CNAPs

Fast and Flexible Multi-Task Classification Using Conditional Neural Adaptive Processes[1]

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Microsoft Research

Department of Engineering

[1] *Requeima, J., *Gordon, J., and *Bronskill, J., Nowozin, S. and Turner, R.E. " Fast and Flexible Multi-Task Classification Using Conditional Neural Adaptive Processes." arXiv preprint arXiv:1906.07697 (2019). **Authors contributed equally*.

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- Humans can learn a new concept from just a few examples.[1]

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Strategy:

- Learn across *many tasks* in order to generalize to a new unseen task.

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Multiple tasks, few training examples

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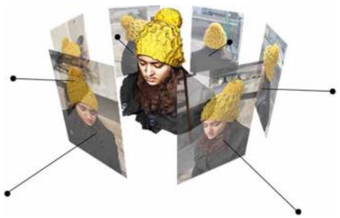

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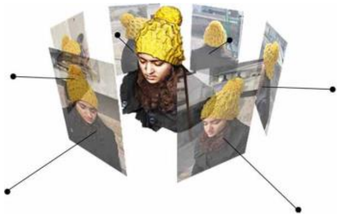

- Recommendation/personalization:
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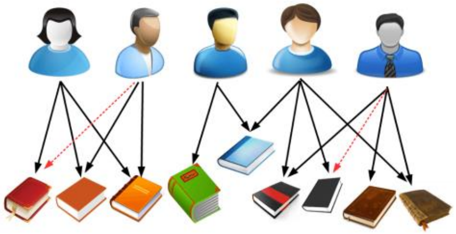

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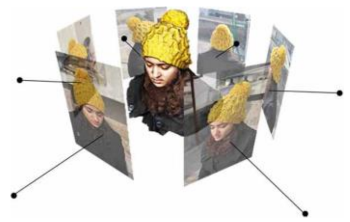

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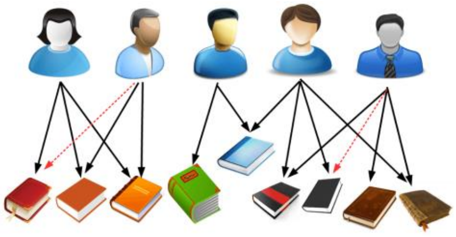


- Face recognition/tagging within groups:
  - Many groups of different sizes, with varying number of photos per person.

Training Images (*Context Set*)

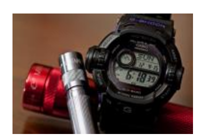
Stop Watch


Digital Clock

Digital Watch


Wrist Computer Tells Time Without Hands


Parking Meter


Test Images (*Target Set*)

Training Images (*Context Set*)

Predictions

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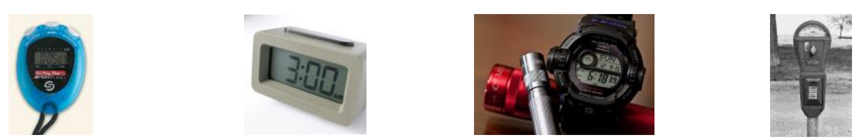
0.69	0.02	0.07	0.24
0.04	0.13	0.11	0.32
0.27	0.85	0.80	0.35
0.00	0.01	0.02	0.10



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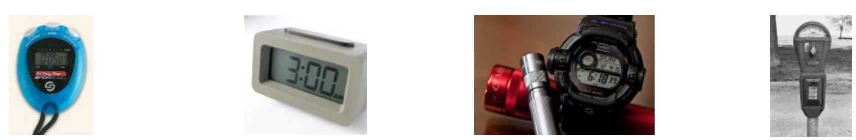

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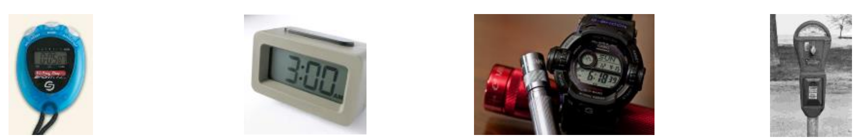

Test Images (*Target Set*)

2/4 correct

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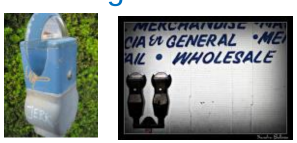

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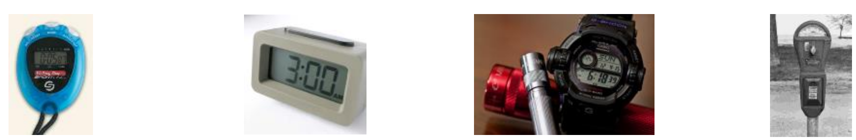

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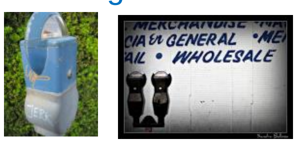

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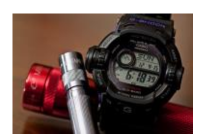


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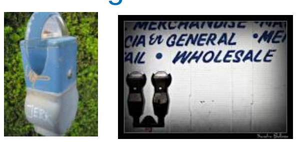

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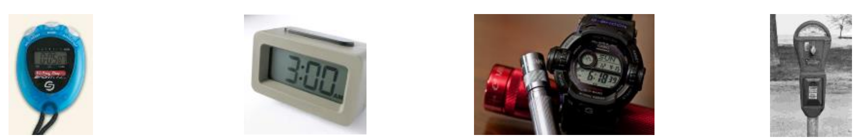

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3/4 correct

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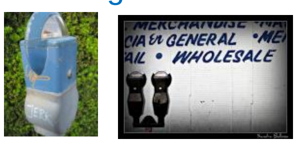

Sundial

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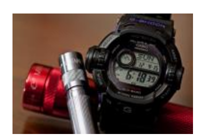

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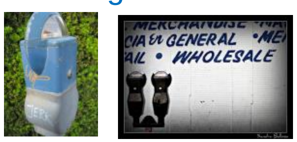

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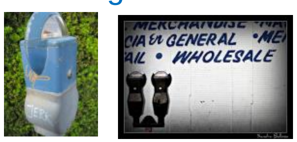

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Probabilistic Models: old and new

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Relates to Conditional Neural Processes [1] and auto-regressive models.

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ϕ is trained via maximum likelihood.

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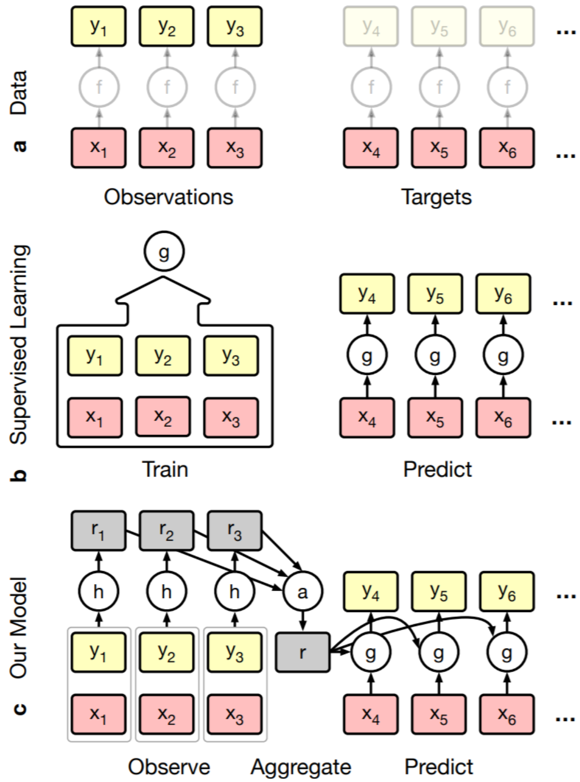
Conditional Neural Processes



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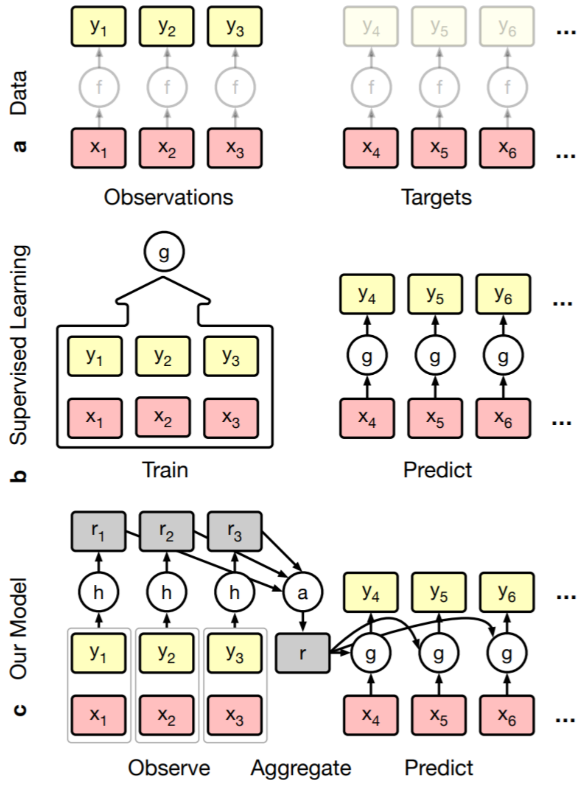

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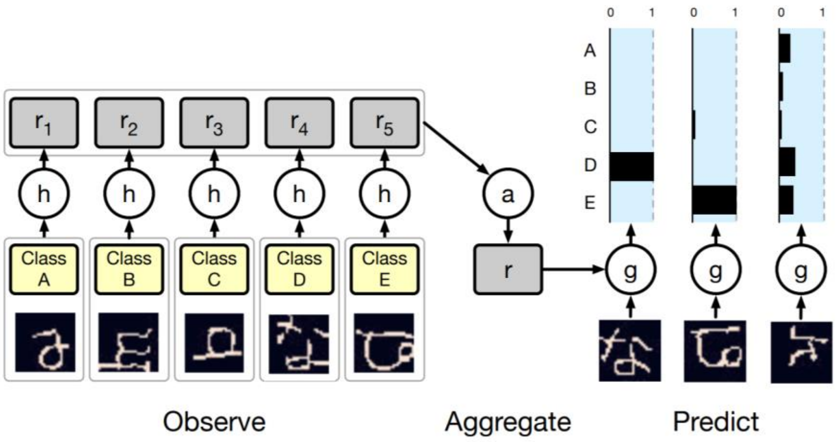

Classification

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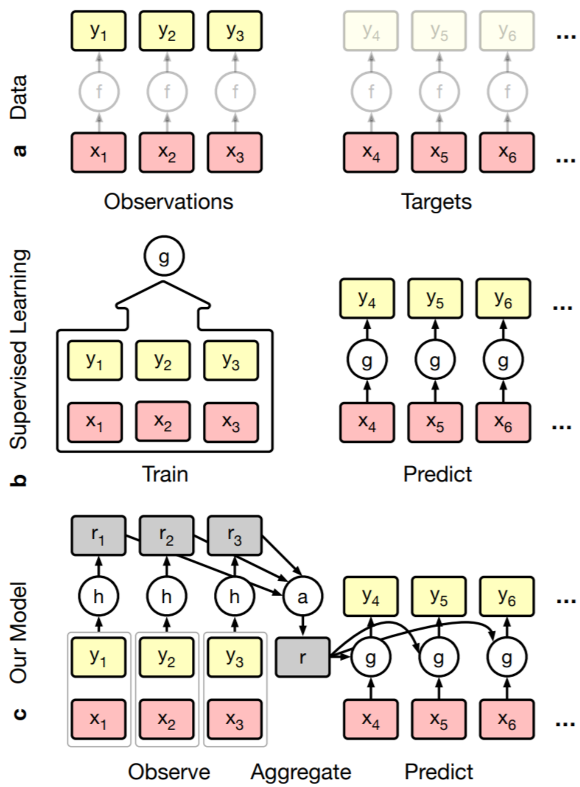
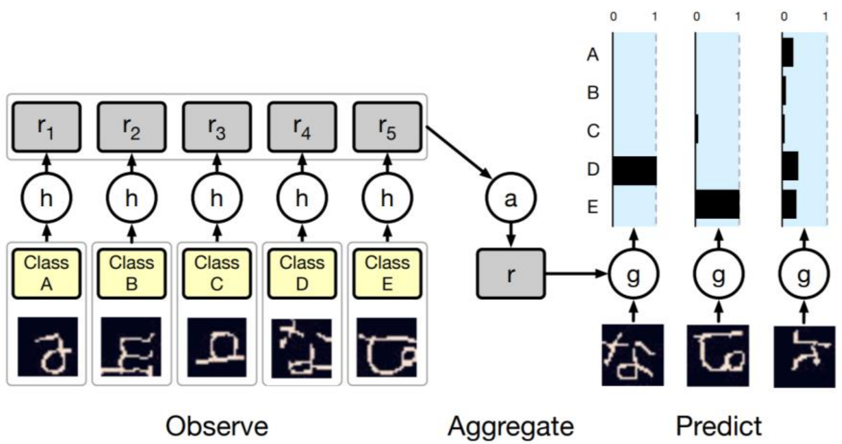


Regression

For classification:

- Aggregation is class by class.
- 'r' grows with number of classes
- Parameters in 'g' grow with number of classes
- CNP limited to fixed way classification



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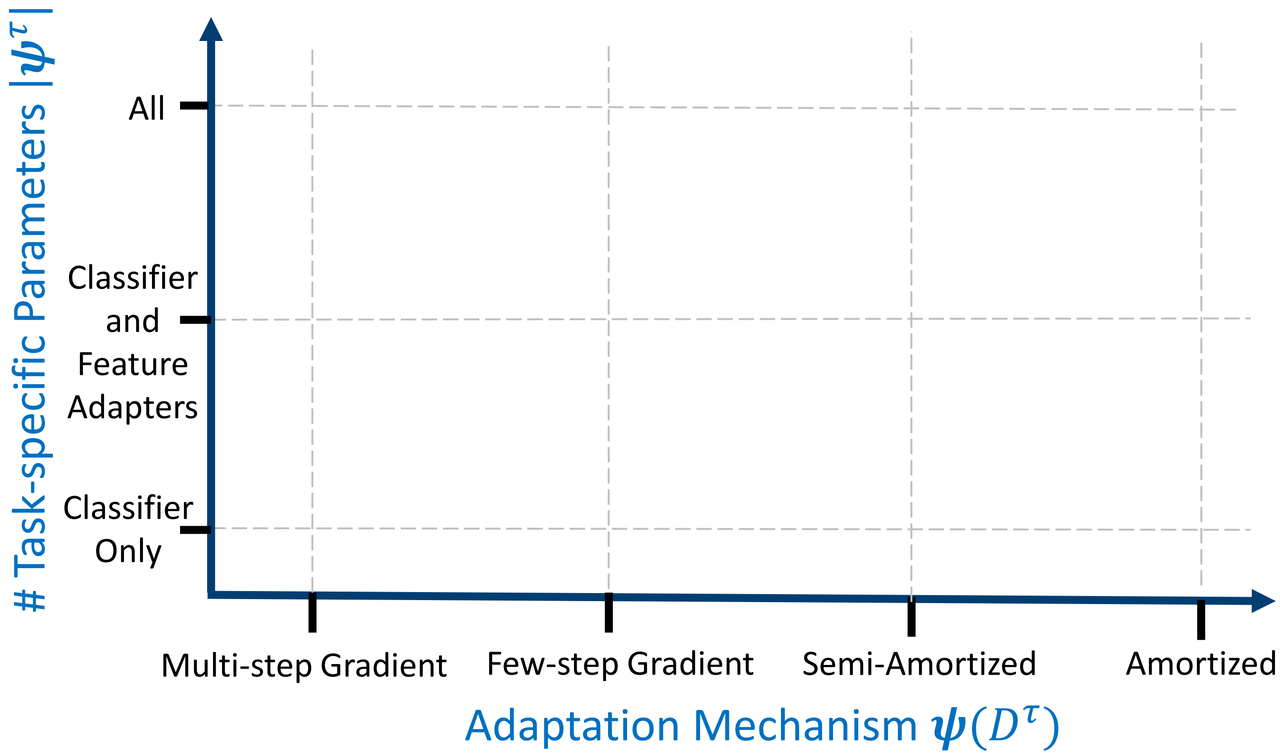
    - Allows support for continual learning in a natural way (more on this later)
- Two-step training procedure facilitates multi-task and transfer learning geared toward to diverse tasks.

