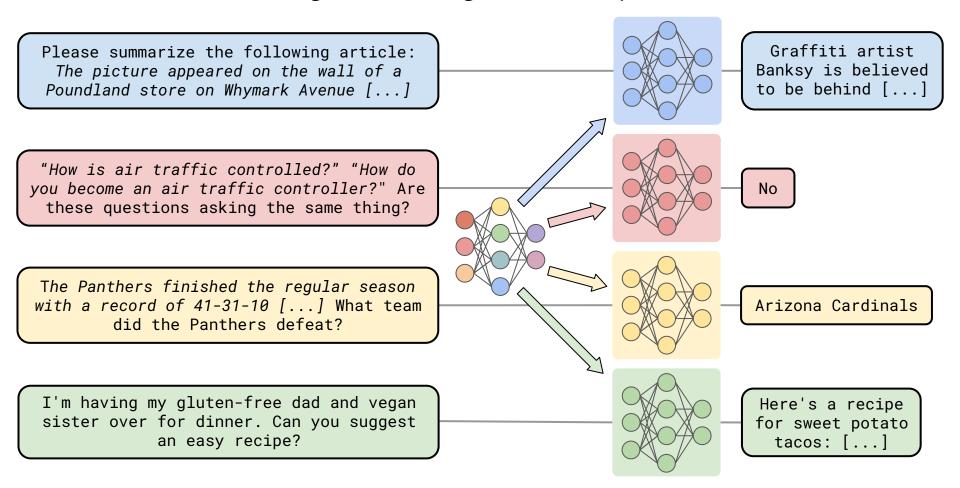
# Build an Ecosystem, Not a Monolith Colin Raffel



## Transfer learning: fine-tuning to create specialized models



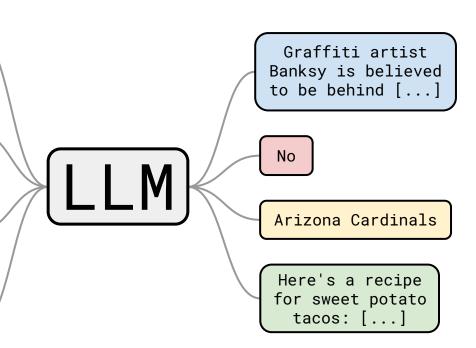
## LLMs as general-purpose monolithic models

Please summarize the following article: The picture appeared on the wall of a Poundland store on Whymark Avenue [...]

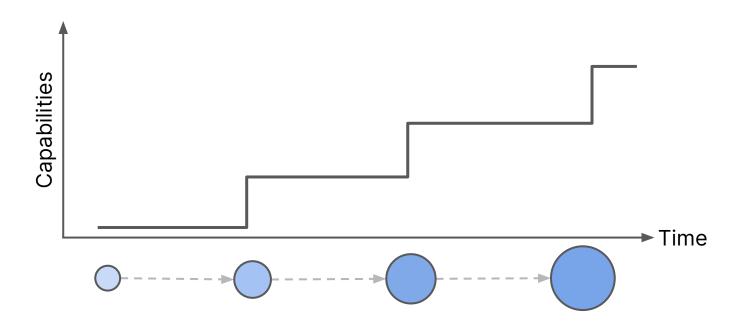
"How is air traffic controlled?" "How do you become an air traffic controller?" Are these questions asking the same thing?

The Panthers finished the regular season with a record of 41-31-10 [...] What team did the Panthers defeat?

I'm having my gluten-free mom and vegan sister over for dinner. Can you suggest an easy recipe?



## Monolithic model development involves wholesale replacement



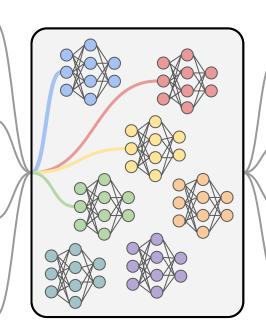
## Ecosystems of specialist models?

