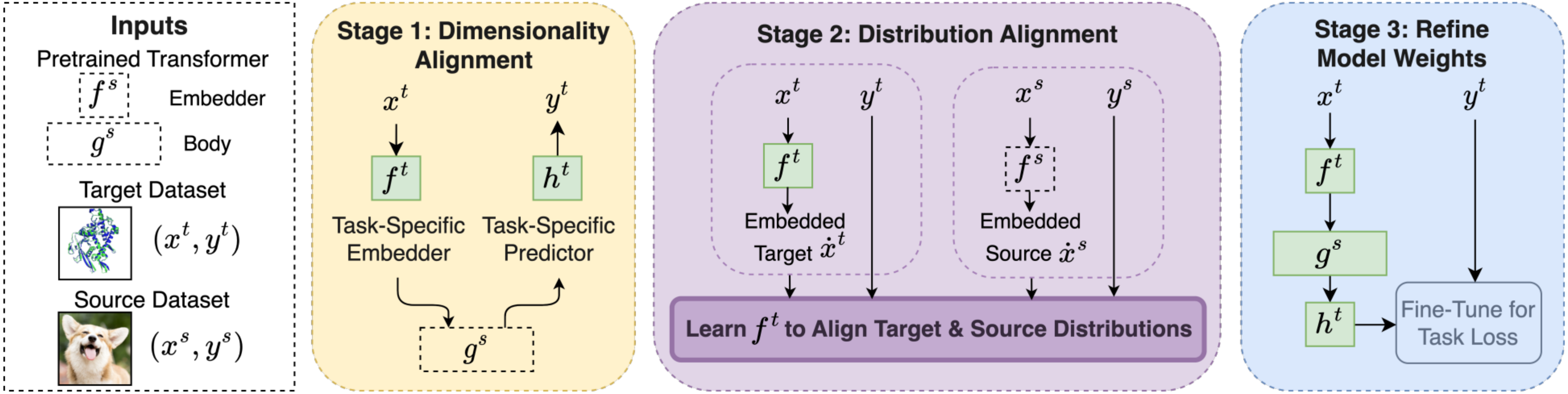
Lu et al, 21

Cross-Modal: **ORCA**

Performance bottleneck in FPTs

A more powerful approach: ORCA (Shen et al ‘23)

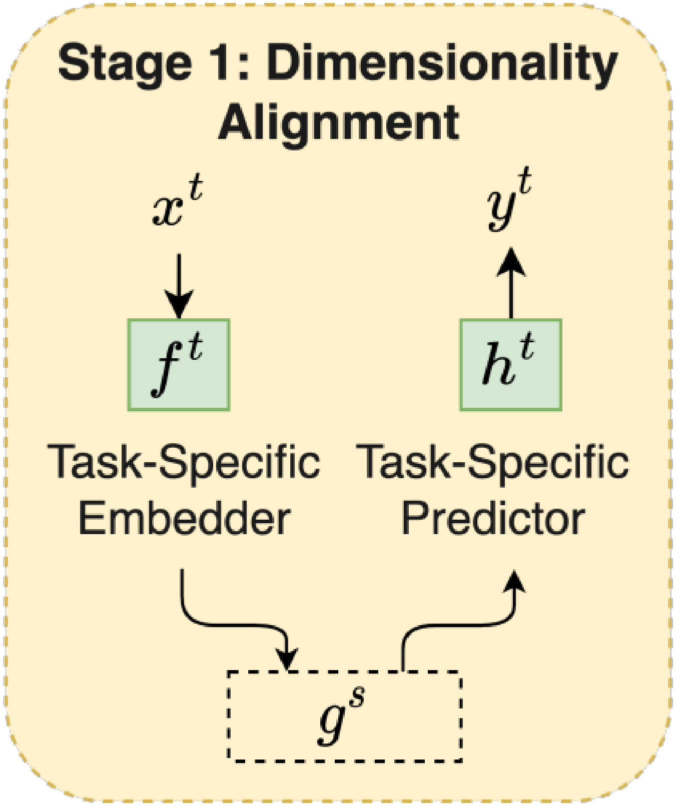
- Adds: distribution alignment step (align then refine)



ORCA: **Stage 1**

Let’s understand each stage of ORCA

- Stage 1: compatibility for inputs and outputs
- Custom input and output embedders that depend on the task
  - Input example: convolutional layers for image settings
  - Output example: average pooling+linear layer for classification