Competitive Landscape



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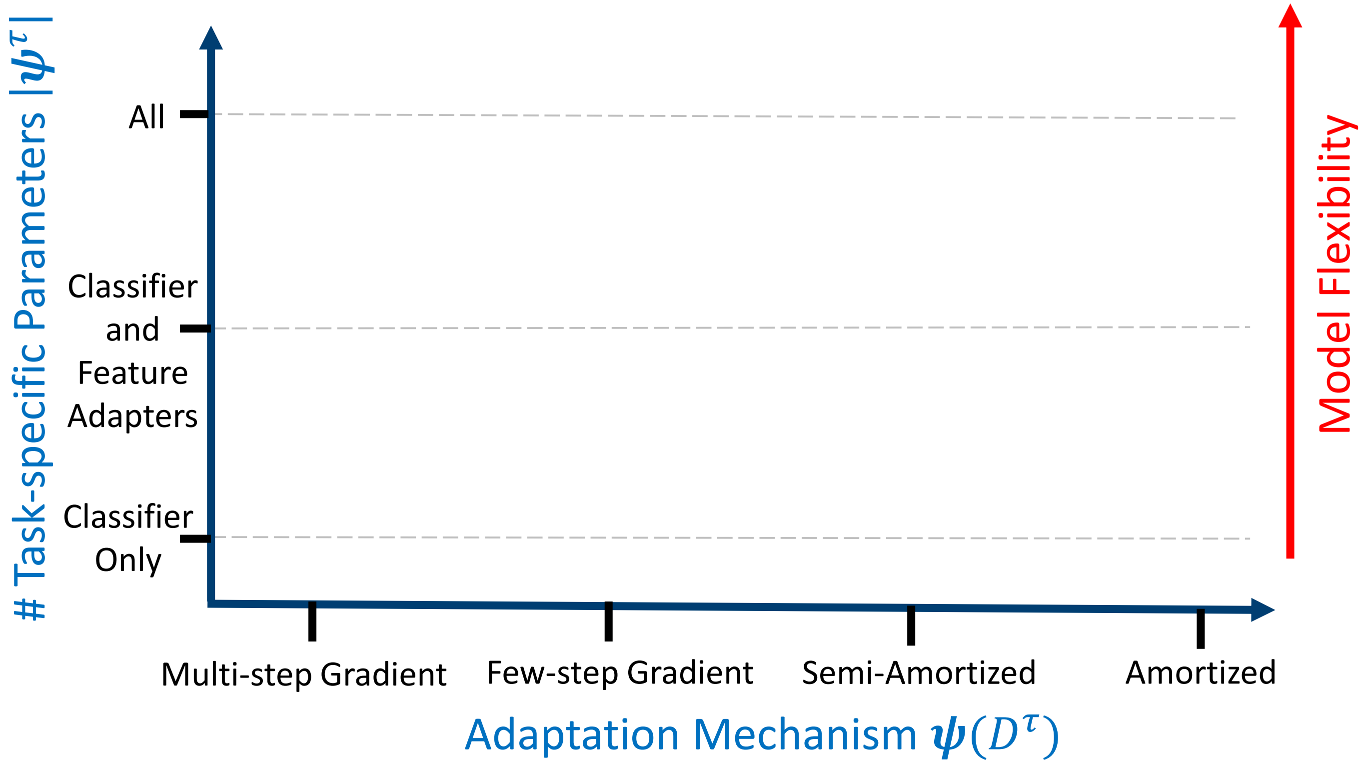

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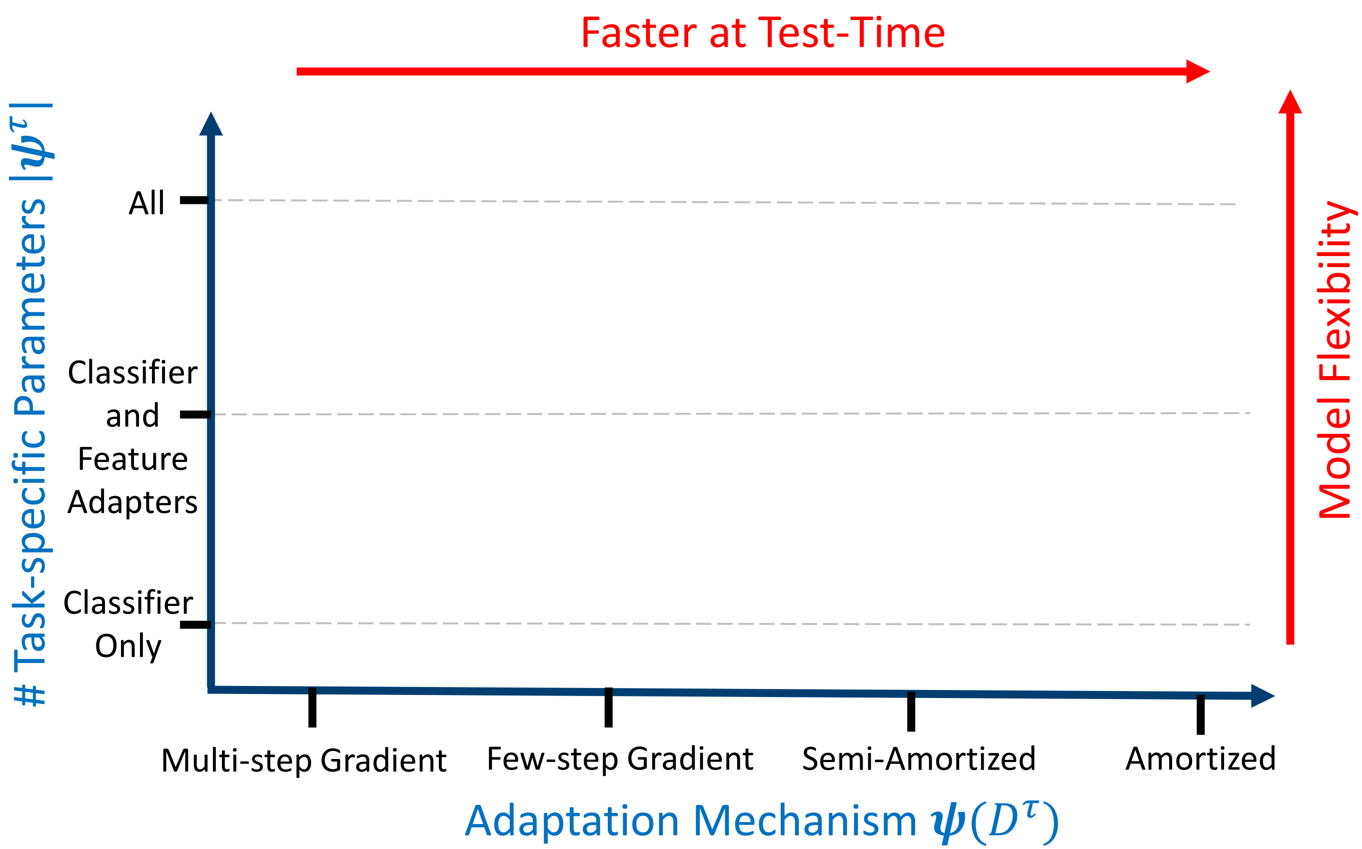

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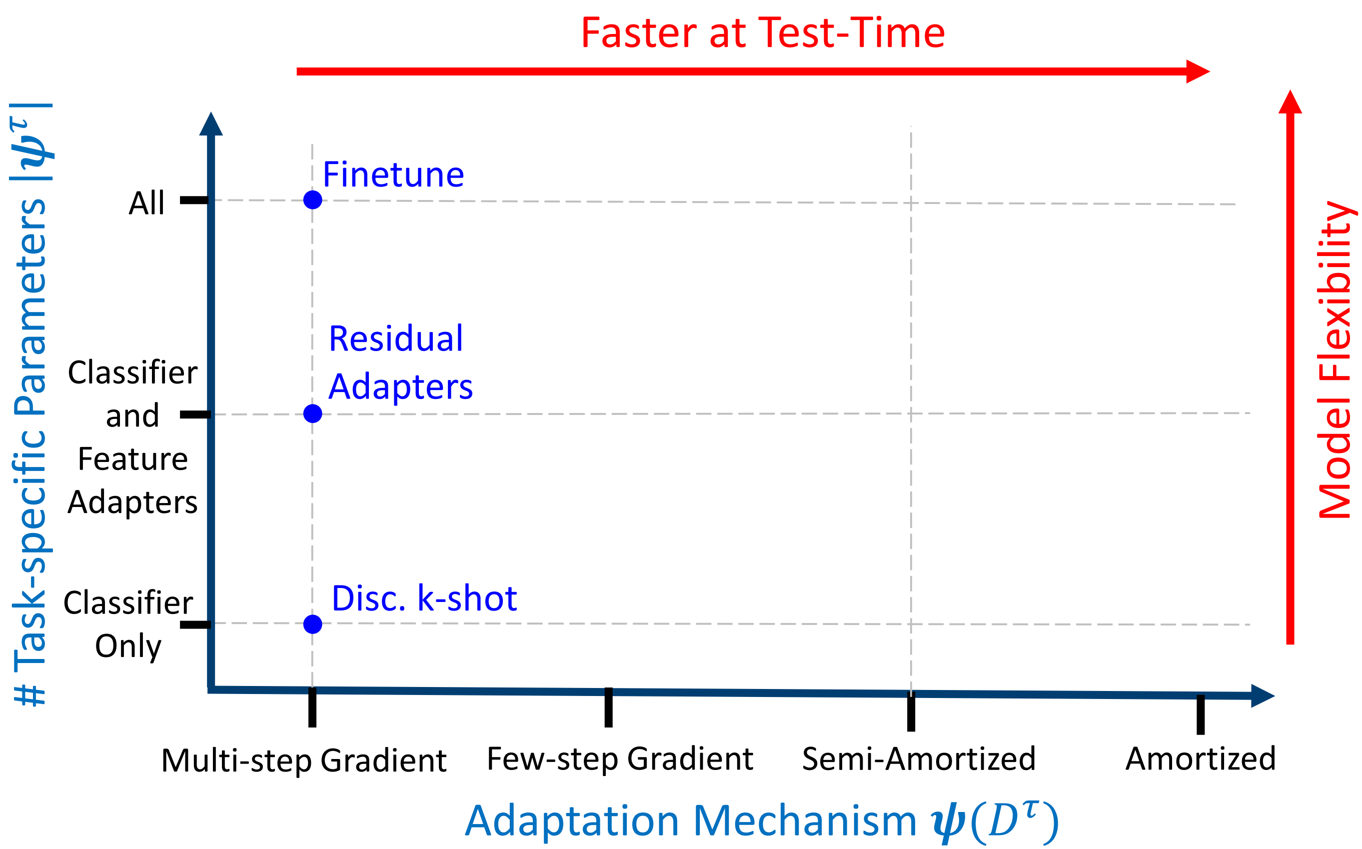

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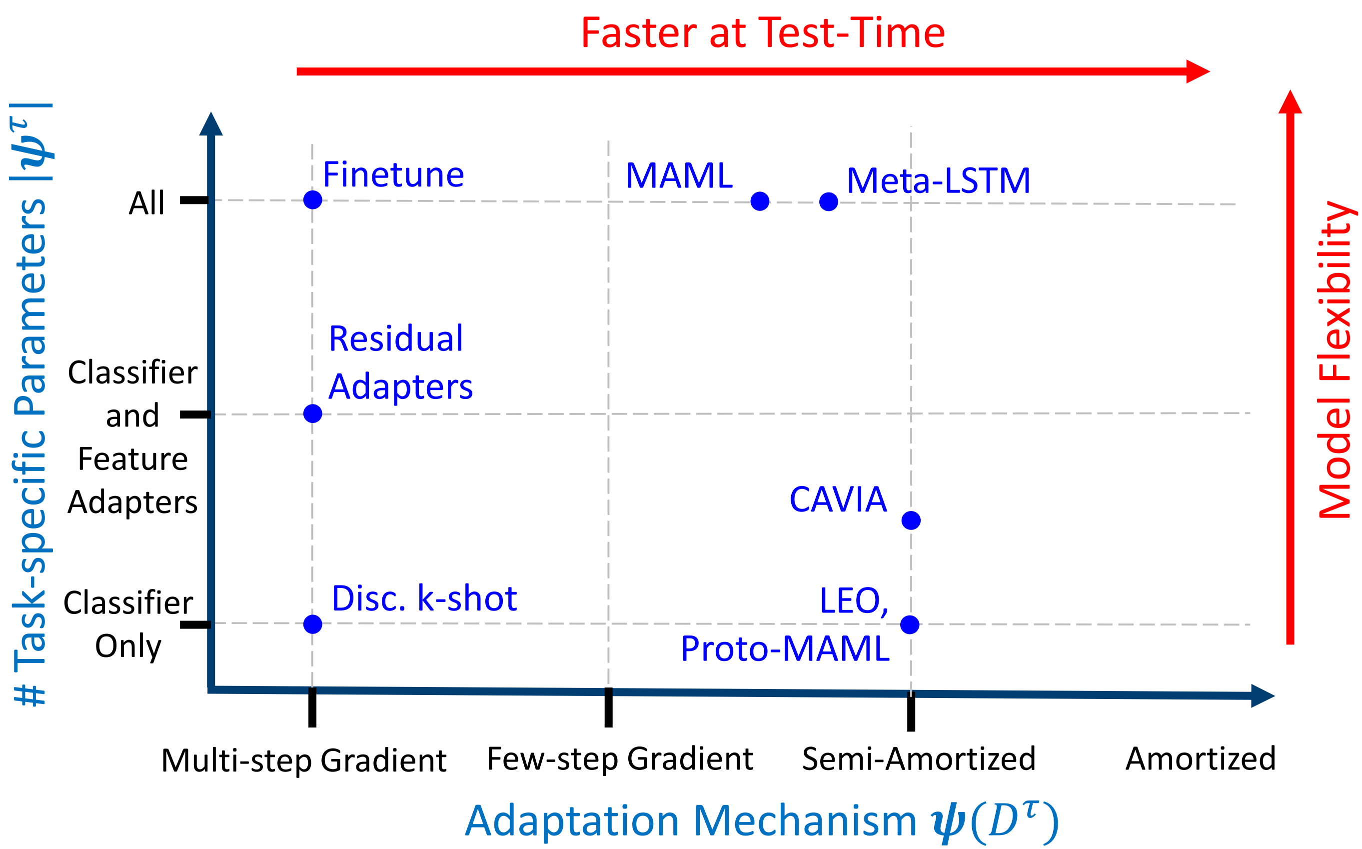

