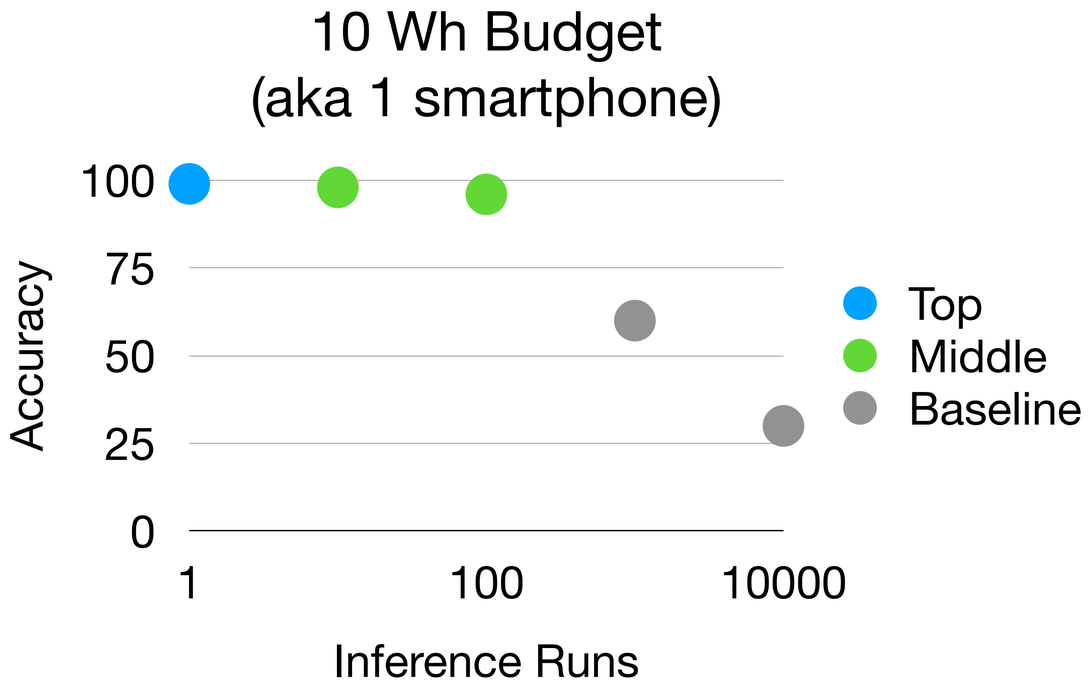
Main plot in final report

How many times can I run inference on a phone battery?

- Produce a performance-under-budget curve:
  Model accuracy vs *Number of times you can run inference*.



- We have provided all teams with multimeters to measure device power draw.
- Teams with server-level projects can use nvidia-smi, Intel RAPL interface, etc.
- Not all data points need to be “same” model
  1. Different detectors
  2. Different feature extractors
  3. Different size vocabularies
  4. Different image resolutions

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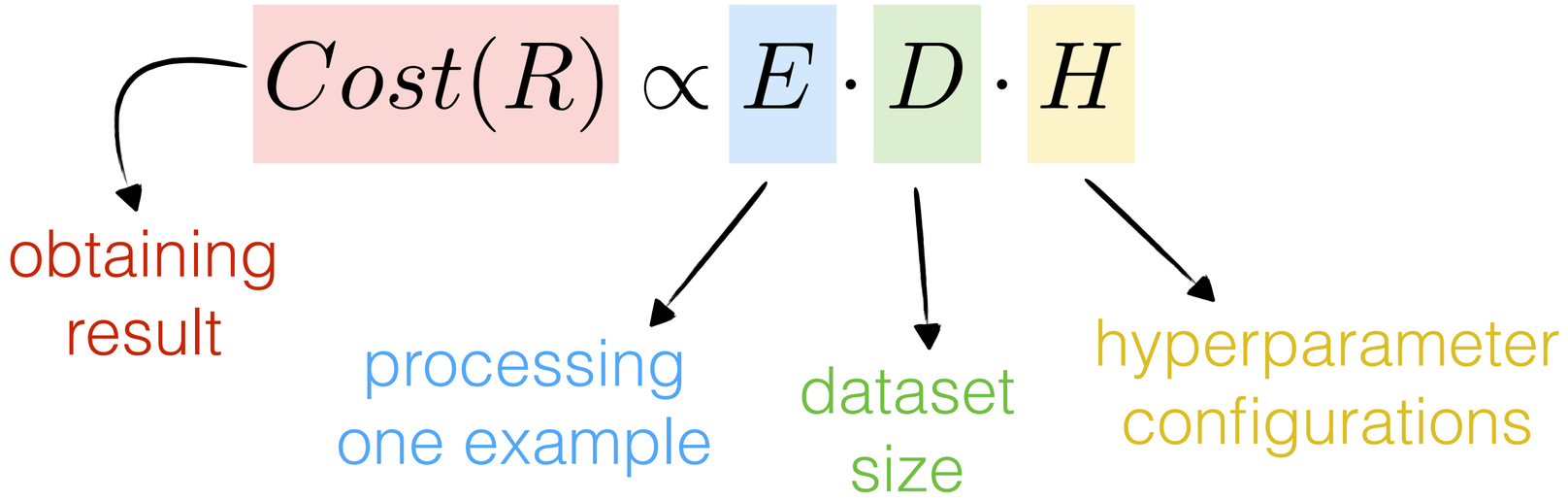
Accelerating Training

Off- and on-device

Emma Strubell & Yonatan Bisk

Training efficiency



Equation from: Schwartz, Dodge, Smith, Etzioni. Green AI. Communications of the ACM, December 2020.