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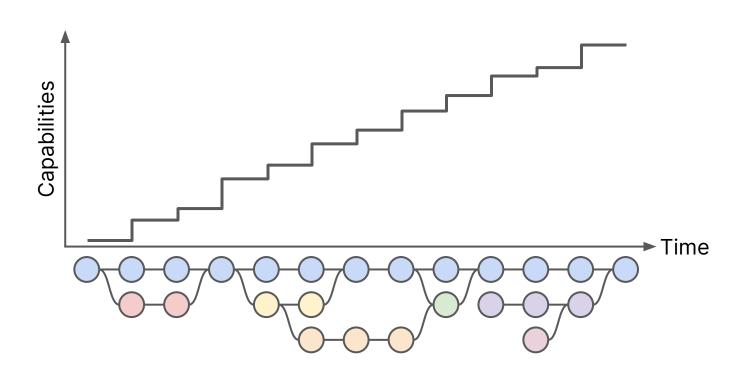
Graffiti artist Banksy is believed to be behind [...]

No

Arizona Cardinals

Here's a recipe for sweet potato tacos: [...]

## Collaborative ecosystem development will lead to continual improvements

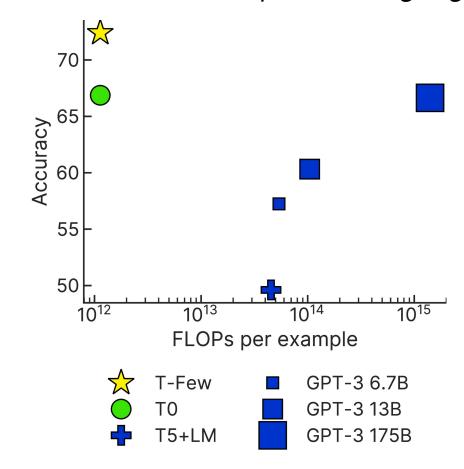


How and why should we build ecosystems of specialist models instead of monolithic models?

How and why should we build ecosystems of specialist models instead of monolithic models?

Specialist models are often **cheaper** and sometimes **better**.

## Smaller fine-tuned models often outperform larger generalist models



From "Few-Shot Parameter-Efficient Fine-Tuning is Better and Cheaper than In-Context Learning" by Liu et al.

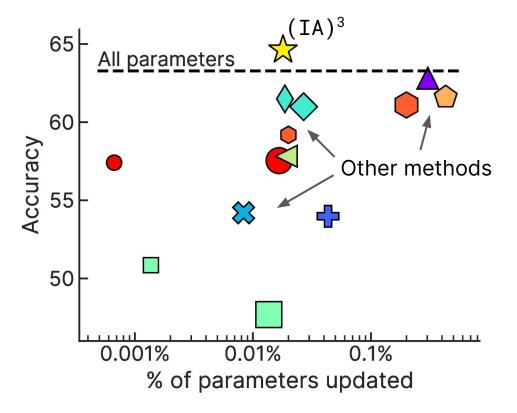
# Smaller fine-tuned models often outperform larger generalist models

	•		SOTA	GPT-4	PaLM	PaLM :	2
	•	WinoGrande	87.5 <sup>a</sup>	87.5 <sup>a</sup> (5)	85.1 <sup>b</sup> (5)	<b>90.9</b> (5)	
<b>O</b> 15 5	ecialist _ <b>-</b> nodels	ARC-C	<b>96.3</b> <sup>a</sup>	<b>96.3</b> <sup>a</sup> (25)	$88.7^c$ (4)	95.1 (4)	
Spe		<u>DROP</u> →	<b>►88.4</b> <sup>d</sup>	$80.9^{a}$ (3)	$70.8^b$ (1)	85.0 <sub>(3)</sub>	
me		StrategyQA	81.6 <sup>c</sup>	-	$81.6^{c}$ (6)	<b>90.4</b> (6)	
,,,,	1		<b>-91.2</b> <sup>e</sup>	-	$80.7^c$ (7)	90.4 (7)	
	1	XCOPA	$89.9^{g}$	-	$89.9^g$ (4)	<b>94.4</b> (4)	
	1	BB Hard	$65.2^{f}$	-	$65.2^{f}$ (3)	<b>78.1</b> (3)	
F_							
		Chi	→German				
	1	BLEURT	↑ MQN	(Human)	↓ BLEU	$RT \uparrow N$	MQM (Human)↓
-	PaLM 🔻	67.4		3.7	71.	7	1.2
	Google Transl	ate 68.5		3.1	73.	0	1.0
	PaLM 2	69.2		3.0	73.	3	0.9

How and why should we build ecosystems of specialist models instead of monolithic models?