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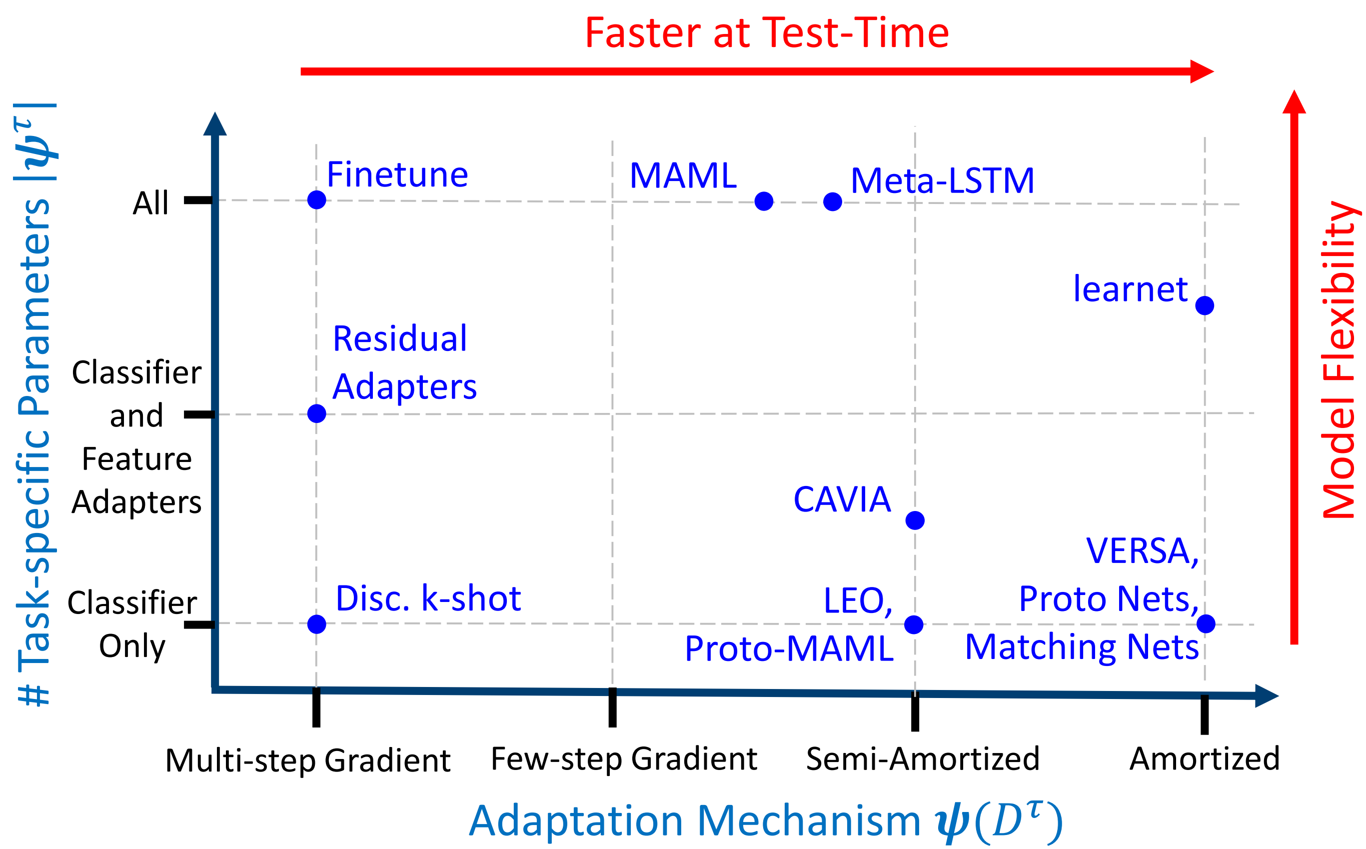

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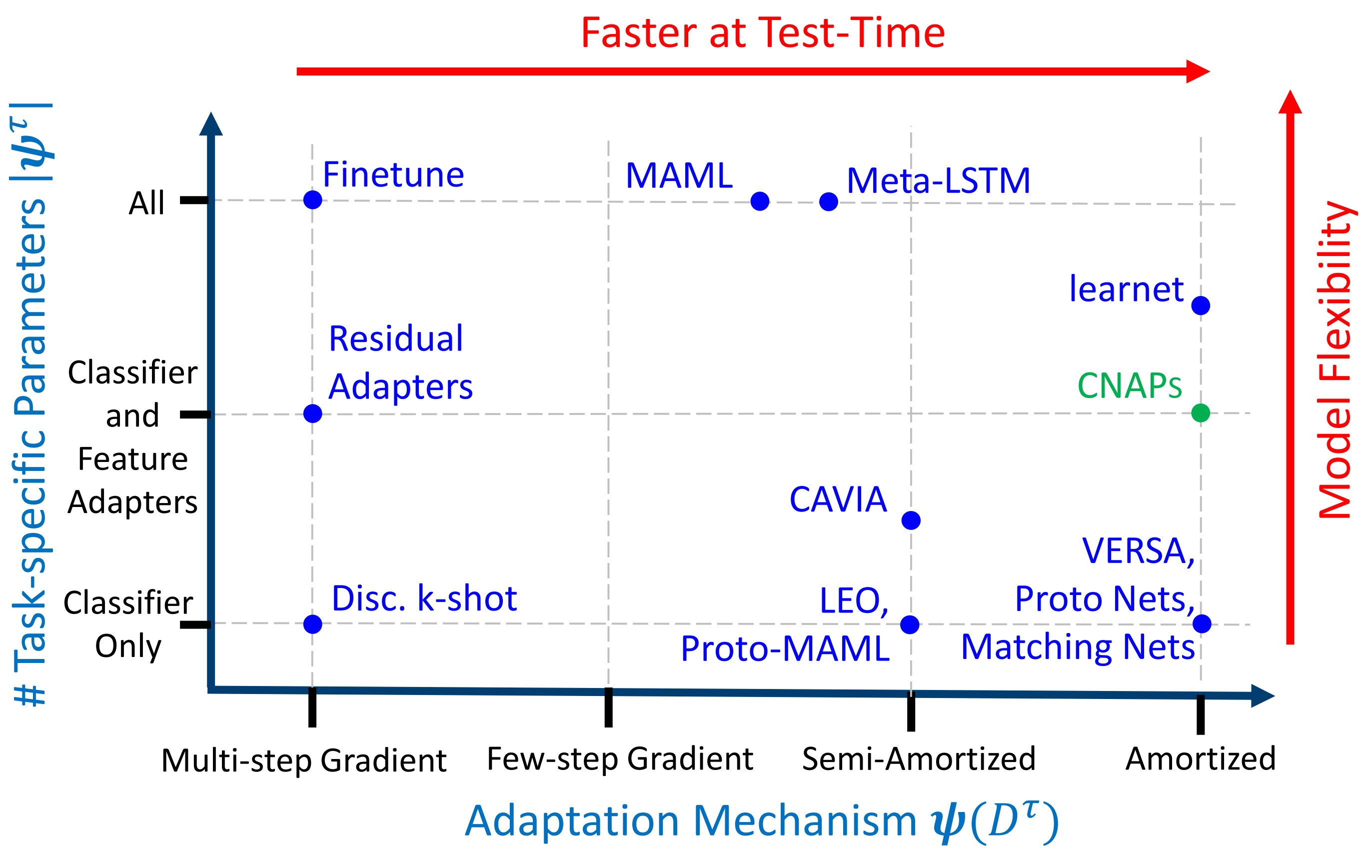
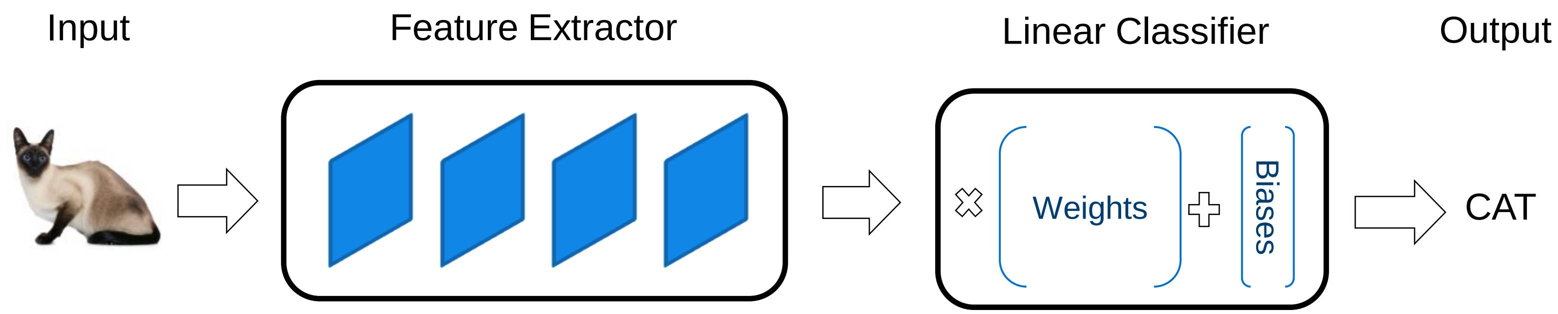


Task specific parameters: adapting a classifier



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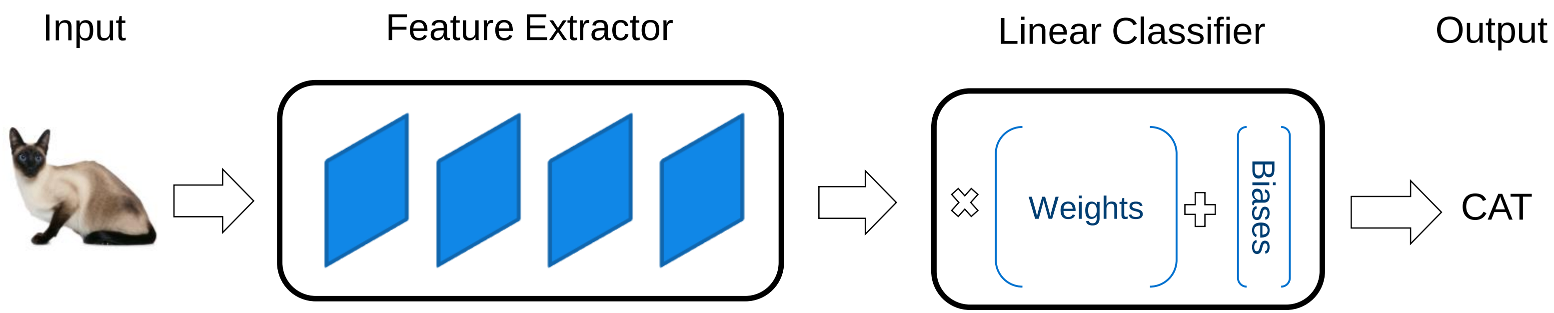
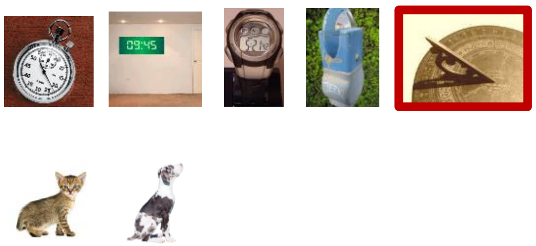


different head for each task
(different classes and different numbers of classes in each task)



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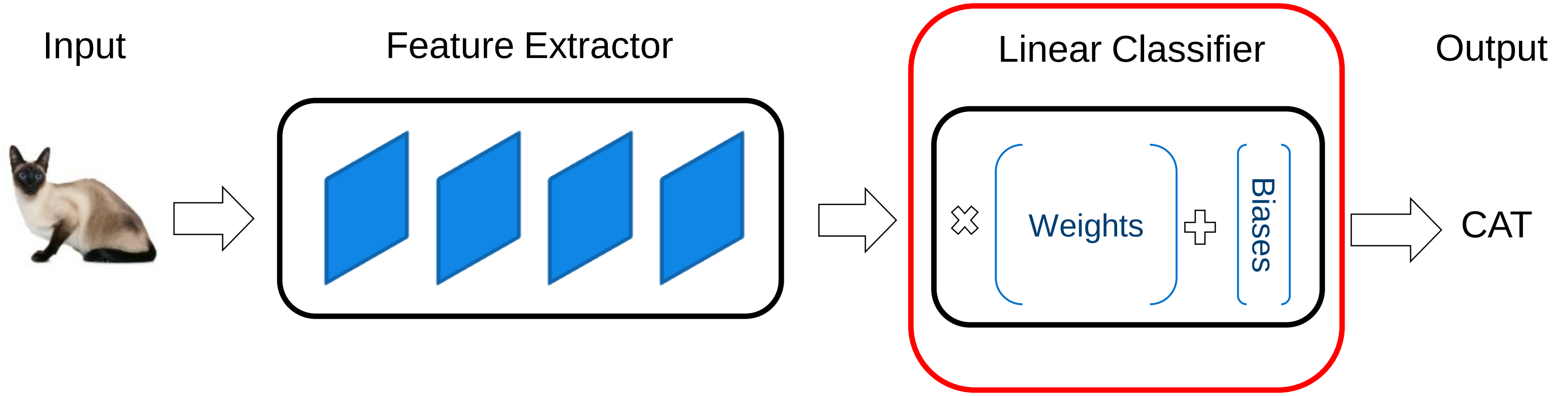