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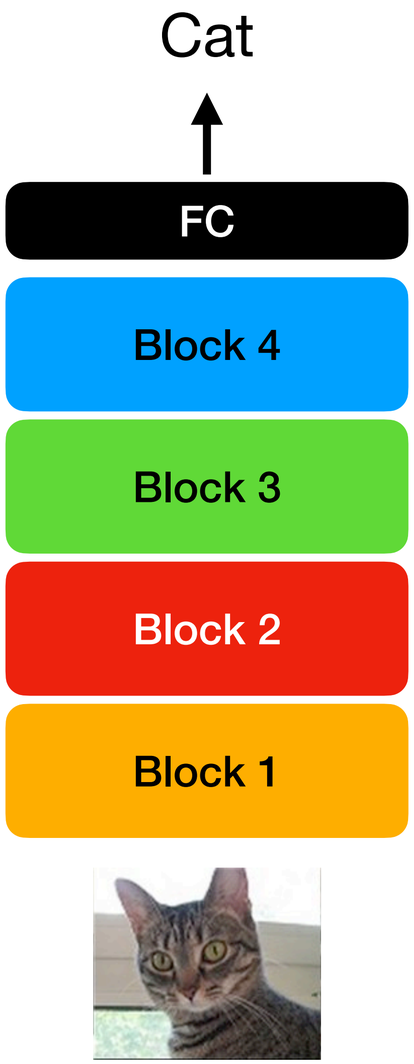
Avoiding ~~Accelerating~~ Training

Off- and on-device

Emma Strubell & Yonatan Bisk

When and What to train?



Which layer should change?

New class:

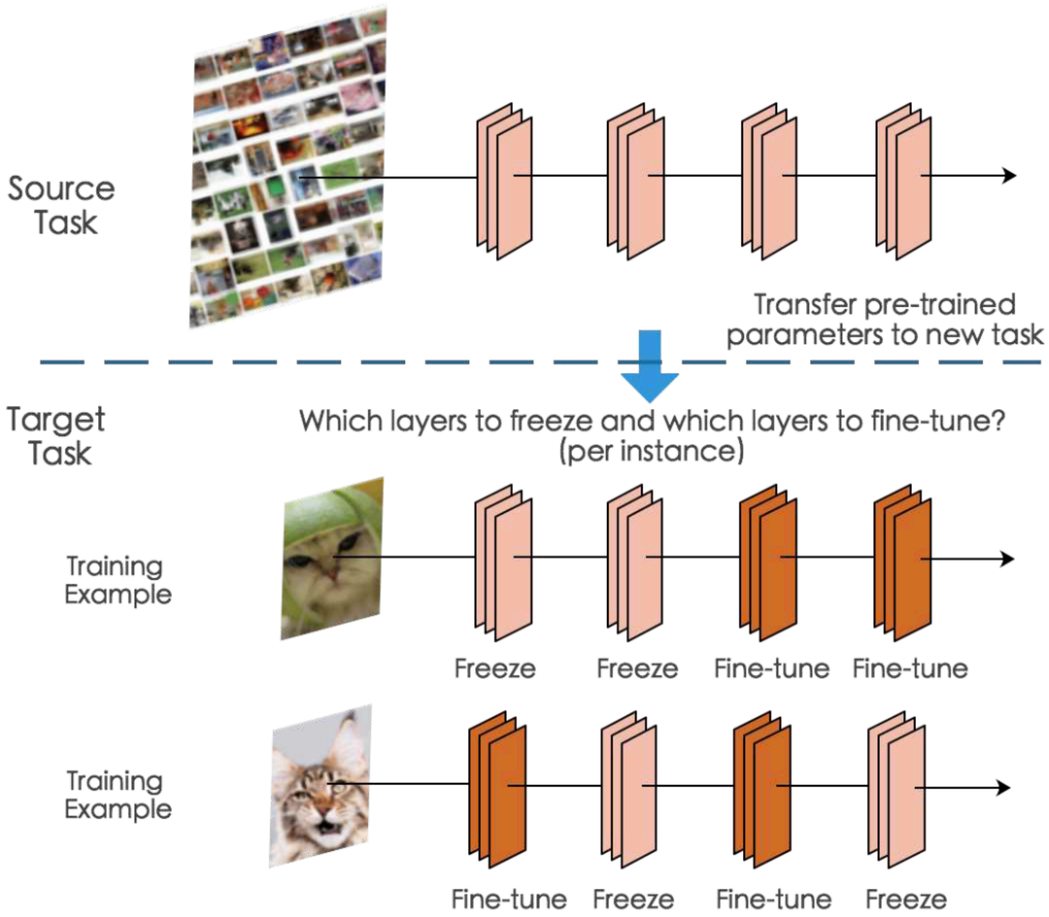
Felis catus

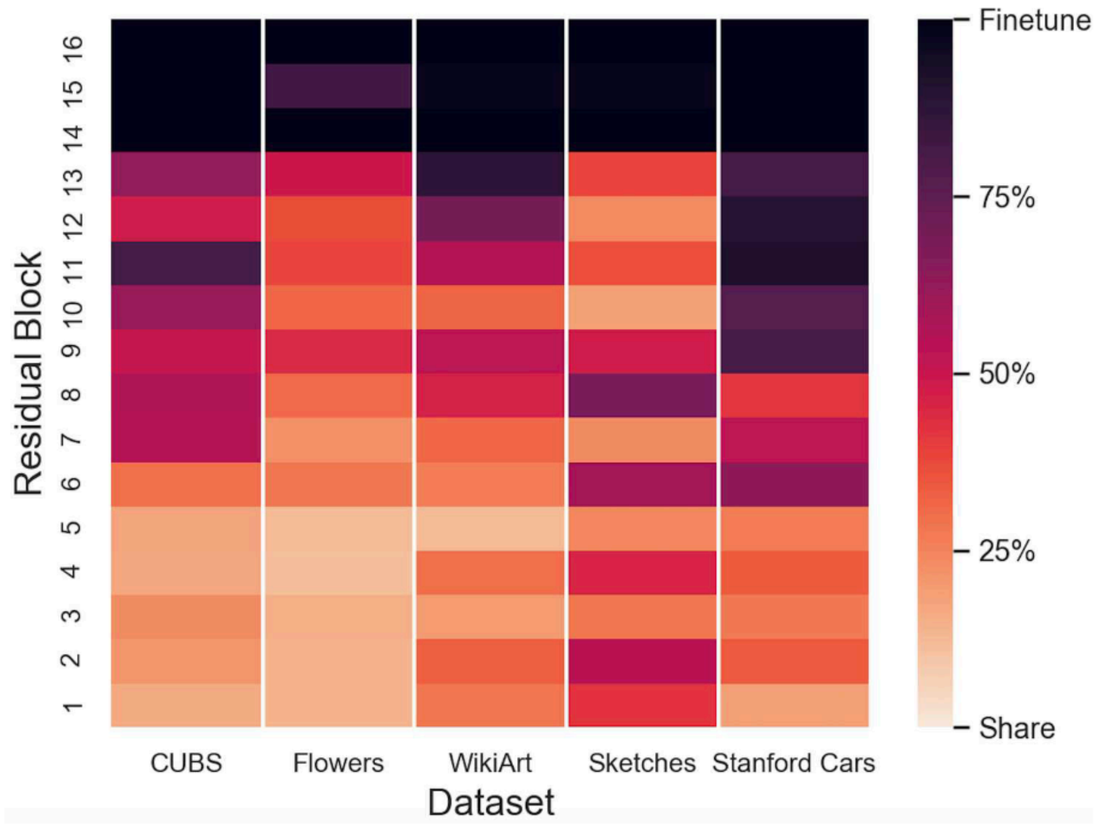
Dog

Yellow

Tumor

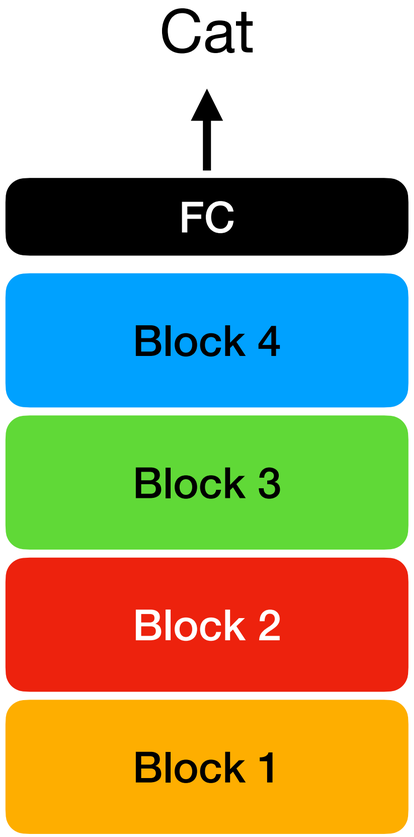
Learn where to adapt





SpotTune: Transfer Learning through Adaptive Fine-tuning
CVPR 2019

When and What to train?



Which should change?

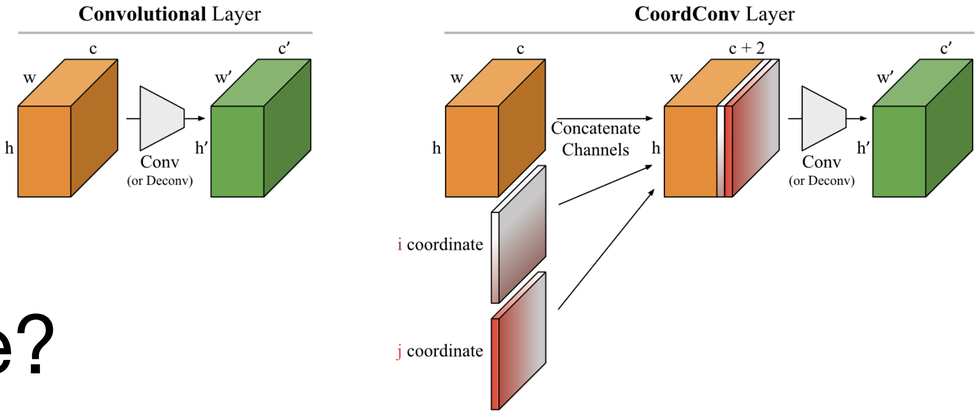
New task:

Coordinate of cat's nose

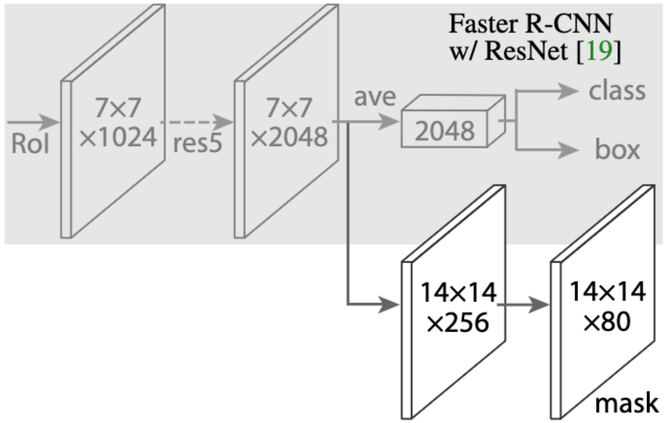
Training CLIP

Input to captioning model

Mask prediction



https://arxiv.org/abs/1807.03247v2



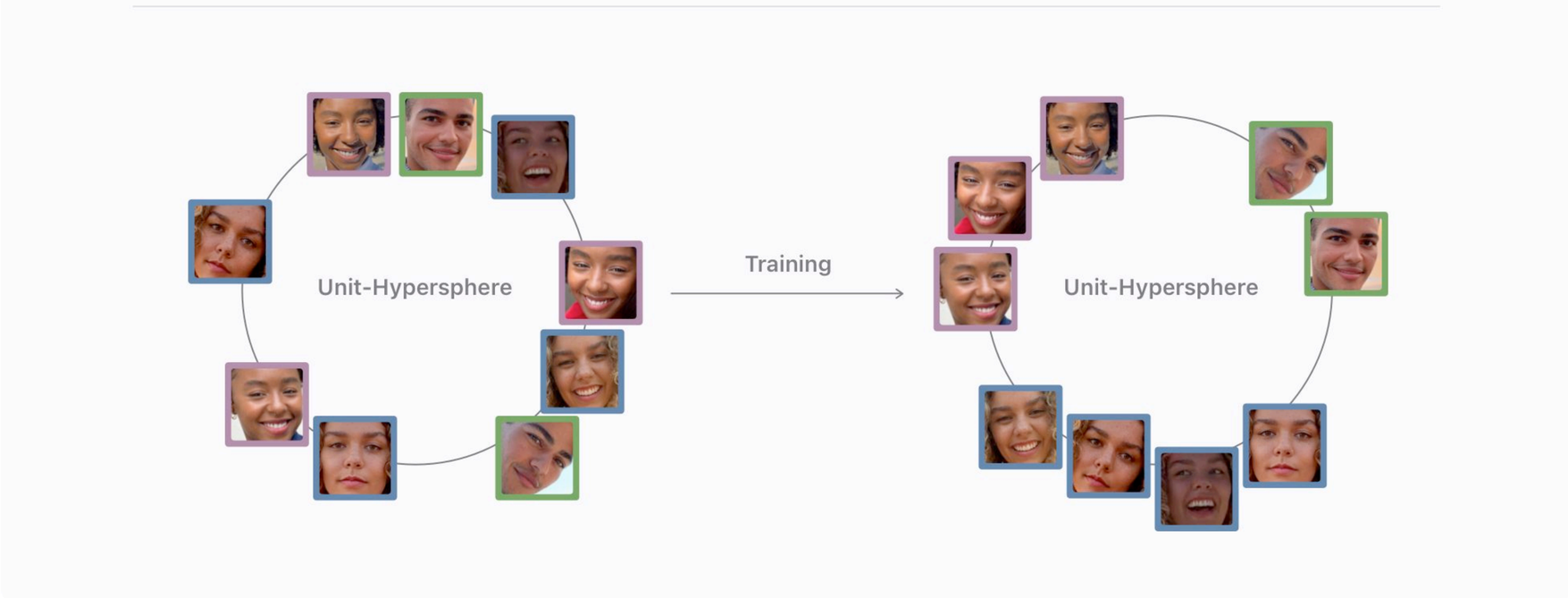
Domain and temporal shift

When do models have “zero-shot” performance?

When do models have “few-shot” performance?

Remember week 1?

- Learned exemplars
- Maximize margins

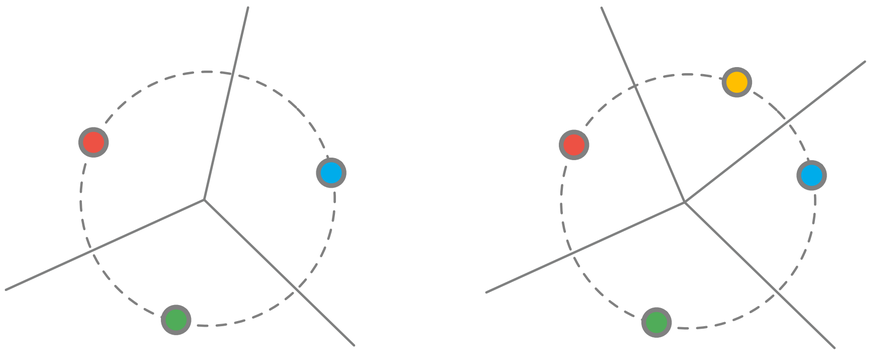


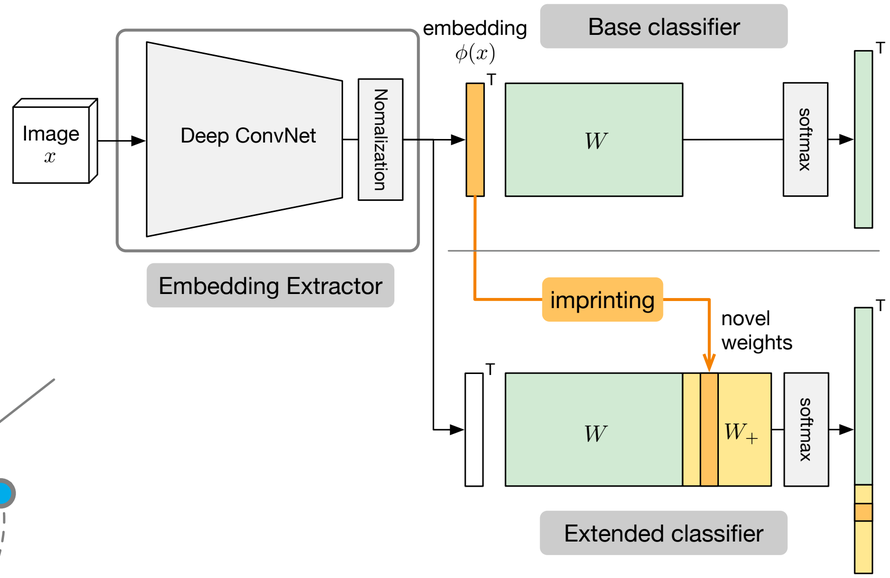
https://arxiv.org/abs/1712.07136

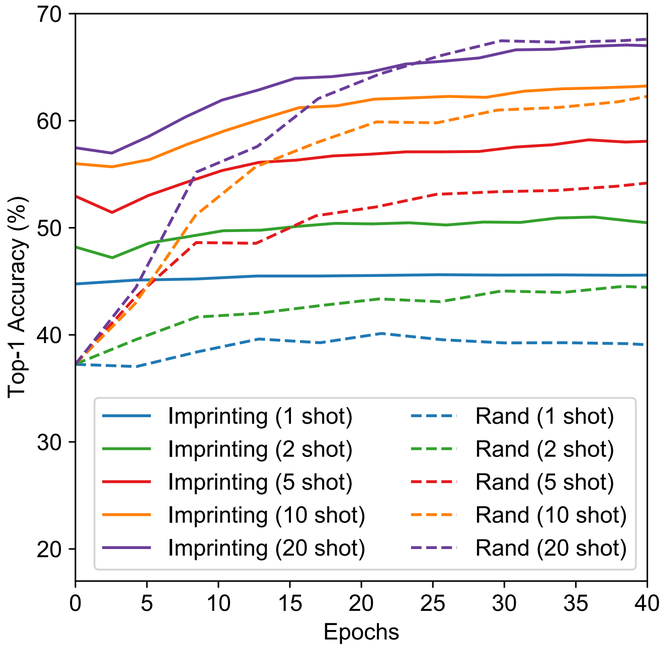
Weight imprinting

What is “learning”

If representations are sufficiently:
1.Consistent
2.Disjoint
We can add classes via exemplars