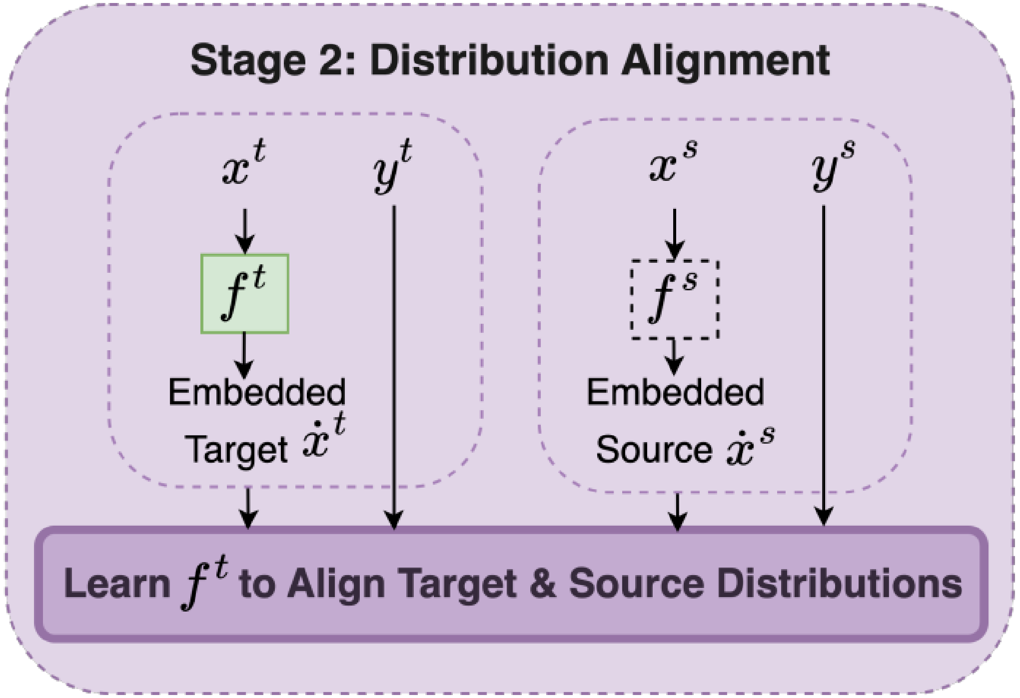
ORCA: **Stage 2**

Let's understand each stage of ORCA

- Stage 2: distribution alignment
- Intuition:
  - Change embeddings so target features **resemble** source features

- Learn the function f^t **that minimizes distance between**

  $(f^t(x^t), y^t)$ and $(f^s(x^s), y^s)$

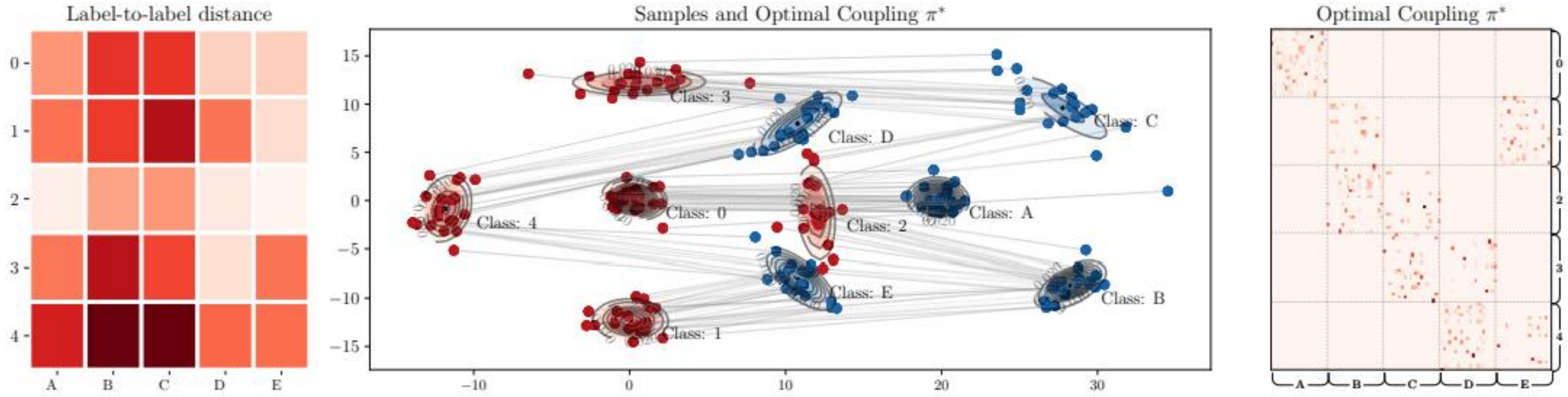


ORCA: **Distributional Distances**

Want: learn the function f^t **that minimizes distance between**

$(f^t(x^t), y^t)$ and $(f^s(x^s), y^s)$

- How?
- Need a distance function on these distributions
- Here, **optimal transport dataset distance** (OTDD)