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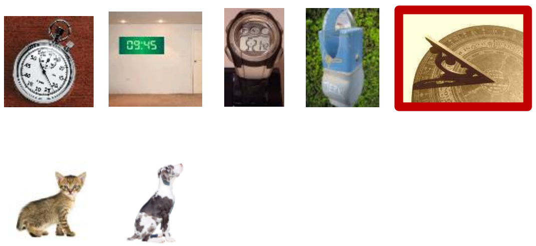

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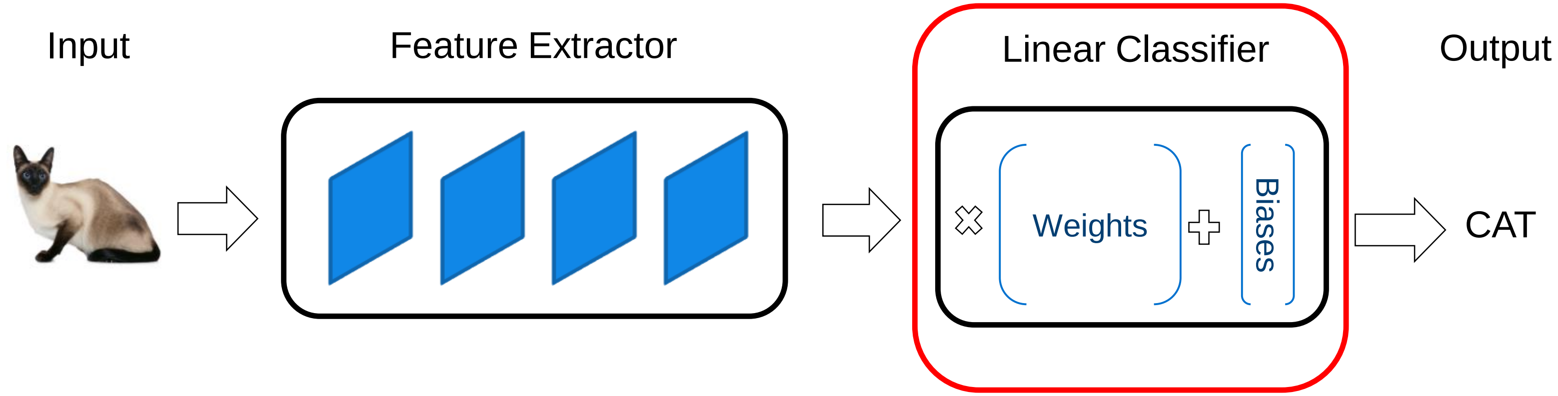

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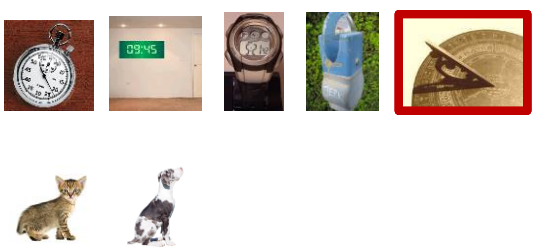

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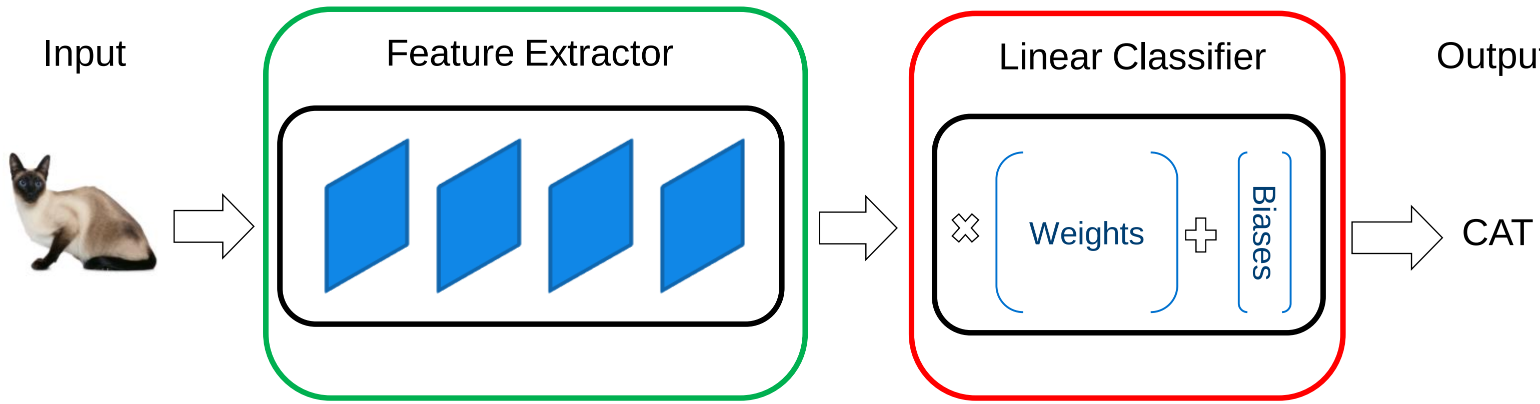

adapt feature extractor
(very different types of input image)

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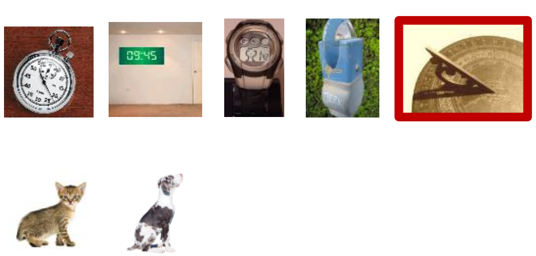

Adapting the feature extractor: FiLM layers[1]

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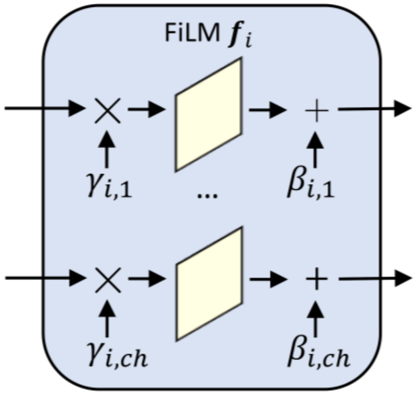
[1] Perez, Ethan, et al. "Film: Visual reasoning with a general conditioning layer." Thirty-Second AAAI Conference on Artificial Intelligence. 2018.

Adapting the feature extractor: FiLM layers[1]

- FiLM (Feature-wise Linear Modulation) layer:
    - scales (by factor γ); and
    - shifts (with offset β)

  convolutional layer feature maps.



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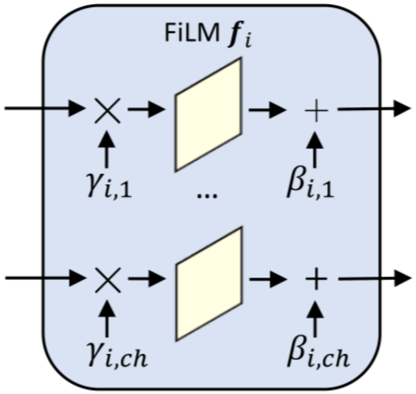

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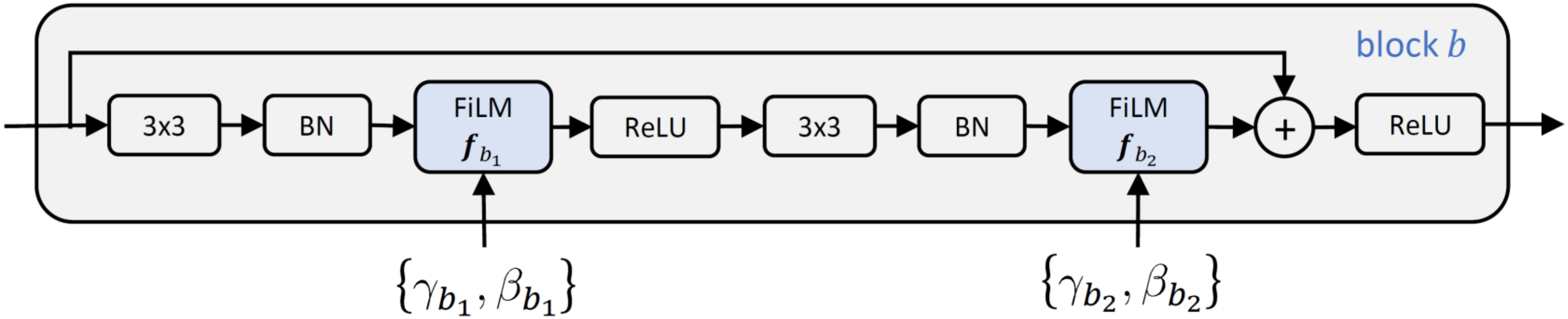

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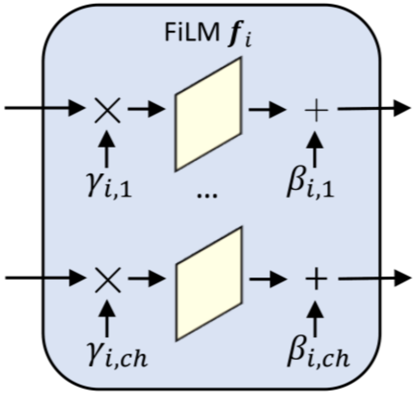

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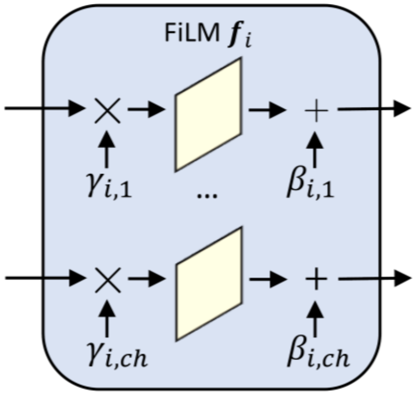

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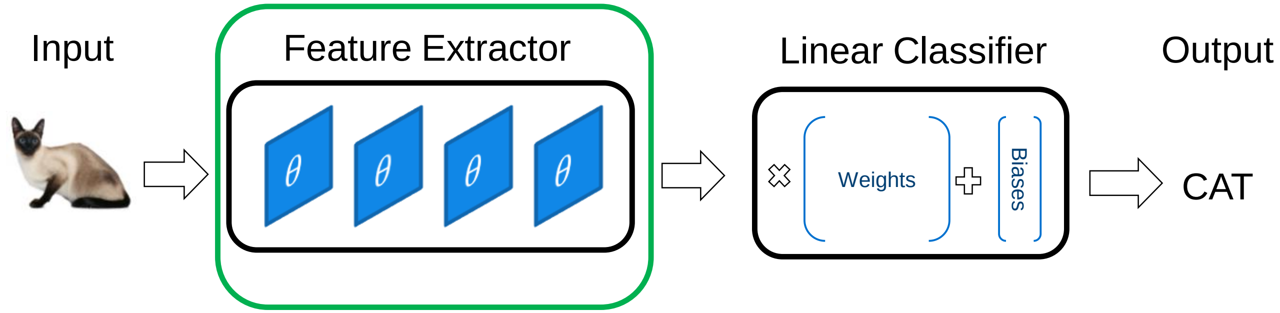

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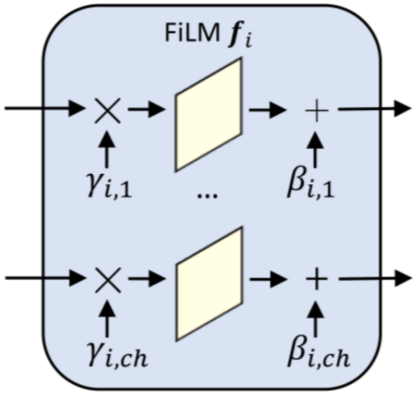

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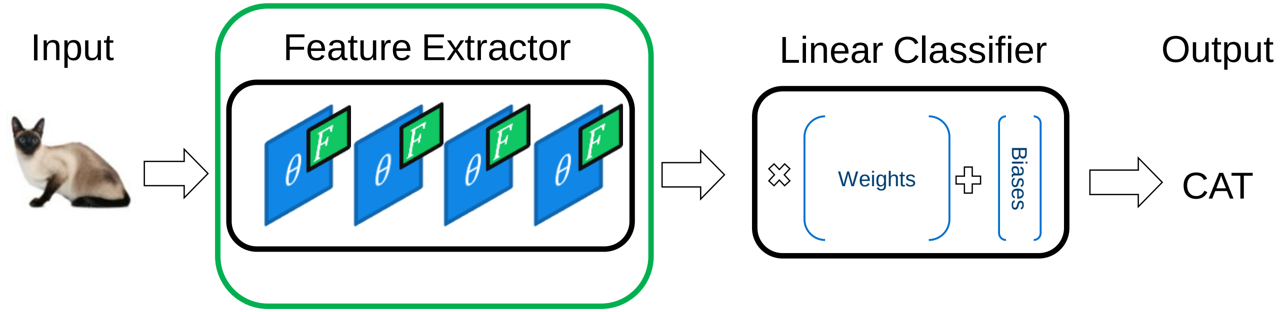

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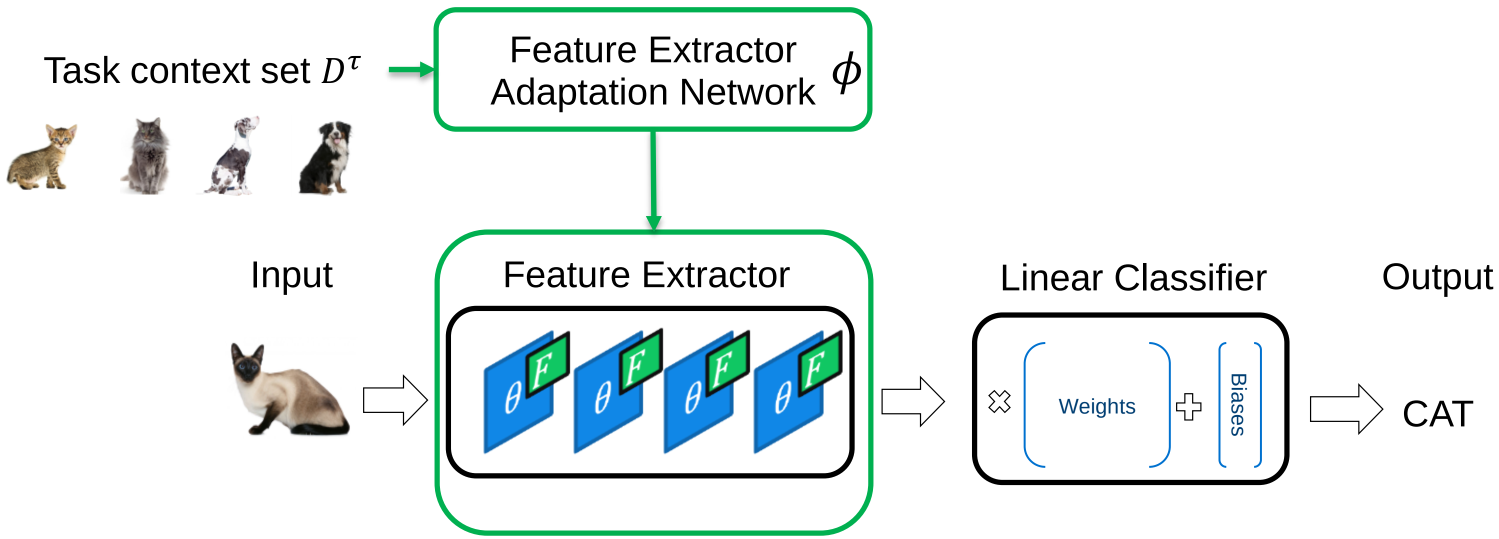

Feature Extractor Adaptation Network

- PointNet[1] / Deep Sets[2] / Neural Statistician[3] statistics network → permutation invariance.