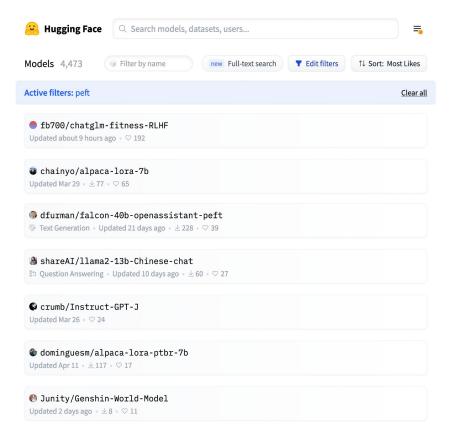
Each specialist model can be a **cheaply communicable** update to a base model.

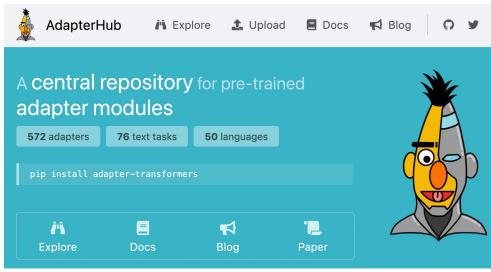
## $(IA)^3$ outperforms standard training while updating 0.01% of parameters



From "Few-Shot Parameter-Efficient Fine-Tuning is Better and Cheaper than In-Context Learning" by Liu et al.

## Existing "adapter" hubs have thousands of specialized models

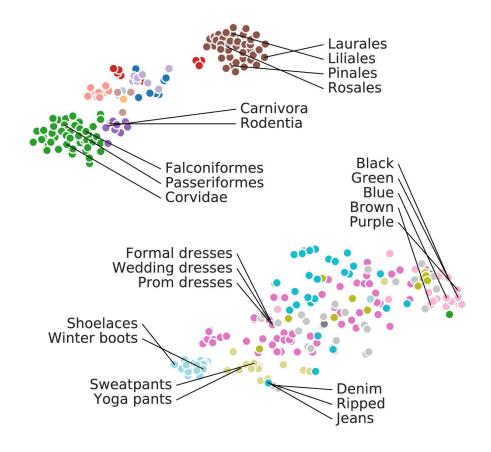




How and why should we build ecosystems of specialist models instead of monolithic models?

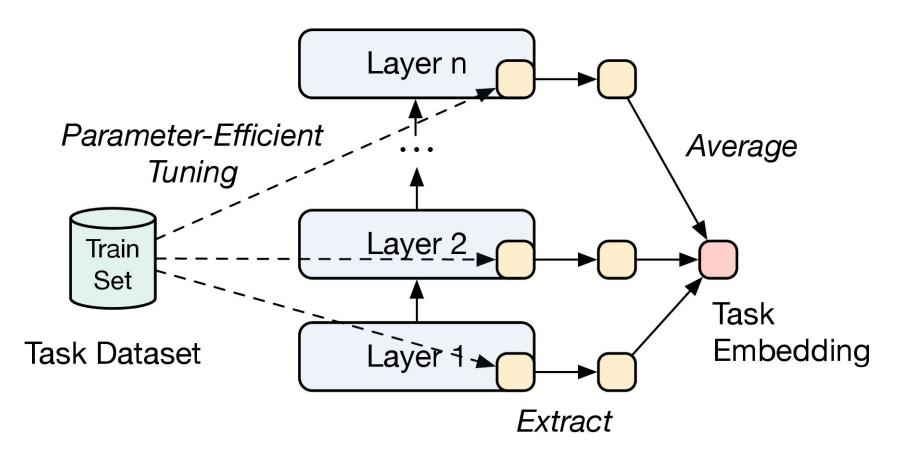
The appropriate model for a query should be **chosen automatically**.

## task2vec encodes task similarity via the Fisher information matrix



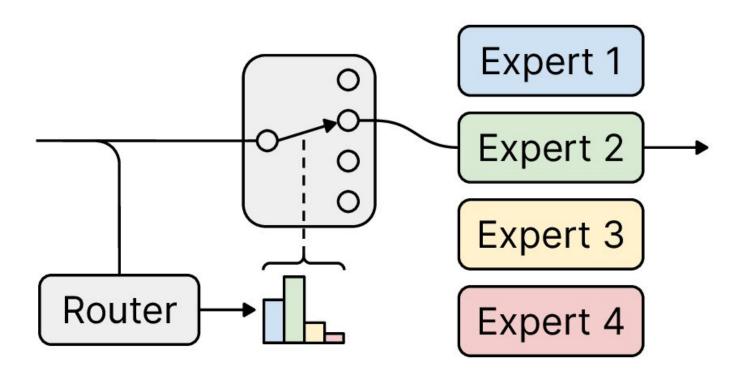
From "task2vec: Task Embedding for Meta-Learning" by Achille et al.