Interlude: **Optimal Transport**

In optimal transport, we solve

$$\inf\left\{\int_{X\times Y} c(x,y)\,\mathrm{d}\gamma(x,y)\,\middle|\,\gamma\in\Gamma(\mu,\nu)\right\},$$

Cost or **distance** of moving x to y

The two **marginals** we care about, i.e., on x and y

- Want to "move" distribution on *x* to one on *y*
  - Output is a joint distribution with the original marginals
- But there's a cost to moving x to y, given by c(x,y)

ORCA: **Distributional Distances**

Want: learn the function f^t **that minimizes distance between**

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- Need a distance function on these distributions
- Here, **optimal transport dataset distance** (OTDD)

$$d_{\mathcal{Z}}\big((x,y),(x',y')\big) \triangleq \big(d_{\mathcal{X}}(x,x')^p + \mathbf{W}_p^p(\alpha_y,\alpha_{y'})\big)^{1/p}$$

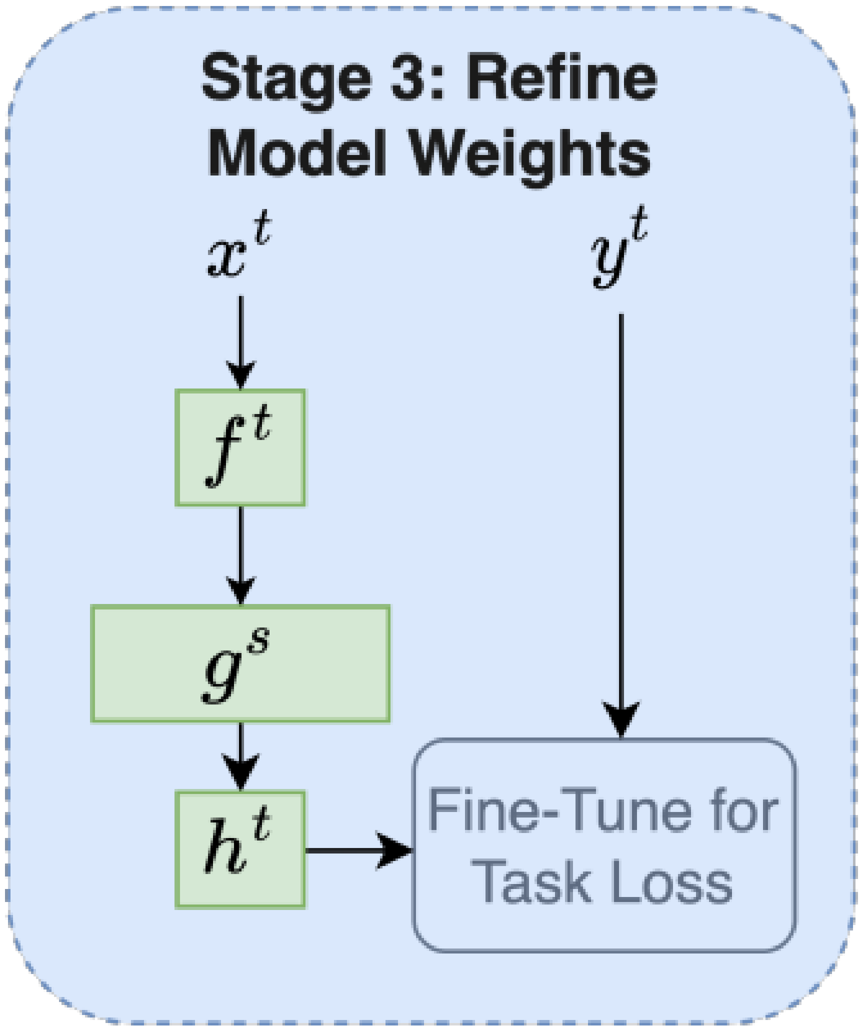
i.e., Euclidean distance

p-**Wasserstein distance** on P(x|y)