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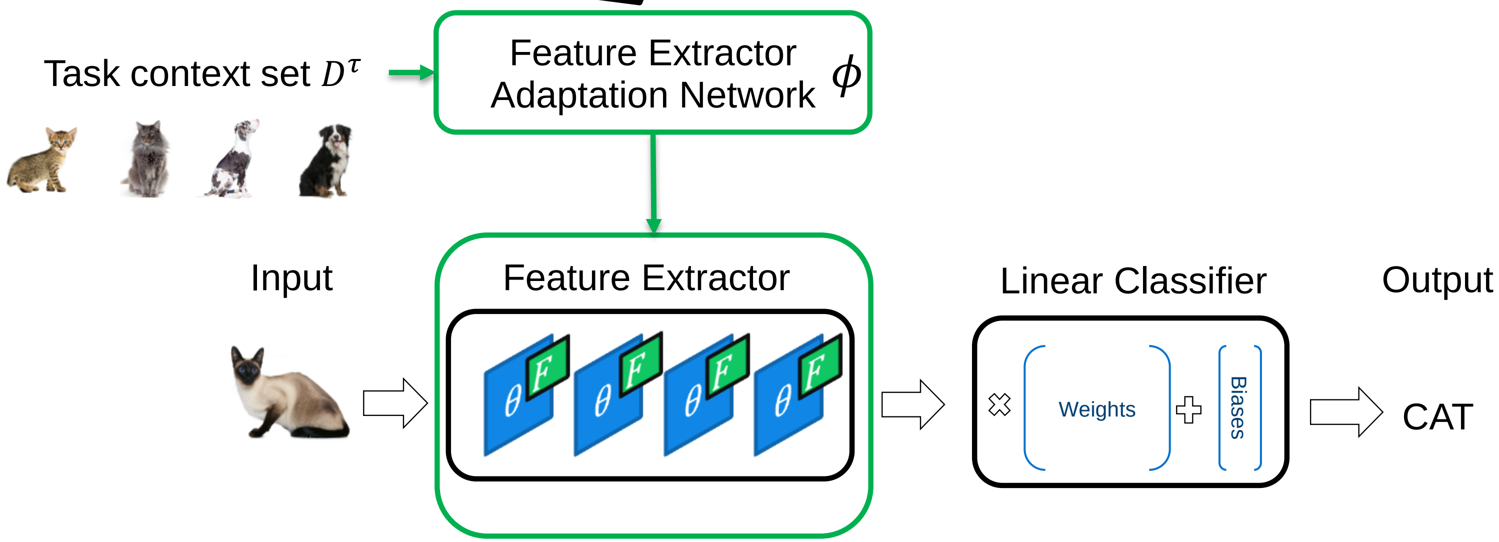

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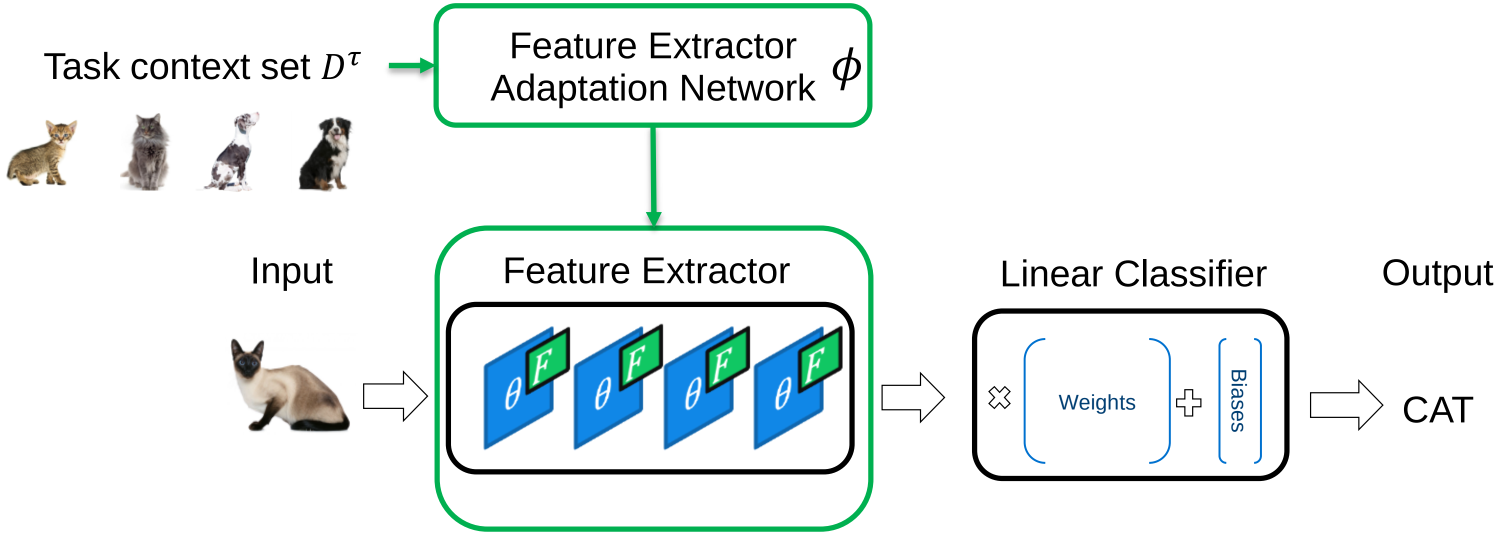

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- Continual learning supported by running averages of task set encoding.

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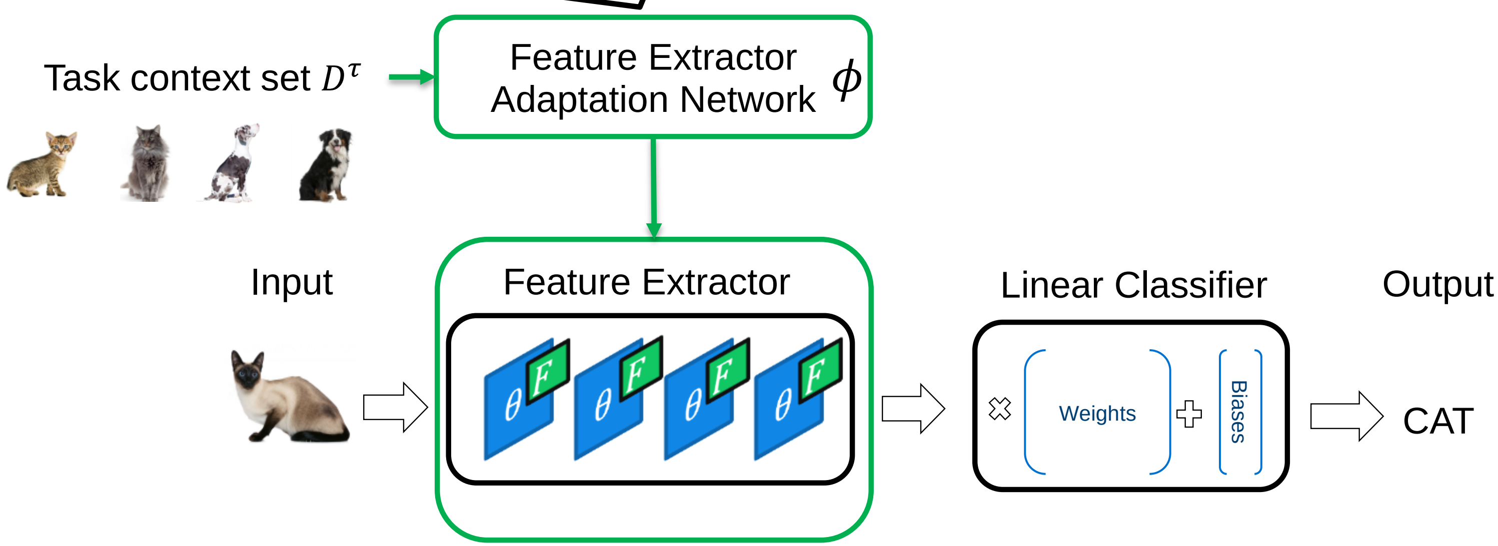

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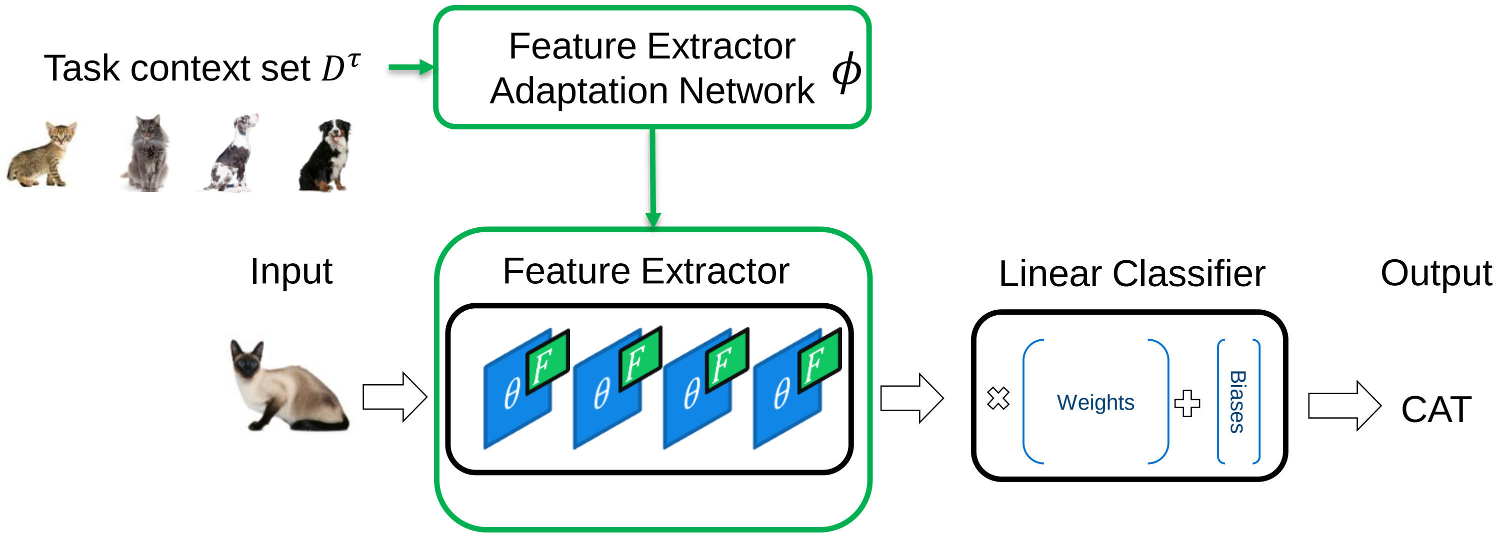

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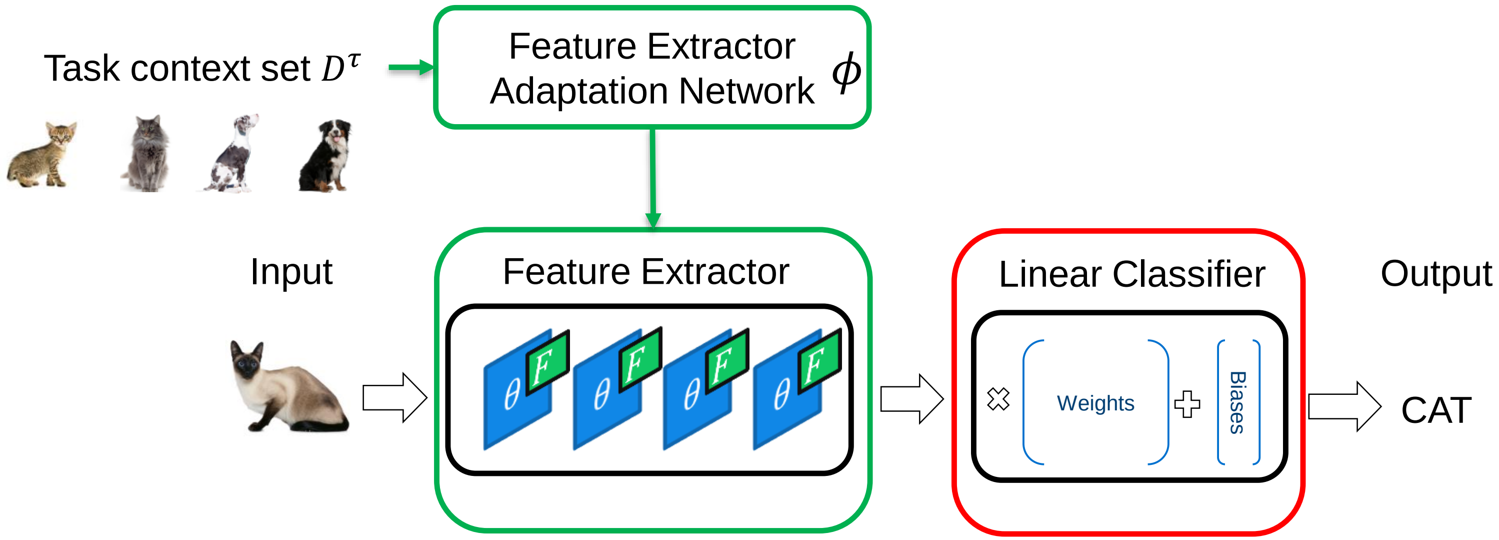