## Adapter parameters also encode task similarity



From "Efficiently Tuned Parameters are Task Embeddings" by Zhou et al.

Mixture-of-experts models perform adaptive routing inside the model

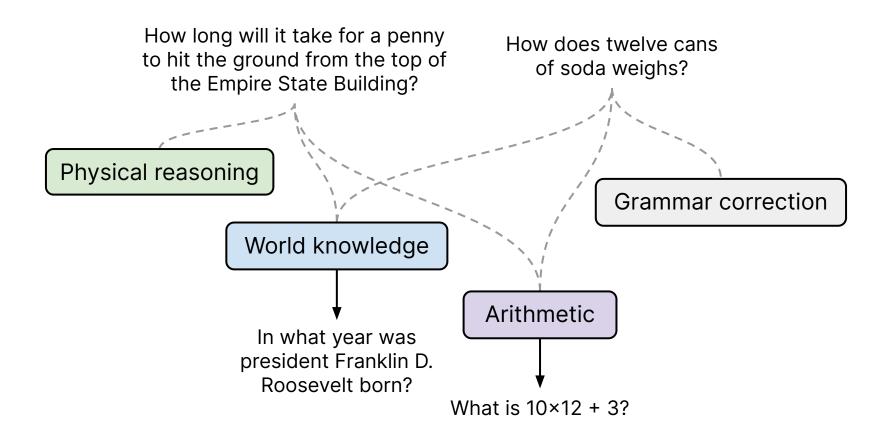


From "Soft Merging of Experts with Adaptive Routing" by Mugeeth et al.

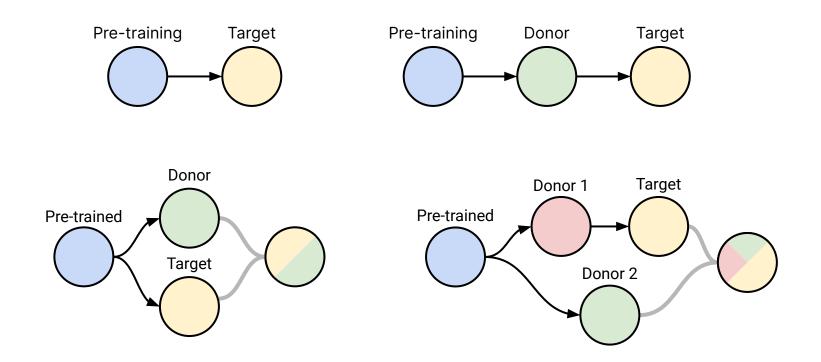
How and why should we build ecosystems of specialist models instead of monolithic models?

Capabilities can be **merged** across models.

## Tasks can be considered as a composition of skills

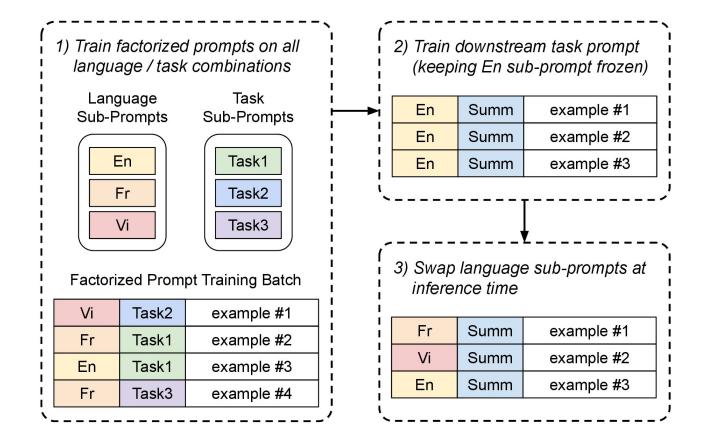


## Merging models enables new paths for transferring capabilities



From "Merging Models with Fisher-Weighted Averaging" by Matena et al.