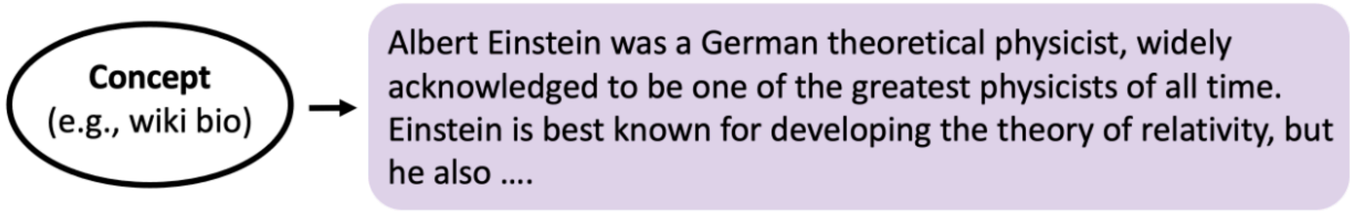


Shares conceptually with Nearest Neighbors

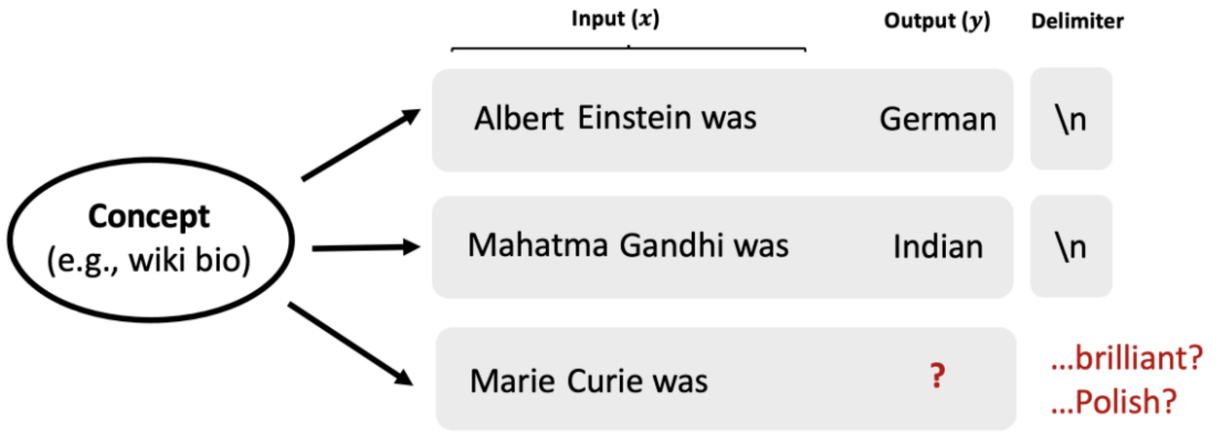
In-Context Learning

p("Polish" | "Albert Einstein was German \n Mahatma Gandhi was Indian \n Marie Curie was")

1. Pretraining documents are conditioned on a **latent concept** (e.g., biographical text)



2. Create **independent examples** from a **shared concept.** If we focus on full names, wiki bios tend to relate them to nationalities.



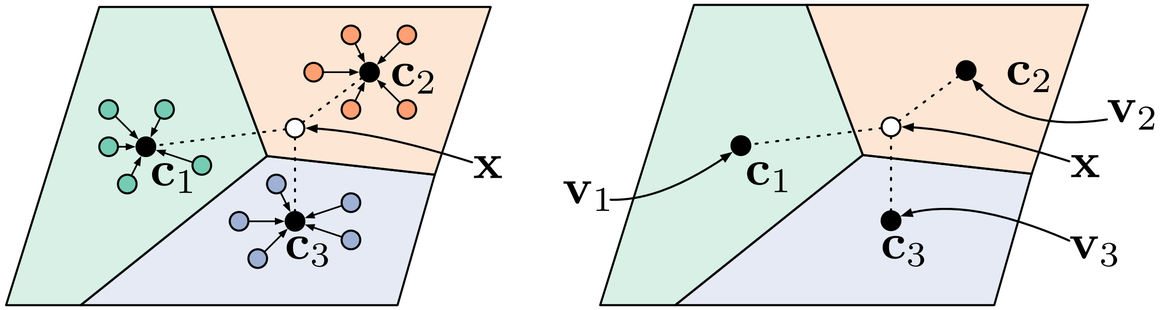
3. Concatenate examples into a prompt and predict next word(s). **Language model (LM) implicitly infers the shared concept** across examples despite the unnatural concatenation

https://arxiv.org/abs/2111.02080

Training on device

Can we get away with collecting and training on just a handful of examples?

- Few-shot and zero-shot learning:
  - 5, 10, 100 examples per label?
  - 0 examples?
- Metalearning: “learning to learn.”
  - Can we train the model to to be able to learn quickly later?
  - Compute/estimate gradients of gradients, e.g. MAML (Finn et al. 2017), Reptile (Nichol et al. 2018).



(a) Few-shot (b) Zero-shot

Figure: Snell et al. 2017

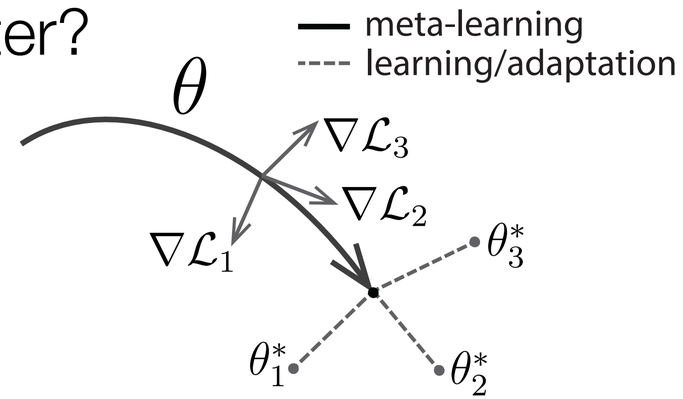


Figure: Finn et al. 2017.

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Accelerating ~~Training~~ Finetuning

Off- and on-device

Emma Strubell & Yonatan Bisk

Parameter-efficient fine-tuning

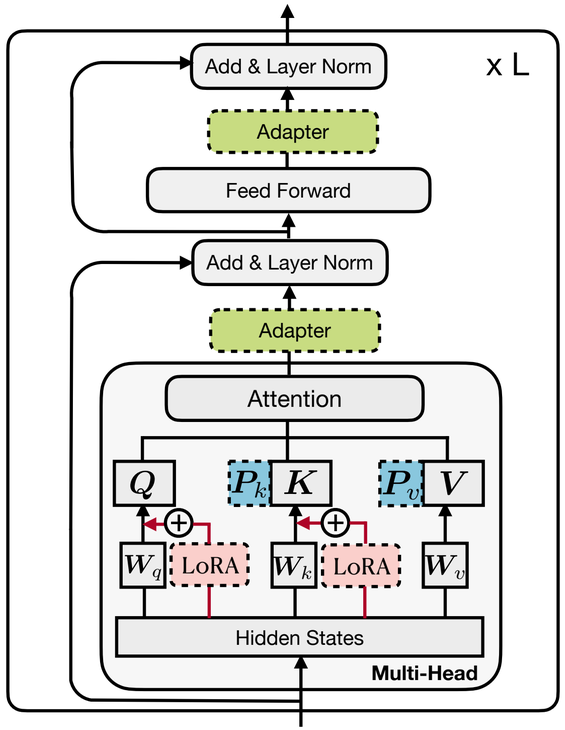
Motivation: BERT as fixed feature extractor is sub-optimal (Devlin et al. 2019).