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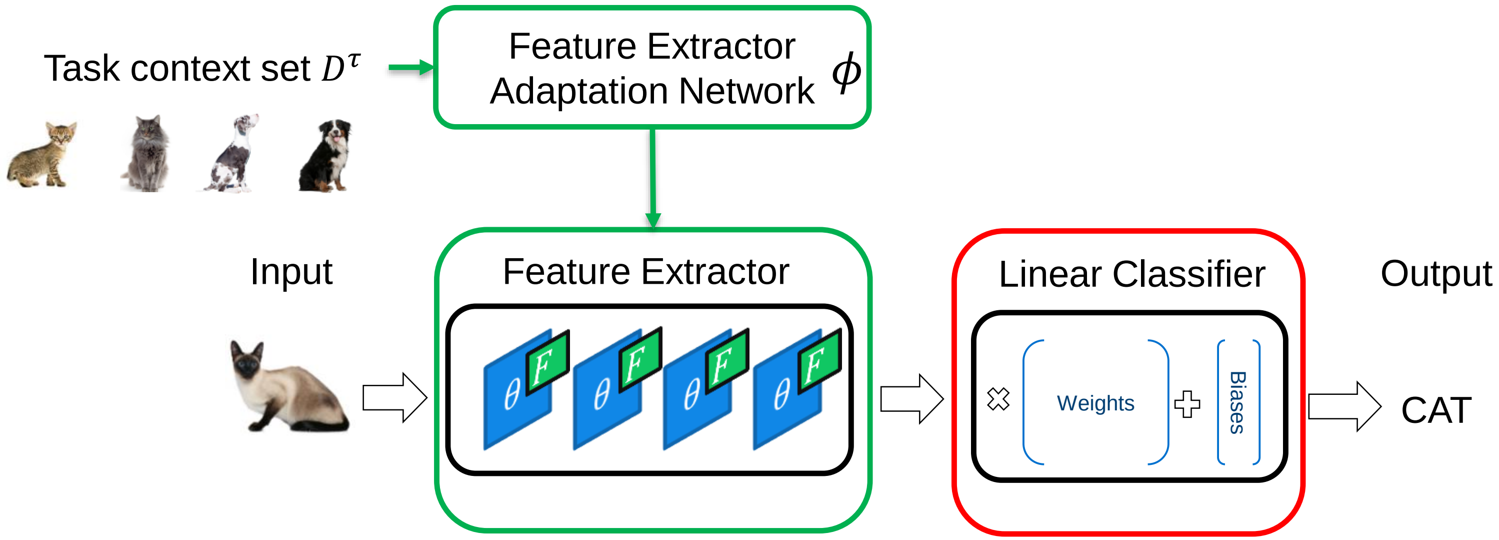

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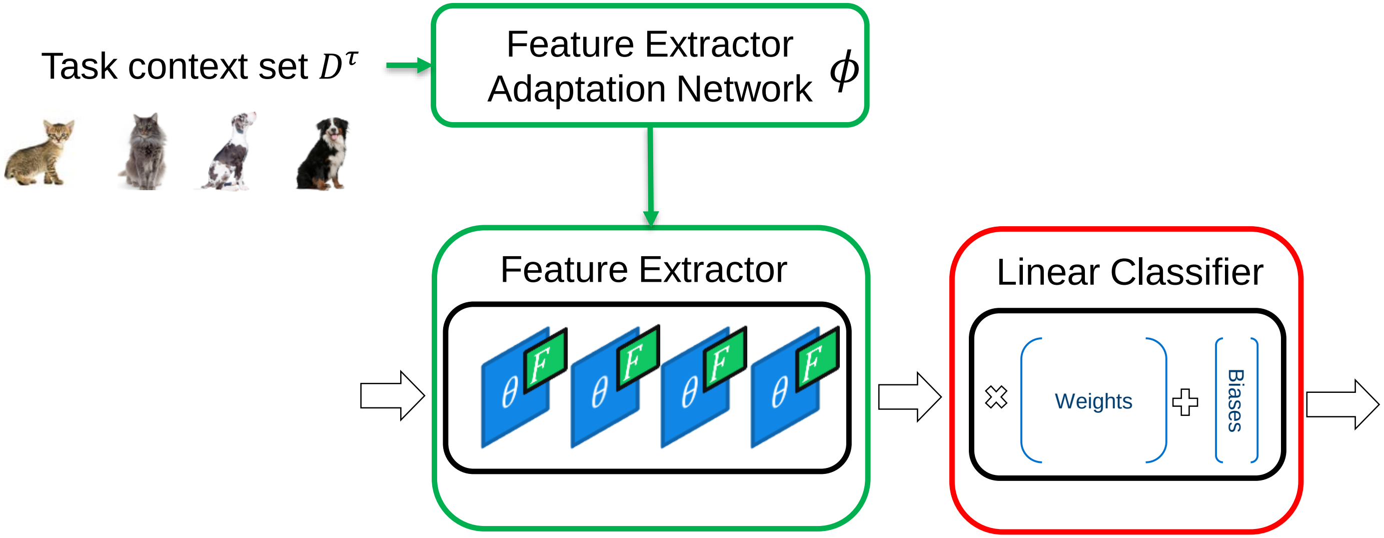

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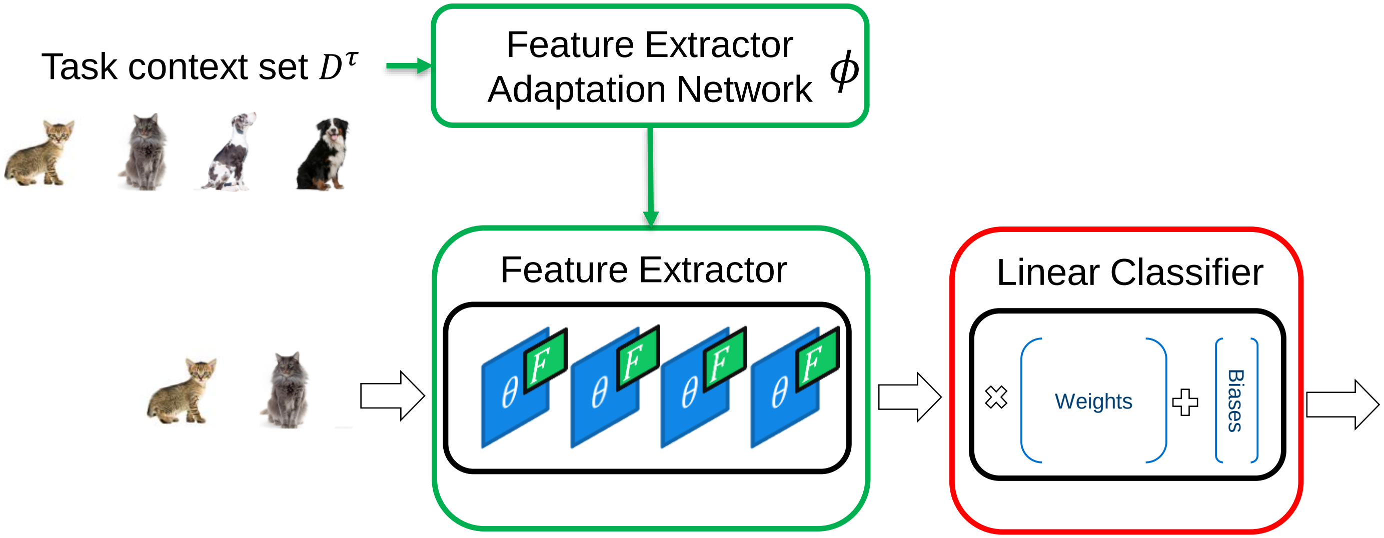

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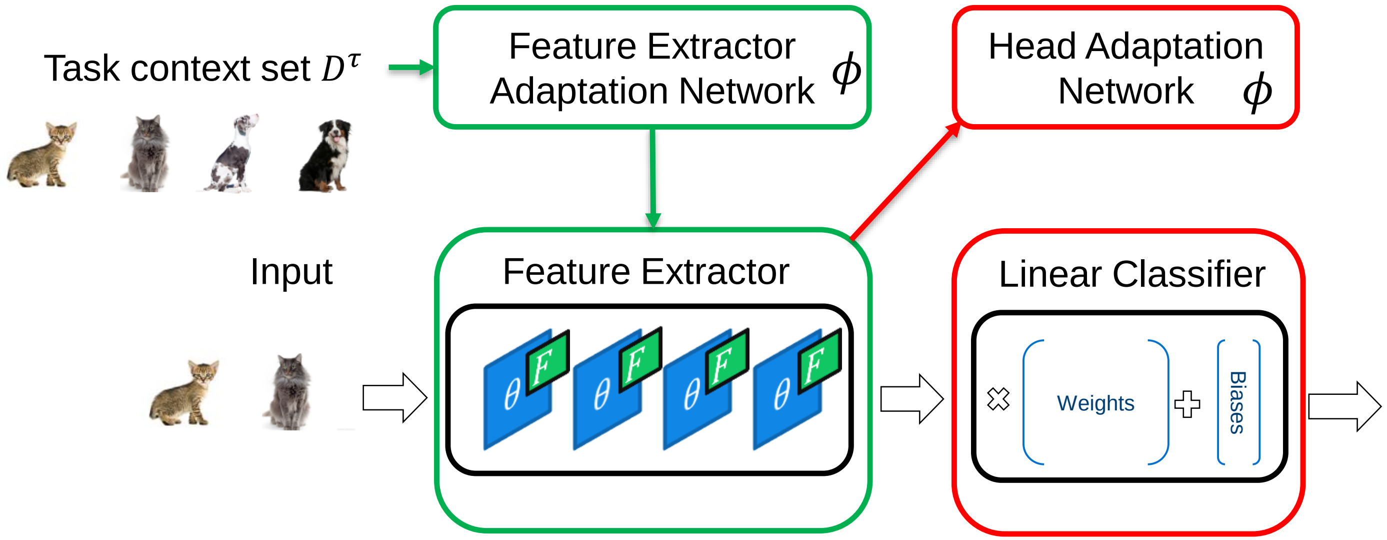

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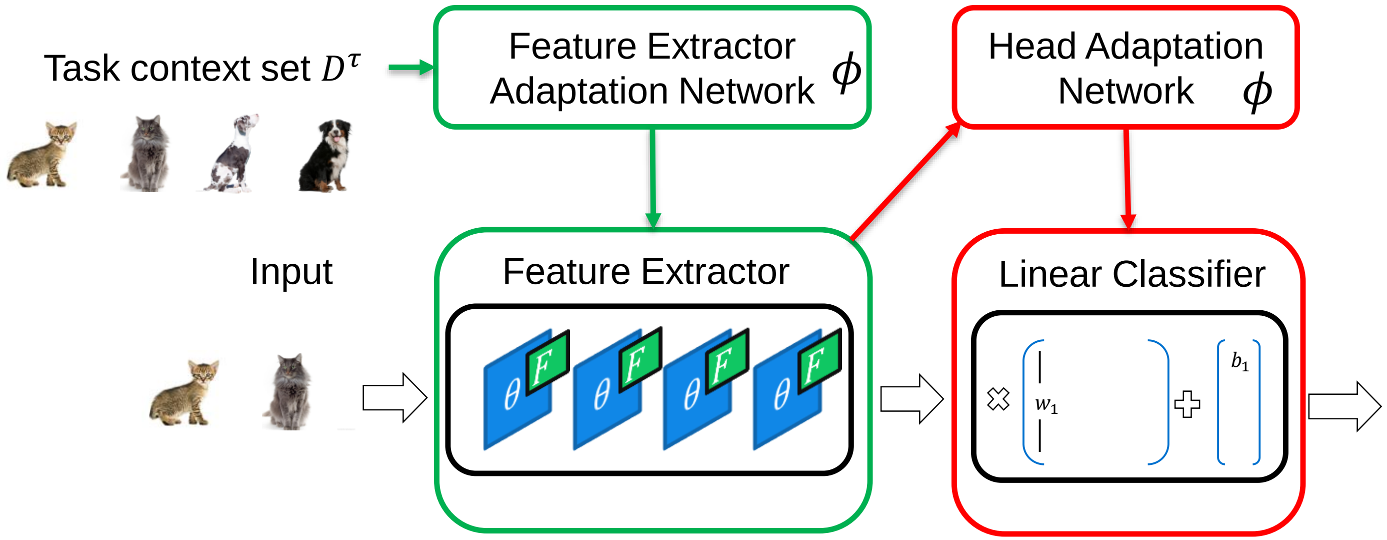

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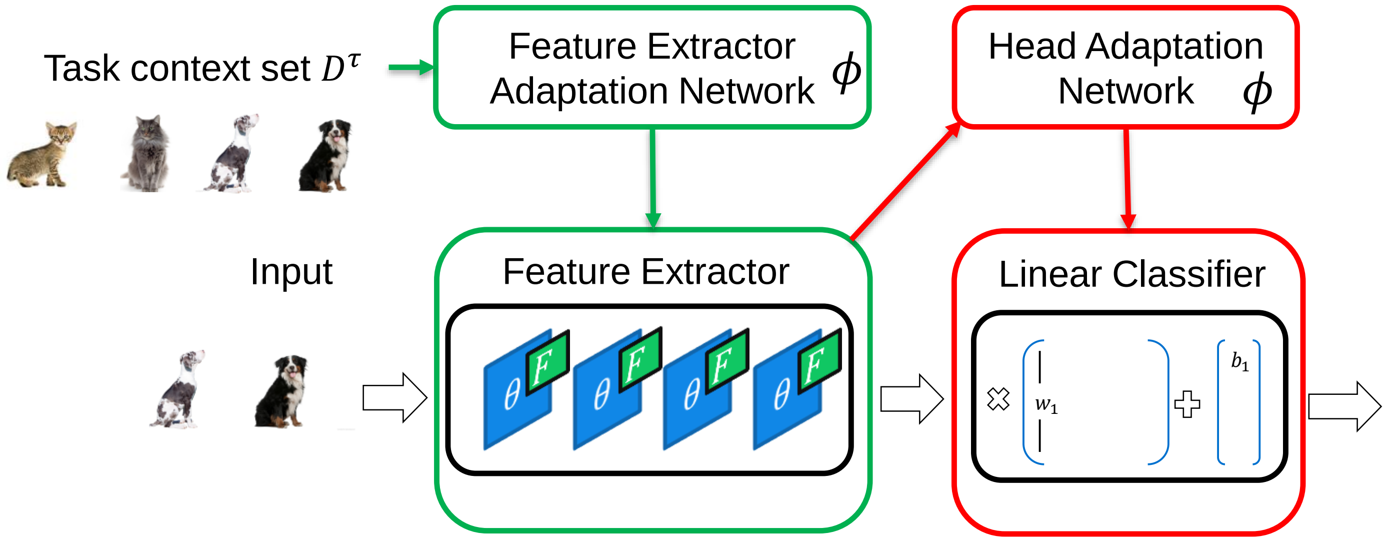