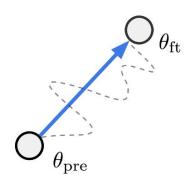
## Learning compositional adapters via prompt tuning



From "Overcoming Catastrophic Forgetting in Zero-Shot Cross-Lingual Generation" by Vu et al.

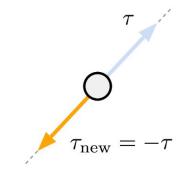
## Editing models with task vectors

a) Task vectors



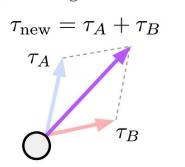
$$au = heta_{
m ft} - heta_{
m pre}$$

b) Forgetting via negation



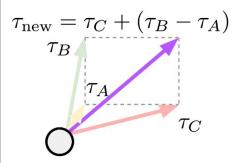
Example: making a language model produce less toxic content

c) Learning via addition



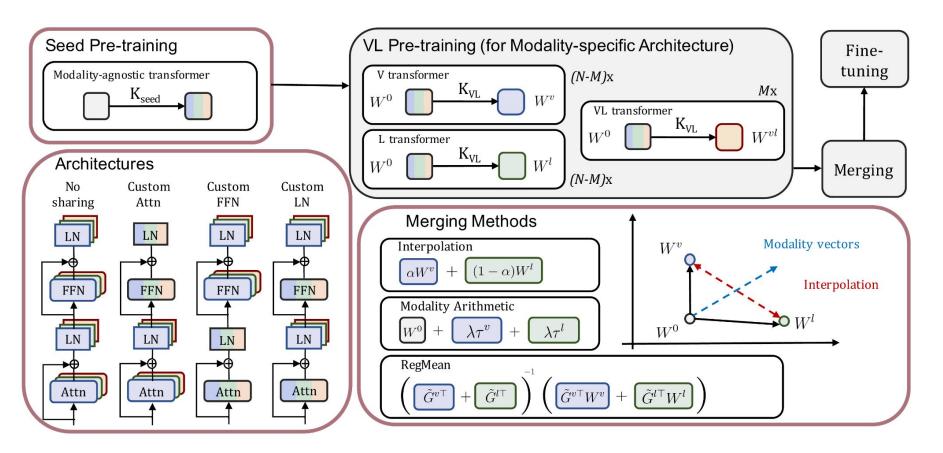
Example: building a multi-task model

d) Task analogies



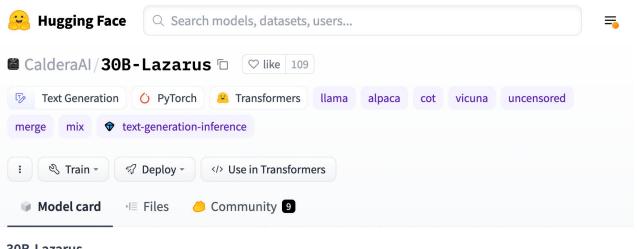
Example: improving domain generalization

## Merging can create multimodal models from unimodal models



From "An Empirical Study of Multimodal Model Merging" by Sung et al.

## Recent community-developed models are built via merging



#### 30B-Lazarus

#### **Composition:**

[] = applied as LoRA to a composite model | () = combined as composite models

[SuperCOT([gtp4xalpaca(manticorechatpygalpha+vicunaunlocked)]+[StoryV2(kaiokendev-SuperHOT-LoRA-prototype30b-8192)])]

## Model merging as an optimization problem

$$\arg\max_{\theta} \sum_{i=1}^{M} \lambda_i \log p(\theta|\mathcal{D}_i)$$

$$\max_{\theta} \sum_{i=1}^{Log\ posterior} \lambda_i \log p(\theta|\mathcal{D}_i)$$
 arg  $\max_{\theta} \sum_{i=1}^{M} \lambda_i \log p(\theta|\mathcal{D}_i)$  Hyperparameter controlling the importance of model  $i$ 