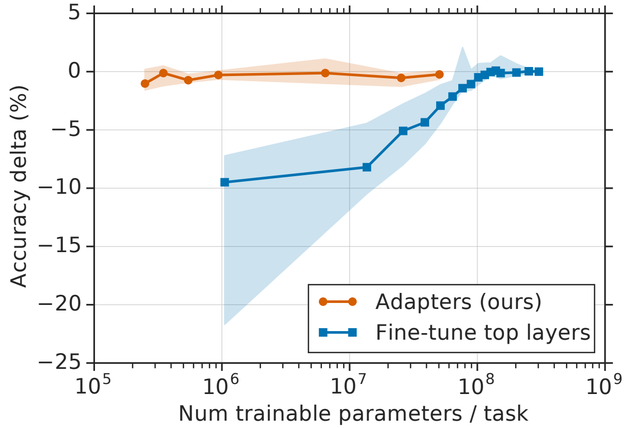
System	Dev F1	Test F1
ELMo (Peters et al., 2018a)	95.7	92.2
CVT (Clark et al., 2018)	-	92.6
CSE (Akbik et al., 2018)	-	**93.1**
Fine-tuning approach		
$\text{BERT}_{\text{LARGE}}$	96.6	92.8
$\text{BERT}_{\text{BASE}}$	96.4	92.4
Feature-based approach ($\text{BERT}_{\text{BASE}}$)		
Embeddings	91.0	-
Second-to-Last Hidden	95.6	-
Last Hidden	94.9	-
Weighted Sum Last Four Hidden	95.9	-
Concat Last Four Hidden	96.1	-
Weighted Sum All 12 Layers	95.5	-

Full fine-tuning (updating all weights) works better than freezing weights and learning small transformation.

Parameter-efficient fine-tuning

Can we get away with updating a few additional parameters?





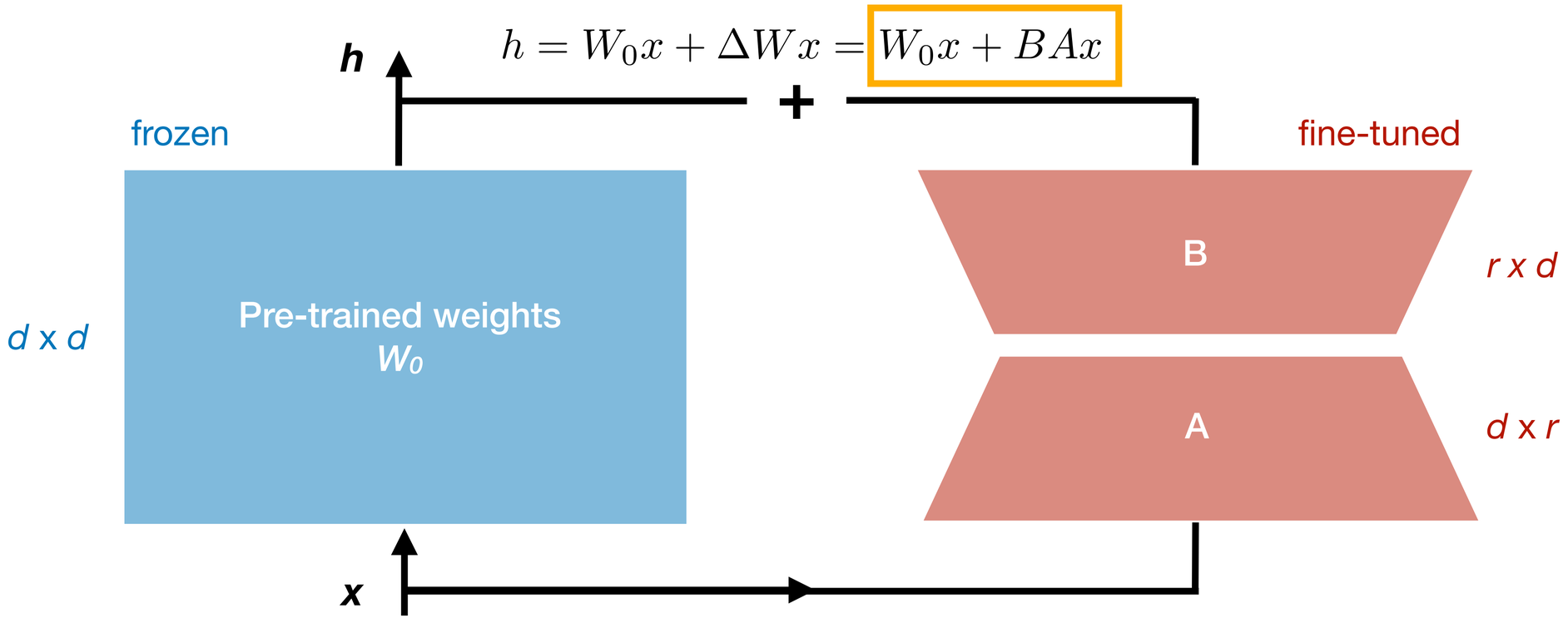
- **Adapters** (Houlsby et al. 2019): insert small feed-forwards between layers & update only those.
- **Prefix/prompt tuning** (Li & Liang, 2021, Lester et al. 2021): prepend learnable "tokens" at input or hidden layers.
- **LoRA** (Hu et al. 2021): learn low-rank approximation for parameter updates.

LoRA: Low-Rank Adaptation of LLMs

- **Idea:** Full fine-tuning requires too much memory.

  Adapters add inference latency, prefix tuning is hard to optimize.

- Instead of adding more model parameters, learn low-rank updates to weights.