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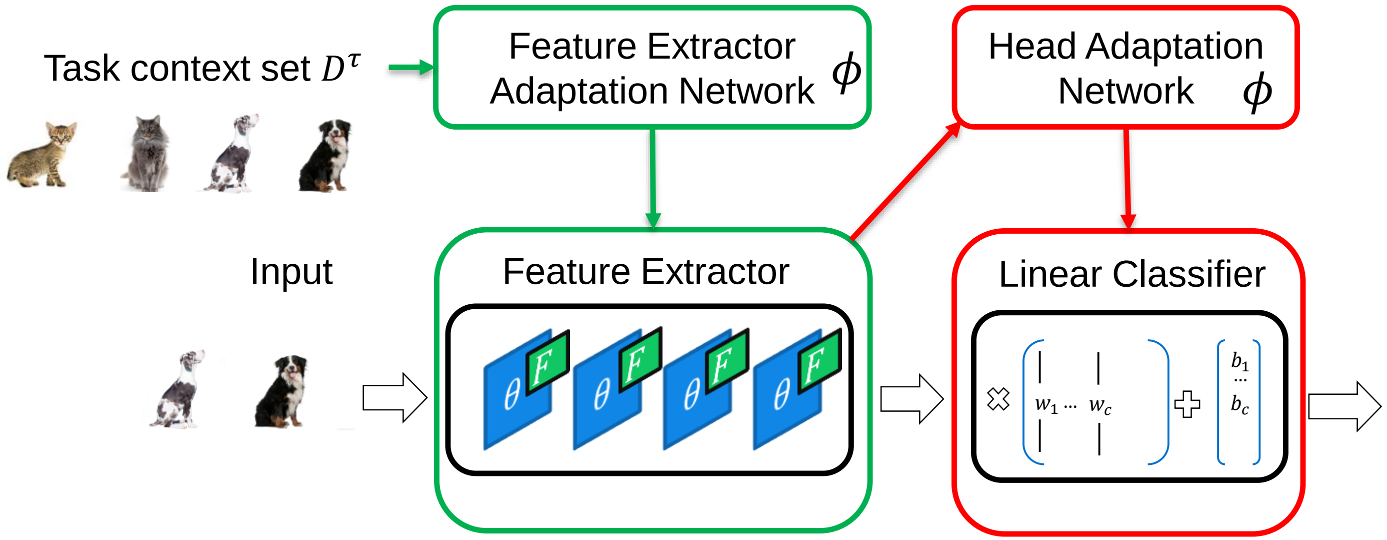

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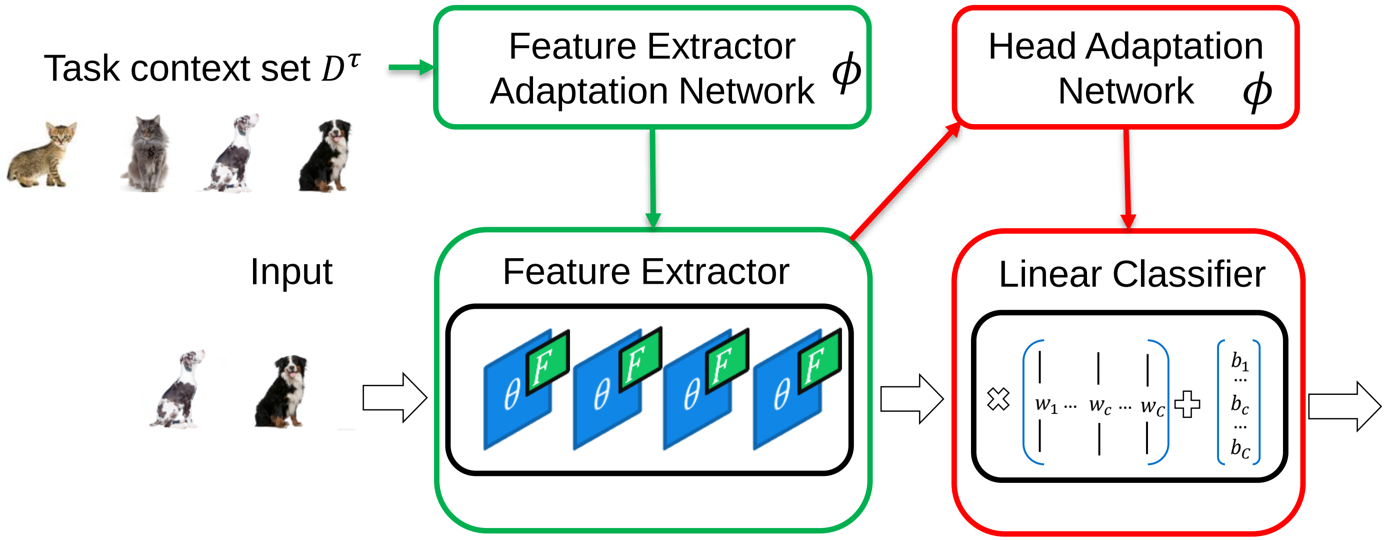

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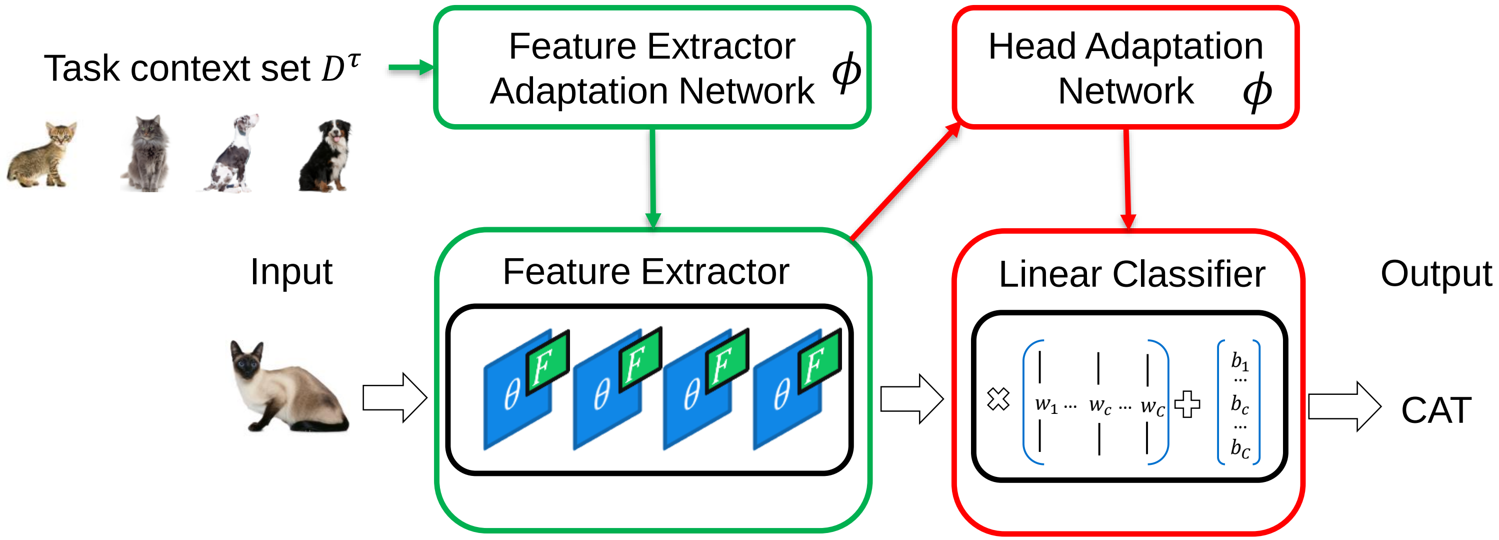

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Summary of Adaptation

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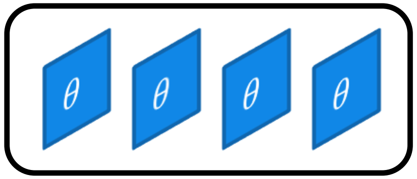

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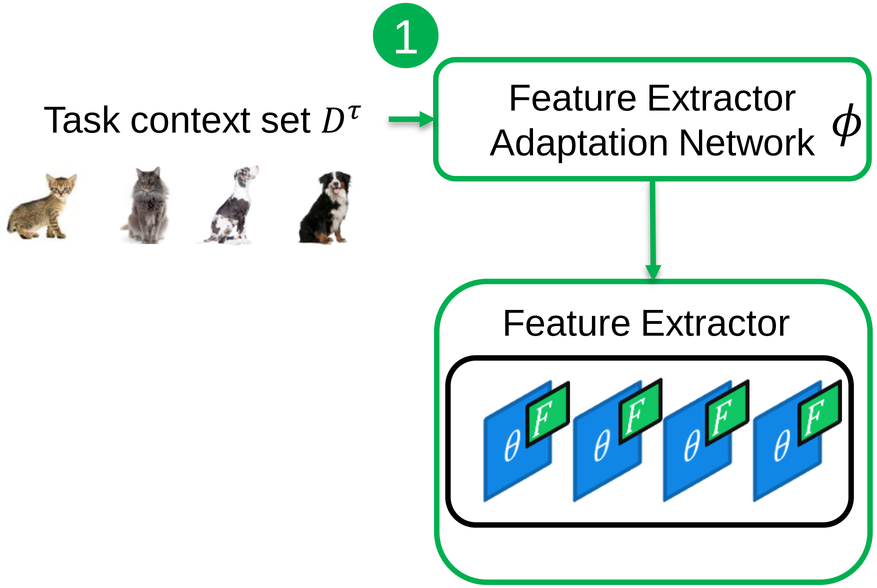

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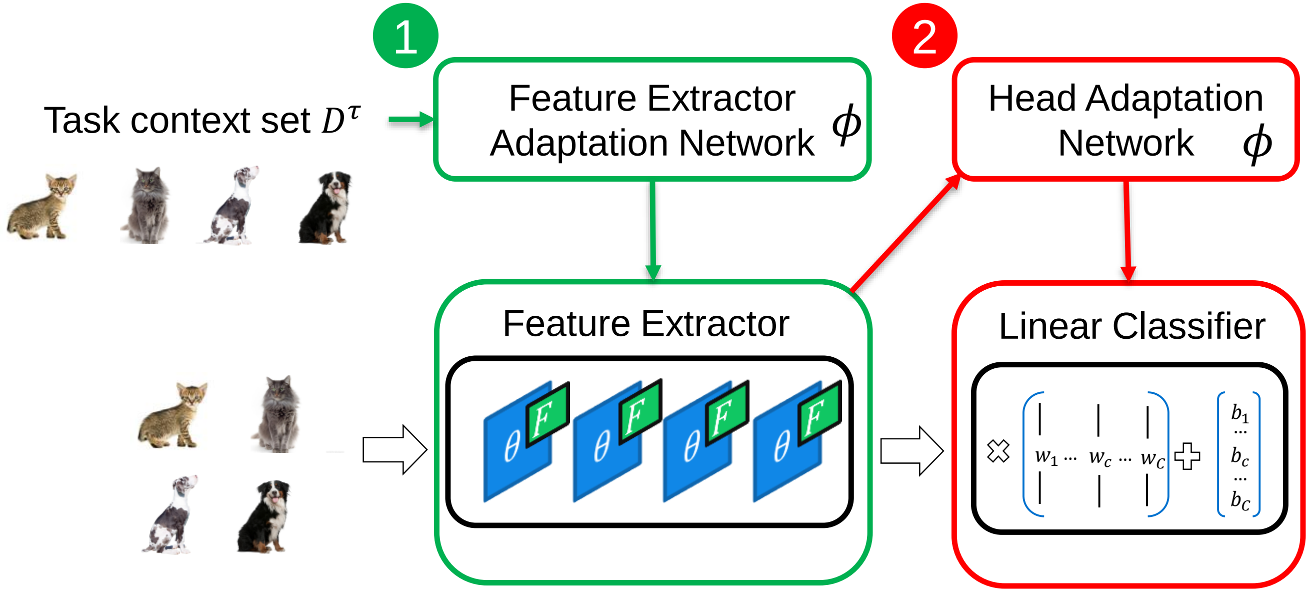

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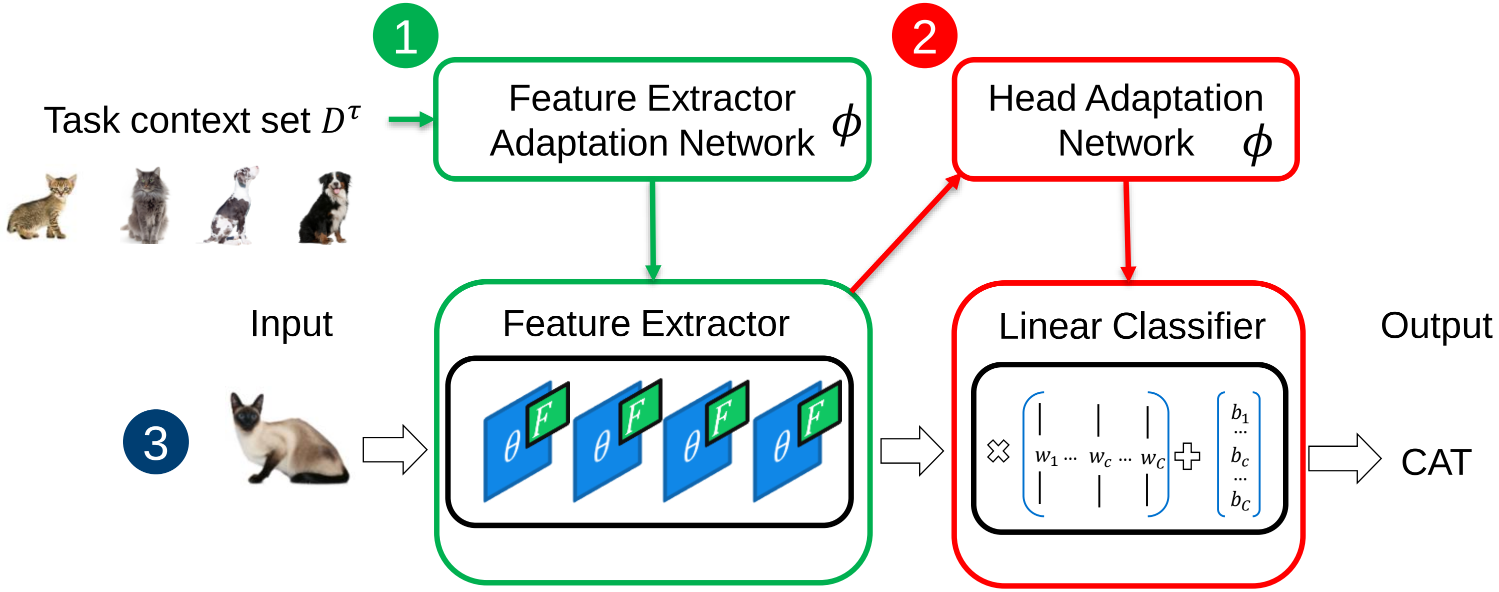
3. Apply adapted network to test examples.