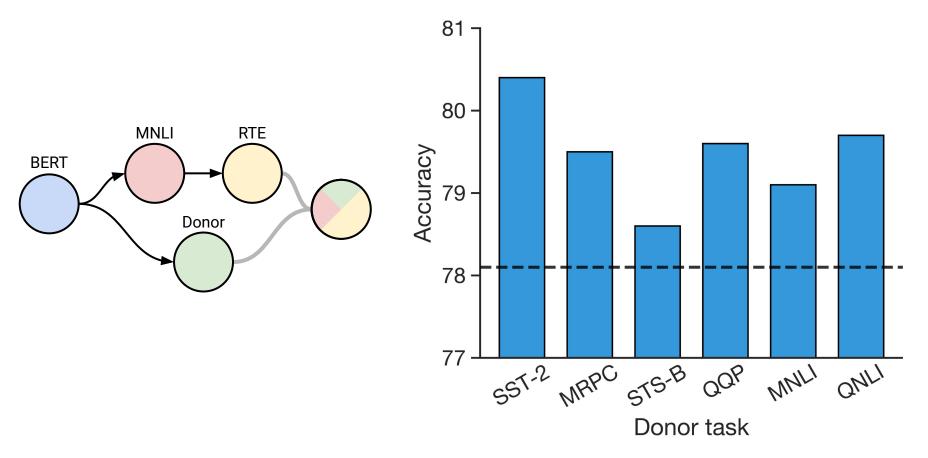
## Fisher merging uses the Laplace approximation

$$\arg \max_{\theta} \sum_{i=1}^{M} \lambda_{i} \log p(\theta | \mathcal{D}_{i})$$

$$\downarrow^{\theta} \sim \mathcal{N}(\theta_{i}, \hat{F}_{i}^{-1})$$

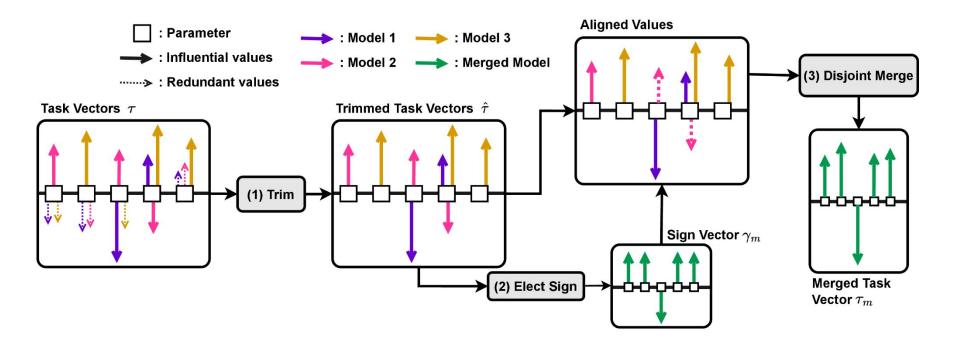
$$\theta^{*} = \frac{\sum_{i} \lambda_{i} \hat{F}_{i} \circ \theta_{i}}{\sum_{i} \lambda_{i} \hat{F}_{i}}$$

## Fisher merging can combine the capabilities of different models

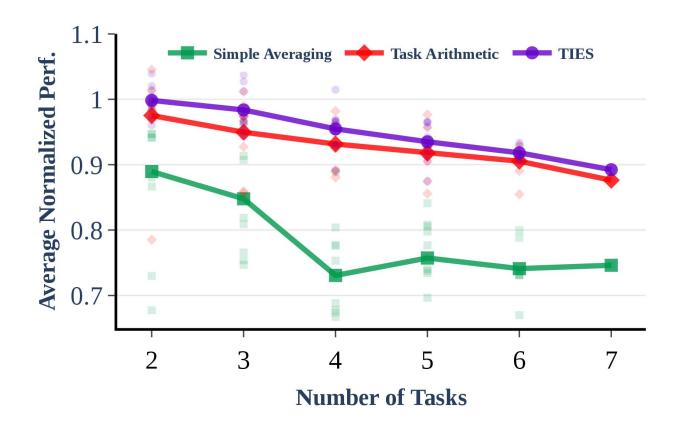


From "Merging Models with Fisher-Weighted Averaging" by Matena et al.