QLoRA: Fine-tuning Quantized LLMs

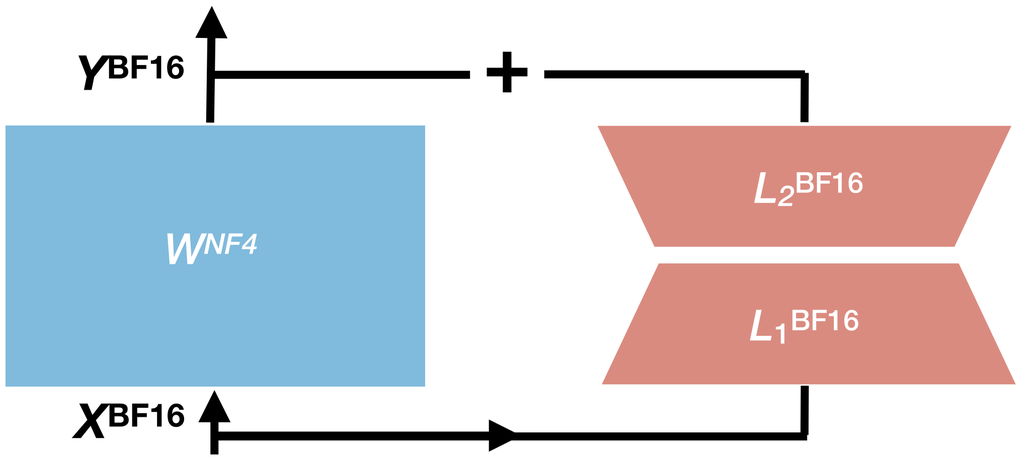
- **Idea:** LLMs *still* too big to fine-tune on a single GPU. Fine-tune quantized model!

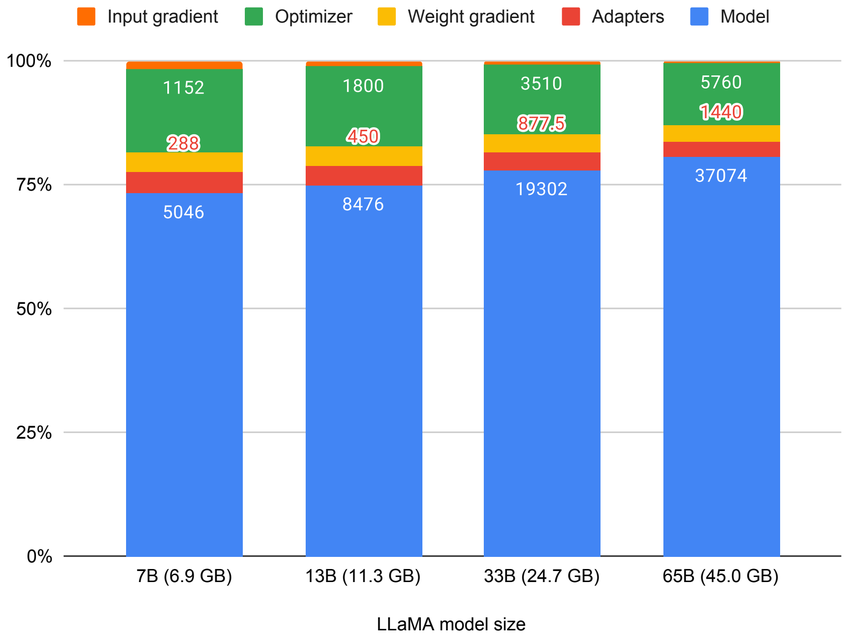
1. Quantize model to 4 bits in *NF4* using *blockwise* k-bit *double* quantization.

$$Q(r) = round(\frac{r}{S} + Z) \qquad \mathbf{Y}^{\text{BF16}} = \mathbf{X}^{\text{BF16}}\text{doubleDequant}(c_1^{\text{FP32}}, c_2^{\text{k-bit}}, \mathbf{W}^{\text{NF4}}) + \mathbf{X}^{\text{BF16}}\mathbf{L}_1^{\text{BF16}}\mathbf{L}_2^{\text{BF16}},$$

2. Fine-tune quantized model using LoRA. Add LoRA to *all* linear layers.

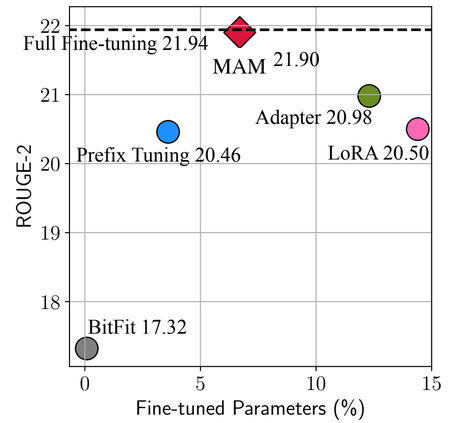
3. Paged optimizer states to handle long sequences.