ORCA: **Stage 3**

Let's understand each stage of ORCA

- Stage 3: fine-tune the input and output network weights
  - For particular tasks
  - Or, could do any other variant of what we've talked about…



ORCA: **Results**

Extremely good, even against state-of-the-art results

- Compare to Neural Architecture Search (NAS)
  - Produces custom architectures that hit sota for various tasks
  - Same procedure on many types of tasks works well:

	CIFAR-100 0-1 error (%)	Spherical 0-1 error (%)	Darcy Flow relative ℓ_2	PSICOV MAE_8	Cosmic 1-AUROC	NinaPro 0-1 error (%)	FSD50K 1- mAP	ECG 1 - F1 score	Satellite 0-1 error (%)	DeepSEA 1- AUROC
Hand-designed	19.39	67.41	8E-3	3.35	**0.127**	8.73	0.62	**0.28**	19.80	0.30
NAS-Bench-360	23.39	48.23	2.6E-2	2.94	0.229	7.34	0.60	0.34	12.51	0.32
DASH	24.37	71.28	7.9E-3	3.30	0.19	**6.60**	0.60	0.32	12.28	**0.28**
Perceiver IO	70.04	82.57	2.4E-2	8.06	0.485	22.22	0.72	0.66	15.93	0.38
FPT	10.11	76.38	2.1E-2	4.66	0.233	15.69	0.67	0.50	20.83	0.37
ORCA	**6.53**	**29.85**	**7.28E-3**	**1.91**	0.152	7.54	**0.56**	**0.28**	**11.59**	0.29

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Model Editing

So far, adapting to new tasks

- But what if we just want to change the model?

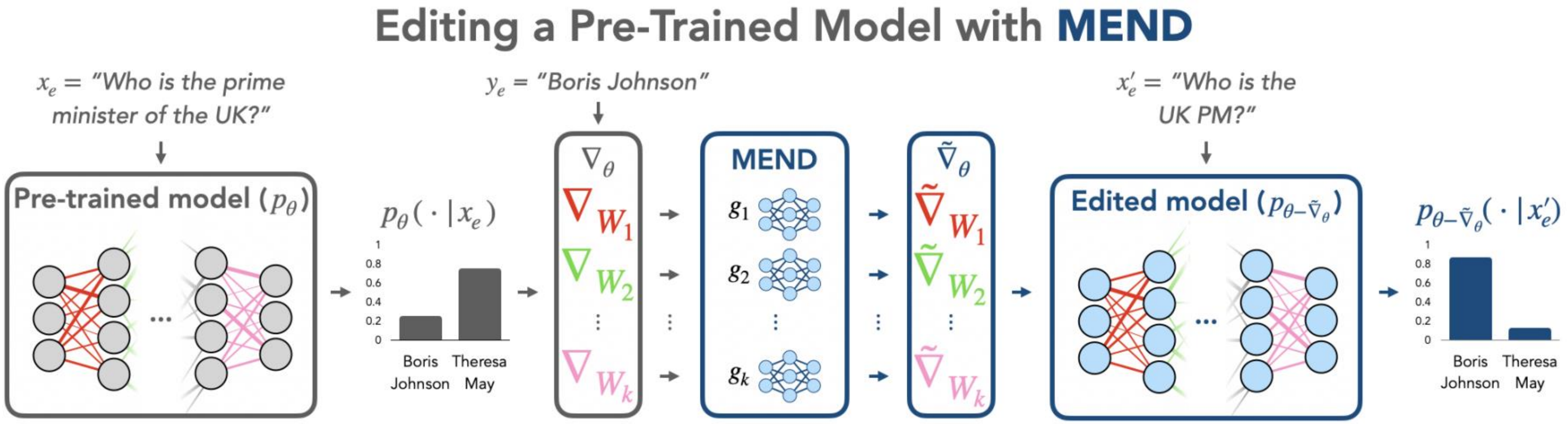
Why?

- Models have outdated (or wrong!) information in them
- Need to update these facts… but fine-tuning on just one point can be hard
  - Overfit to the point
  - May change other aspects

Model Editing: **MEND**

Fast editing with Model Editor Networks with Gradient Decomposition (MEND)

- Mitchell et al '22



Bibliography

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- Houlsby et al ’19, Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin de Laroussilhe, Andrea Gesmundo, Mona Attariyan, Sylvain Gelly, “Parameter-Efficient Transfer Learning for NLP” (https://arxiv.org/abs/1902.00751)

Thank You!