## TIES Merging resolves interference when merging models

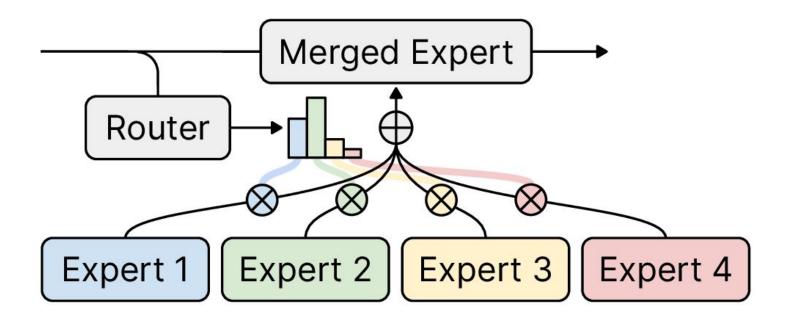


## TIES helps retain specialist model performance

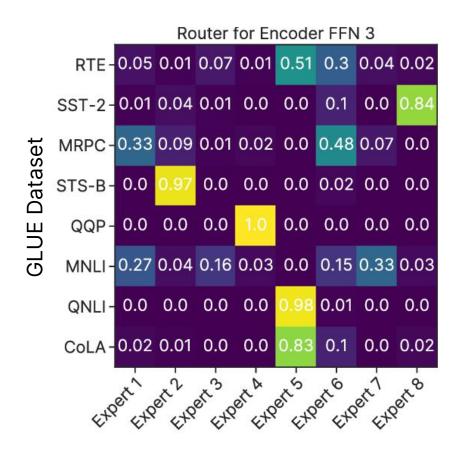


From "Resolving Interference When Merging Models" by Yadav et al.

## Differentiable routing between specialist submodels with SMEAR



## Experts specialize and are shared across different tasks



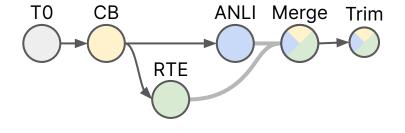
From "Soft Merging of Experts with Adaptive Routing" by Muqeeth et al.

How and why should we build ecosystems of specialist models instead of monolithic models?

An ecosystem can be built and used collaboratively with the right systems.

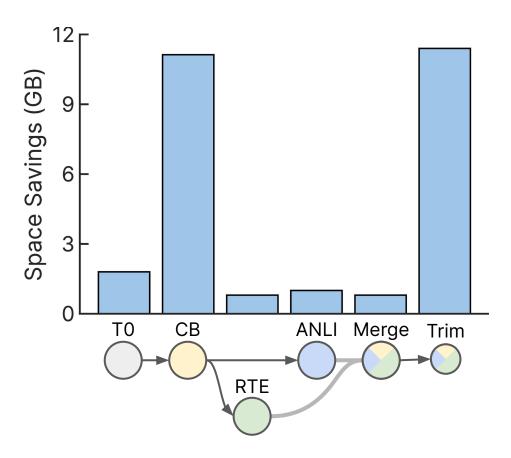
## git-theta tracks, merges, and updates models using the git workflow

```
$ git-theta track model.pt
$ git commit -am "Add initial model"
$ python finetune.py --dataset="cb" --method="lowrank"
$ git commit -am "Fine-tune on CB dataset with LoRA"
$ git checkout -b rte
$ python finetune.py --dataset="rte" --method="dense"
$ git commit -am "Fine-tune on RTE dataset"
$ git checkout main
$ python finetune.py --dataset="anli" --method="dense"
$ git commit -am "Fine-tune on ANLI dataset"
$ git merge rte
Fixing Merge Conflicts in model.pt
Actions:
  avg) average: Average parameter values.
     take_them: Use their change to the parameter.
     take_us: Use our change to the parameter.
     quit
  q)
\theta avg
$ git commit -am "Merge RTE and ANLI models"
$ python trim_unused_embeddings.py
$ git commit -am "Remove embeddings for unused tokens"
```



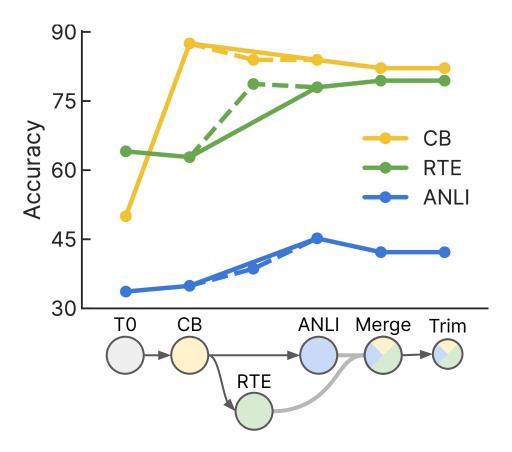
From "Git-Theta: A Git Extension for Collaborative Development of Machine Learning Models" by Kandpal et al.