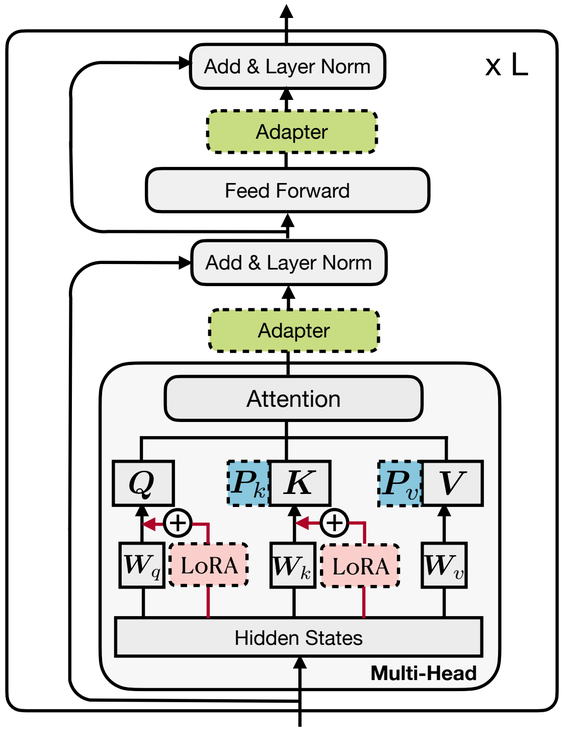


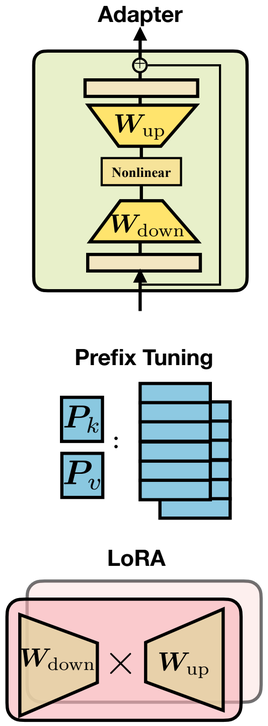


Parameter-efficient fine-tuning

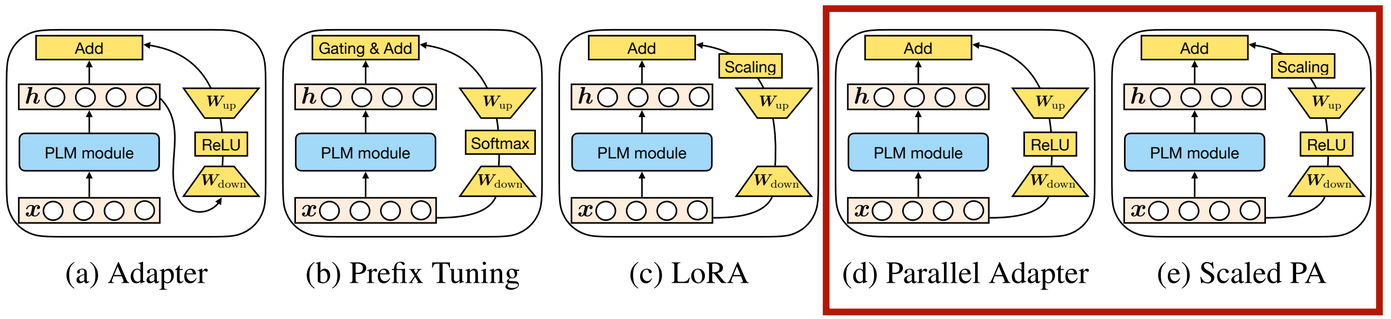
Can we get away with updating a few additional parameters?







- **Adapters** (Houlsby et al. 2019): insert small feed-forwards between layers & update only those.
- **Prefix/prompt tuning** (Li & Liang, 2021, Lester et al. 2021): prepend learnable "tokens" at input or hidden layers.
- **LoRA** (Hu et al. 2021): learn low-rank approximation for parameter updates.
- **MAM** (He et al. 2022): Mix-and-match all of the above.

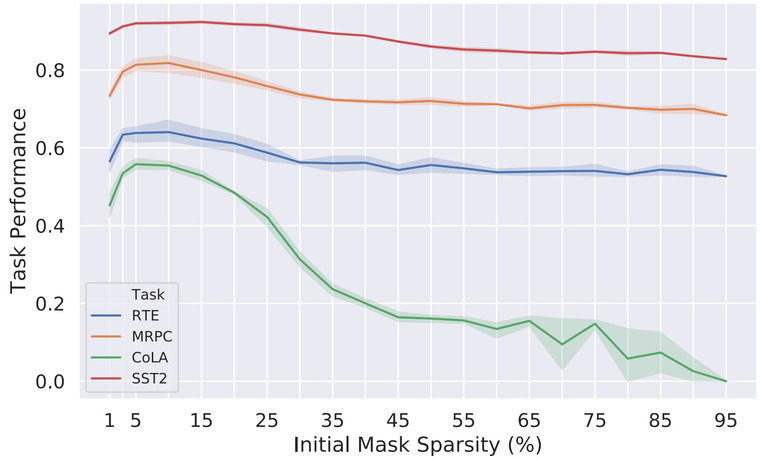


(a) Adapter (b) Prefix Tuning (c) LoRA (d) Parallel Adapter (e) Scaled PA

Parameter-efficient fine-tuning

Can we get away with updating just a subset of parameters, or none at all?

- **Masking** (Zhao et al. 2020): Simply learn a binary mask over all parameters!
- **Diff Pruning** (Guo et al. 2021): Learn a sparse additive mask over all parameters.
- **BitFit** (Zaken et al. 2022): Fine-tune just the bias vectors (or a subset of them).



	Train size	%Param	QNLI 105k	SST-2 67k	MNLI_m 393k	MNLI_mm 393k	CoLA 8.5k	MRPC 3.7k	STS-B 7k	RTE 2.5k	QQP 364k	Avg.
(V)	Full-FT†	100%	**93.5**	**94.1**	**86.5**	**87.1**	**62.8**	**91.9**	89.8	71.8	**87.6**	**84.8**
(V)	Full-FT	100%	91.7±0.1	93.4±0.2	85.5±0.4	85.7±0.4	62.2±1.2	90.7±0.3	**90.0±0.4**	**71.9±1.3**	87.5±0.4	84.1
(V)	Diff-Prune†	0.5%	**93.4**	**94.2**	**86.4**	**86.9**	63.5	91.3	89.5	71.5	**86.6**	**84.6**
(V)	BitFit	0.08%	91.4±2.4	93.2±0.4	84.4±0.2	84.8±0.1	**63.6±0.7**	**91.7±0.5**	**90.3±0.1**	**73.2±3.7**	85.4±0.1	84.2
(T)	Full-FT‡	100%	91.1	**94.9**	86.7	85.9	**60.5**	**89.3**	**87.6**	70.1	**72.1**	**81.8**
(T)	Full-FT†	100%	**93.4**	94.1	86.7	**86.0**	59.6	88.9	86.6	**71.2**	71.7	81.5
(T)	Adapters‡	3.6%	90.7	94.0	84.9	85.1	59.5	89.5	**86.9**	71.5	**71.8**	81.1
(T)	Diff-Prune†	0.5%	**93.3**	94.1	**86.4**	**86.0**	**61.1**	**89.7**	86.0	70.6	71.1	**81.5**
(T)	BitFit	0.08%	92.0	**94.2**	84.5	84.8	59.7	88.9	85.5	**72.0**	70.5	80.9

BitFit: Comparable to adapters, diff pruning while using 45x, 6x fewer parameters.

What about in-context learning?

- Few-shot parameter-efficient fine-tuning is better and cheaper than in-context learning (Liu et al. 2022).