## Communication-efficient updates result in significant space savings



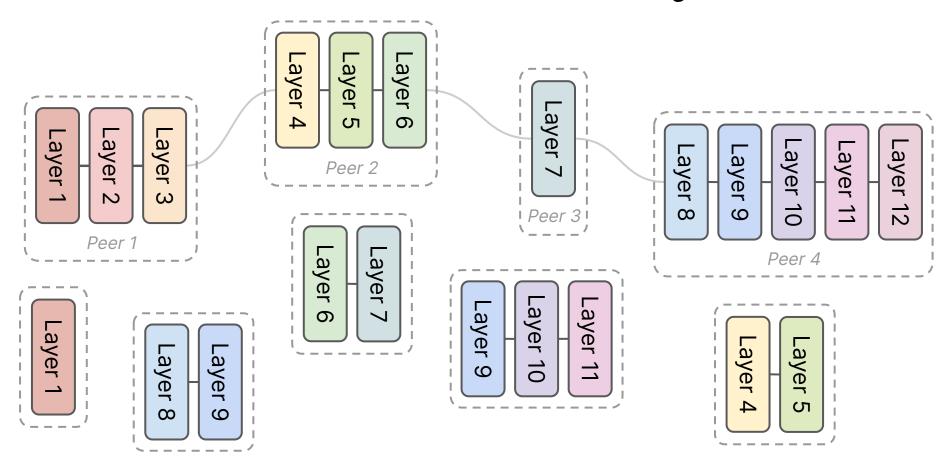
From "Git-Theta: A Git Extension for Collaborative Development of Machine Learning Models" by Kandpal et al.

## git-theta allows for continuous and collaborative model development



From "Git-Theta: A Git Extension for Collaborative Development of Machine Learning Models" by Kandpal et al.

## Petals enables distributed inference and fine-tuning over the internet



From "Petals: Collaborative Inference and Fine-tuning of Large Models" by Borzunov et al.

## Current Petals swarm status



#### Bootstrap peers: ••

#### Model stabilityai/StableBeluga2 (healthy):

Server ID »	Contributor ?	Version	Throughput »	Precision ?	Adapters ?	Cache ?	Avl. ?	Pings ?	Served blocks
vYA3Rn		2.0.1.post2	1333 tok/s	bf16 (nf4)		32768	Direct	Show	0:40
TfceK7		2.0.1.post2	1333 tok/s	bf16 (nf4)		32768	Direct	Show	40:80
uF3WXf	<b>Ç</b> FYY <mark>⊚</mark>	2.0.1.post2	1015 tok/s	bf16 (nf4)		24576	Direct	Show	57:76
sQzHZf	<b>Ģ</b> FYY <mark>⊚</mark>	2.0.1.post1	905 tok/s	f16 (nf4)		24576	Direct	Show	0:19
yRjqCy	Zetta	2.0.1.post2	1001 tok/s	bf16 (nf4)		30720	Relay	Show	19:38
m3Vfh7	<b>Ç</b> FYY <mark>⊚</mark>	2.0.1.post1	324 tok/s	bf16 (nf4)		29044	Direct	Show	69:80
5D4AAQ		2.0.1.post1	100 tok/s	bf16 (nf4)		32768	Relay	Show	75:80
dSkeys	Ç FYY⊚	2.0.1.post2	1015 tok/s	bf16 (nf4)		22528	Direct	Show	38:57

#### Model meta-llama/Llama-2-70b-chat-hf (healthy):

	Served blocks	Pings ?	Avl. ?	Adapters ? Cache ?	Precision ?	Throughput »	Version	Contributor ?	Server ID »
••••••	20:46	Show	Relay	32768	f16 (nf4)	8107 tok/s	2.0.1	jobs.trelent.com	kDJVjh
	0:3	Show	Relay	32768	f16 (nf4)	17 tok/s	2.0.1.post2		bsDGGc
***************************************	46:66	Show	Direct	12288	f16 (nf4)	670 tok/s	2.0.1.post1	nora	MWaAxr
***************************************	60:80	Show	Direct	12288	f16 (nf4)	670 tok/s	2.0.1.post1	nora	rgNAo9
	0:20	Show	Direct	12288	f16 (nf4)	670 tok/s	2.0.1.post1	nora	RPFSct

## Thanks.

Please give me feedback:

http://bit.ly/colin-talk-feedback

craffel@gmail.com