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④ Update $\phi_{new} = \phi_{old} + \eta \nabla_\phi L^\tau$ with learning rate η.

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  b. We want to "train as we test", and only the FiLM parameters will update during test.

Meta-Dataset[1] Multi-task, Few-shot Benchmark

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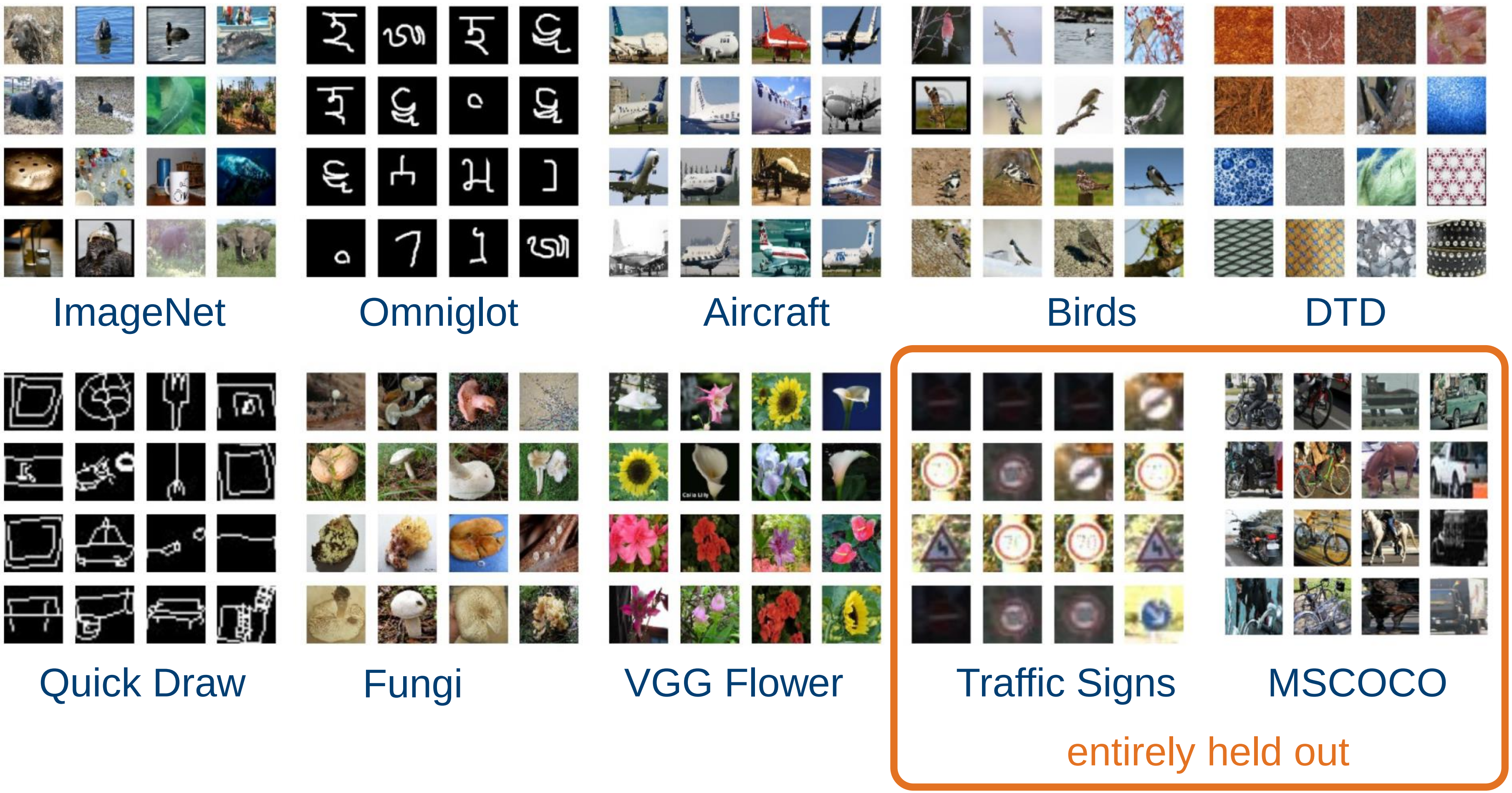

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Meta-Dataset Task Sampling

- Task (τ) sampling procedure:
  - Choose a dataset uniformly at random.
  - Choose a random number of classes (between 5 and 50) from the dataset.
  - Choose a random number of shots per class (minimum of 1, maximum of 500 across all classes).
  - Dataset hierarchy is respected in Omniglot and ImageNet
- Adaptation networks are trained on 100,000 of these tasks.

Meta-Dataset Few-Shot Classification Results

Dataset	Finetune	MatchingNet	ProtoNet	fo-MAML	Proto-MAML	CNAPs
ILSVRC [21]	43.1 ± 1.1	36.1 ± 1.0	44.5 ± 1.1	32.4 ± 1.0	47.9 ± 1.1	**52.3 ± 1.0**
Omniglot [31]	71.1 ± 1.4	78.3 ± 1.0	79.6 ± 1.1	71.9 ± 1.2	82.9 ± 0.9	**88.4 ± 0.7**
Aircraft [32]	72.0 ± 1.1	69.2 ± 1.0	71.1 ± 0.9	52.8 ± 0.9	74.2 ± 0.8	**80.5 ± 0.6**
Birds [33]	59.8 ± 1.2	56.4 ± 1.0	67.0 ± 1.0	47.2 ± 1.1	70.0 ± 1.0	**72.2 ± 0.9**
Textures [34]	**69.1 ± 0.9**	61.8 ± 0.7	65.2 ± 0.8	56.7 ± 0.7	67.9 ± 0.8	58.3 ± 0.7
Quick Draw [35]	47.0 ± 1.2	60.8 ± 1.0	64.9 ± 0.9	50.5 ± 1.2	66.6 ± 0.9	**72.5 ± 0.8**
Fungi [36]	38.2 ± 1.0	33.7 ± 1.0	40.3 ± 1.1	21.0 ± 1.0	42.0 ± 1.1	**47.4 ± 1.0**
VGG Flower [37]	85.3 ± 0.7	81.9 ± 0.7	86.9 ± 0.7	70.9 ± 1.0	**88.5 ± 0.7**	86.0 ± 0.5
Traffic Signs [38]	**66.7 ± 1.2**	55.6 ± 1.1	46.5 ± 1.0	34.2 ± 1.3	52.3 ± 1.1	60.2 ± 0.9
MSCOCO [39]	35.2 ± 1.1	28.8 ± 1.0	39.9 ± 1.1	24.1 ± 1.1	**41.3 ± 1.0**	**42.6 ± 1.1**
MNIST [29]						**92.7 ± 0.4**
CIFAR10 [30]						**61.5 ± 0.7**
CIFAR100 [30]						**50.1 ± 1.0**

held out classes

entirely held out

FiLM Parameter Learning: SGD vs Adaptation Nets

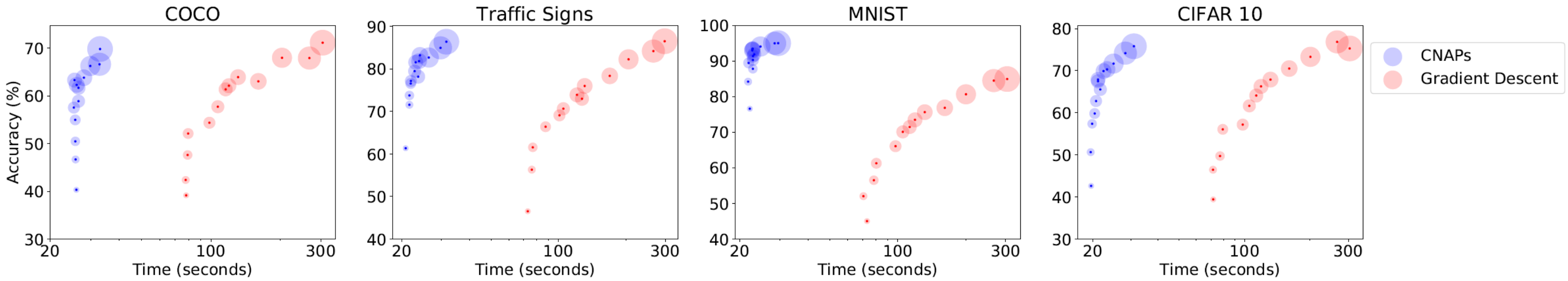


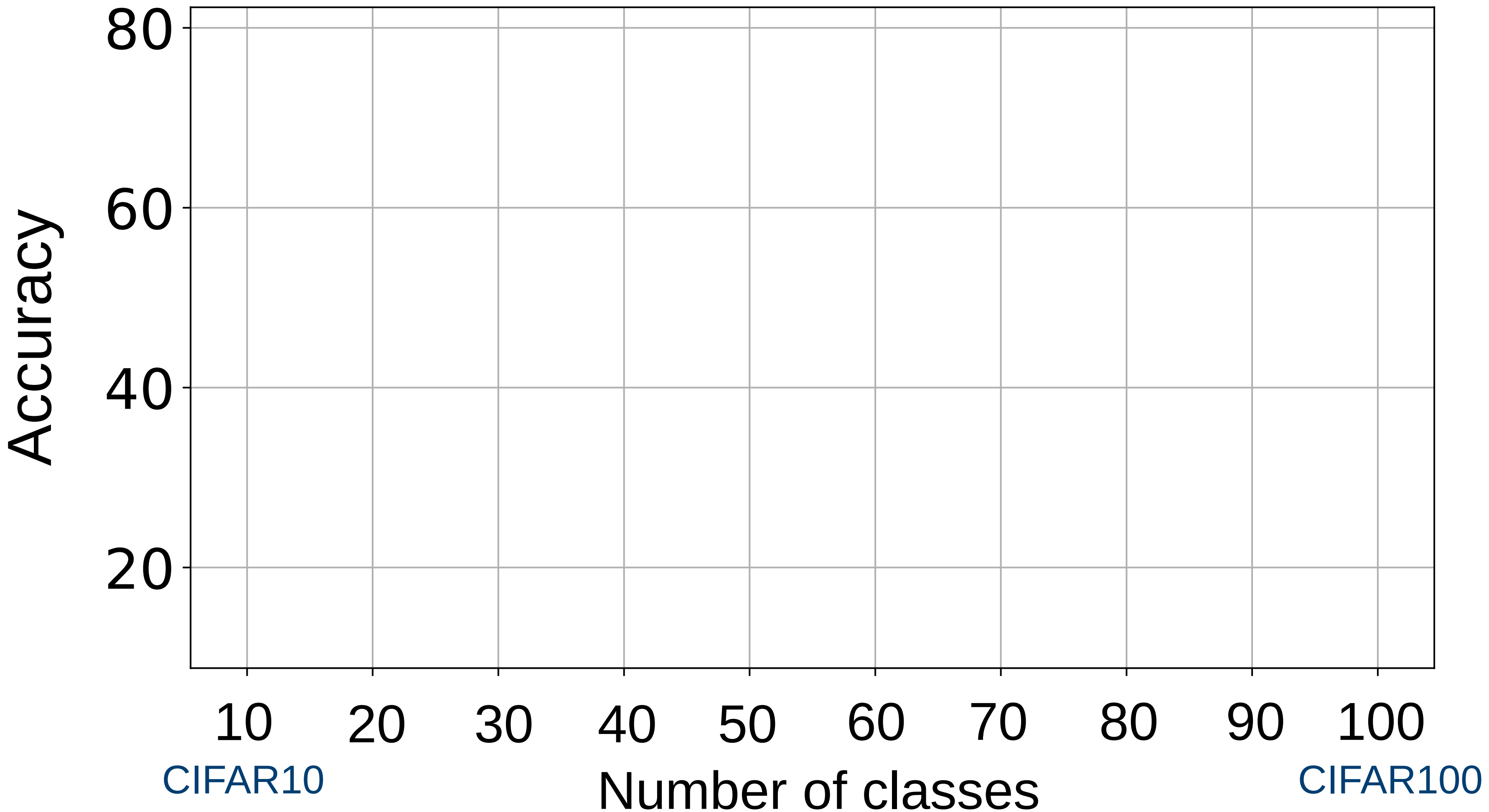
Figure 5: Comparing CNAPs to gradient based feature extractor adaptation: accuracy on 5-way classification tasks from withheld datasets as a function of processing time. Dot size reflects shot number (1 to 25 shots).

- Given sufficient data and processing time, SGD will yield higher accuracy, but:
  - CNAPs is at least 5x faster at test time as it only requires a *single forward pass* through the network while SGD needs multiple forward + backward passes.
  - CNAPs has higher accuracy at low shot, as it is resistant to overfitting as a result of the adaptation network parameters being shared and trained on diverse tasks.

Continual Learning

- Continual (or lifelong) learning involves learning from a sequence of new tasks without forgetting earlier ones.
- We employ the same meta-trained model that was use in the few-shot, multi-task classification experiments.
- Memory:
  - We allow our model to “remember” by storing running averages of the adaptation networks set encodings as new tasks are encountered.
- The following results are an “apples to oranges” comparison:
  - Model has been meta-trained on many datasets and has learned to adapt!

Continual Learning Results: Single head, CIFAR 100



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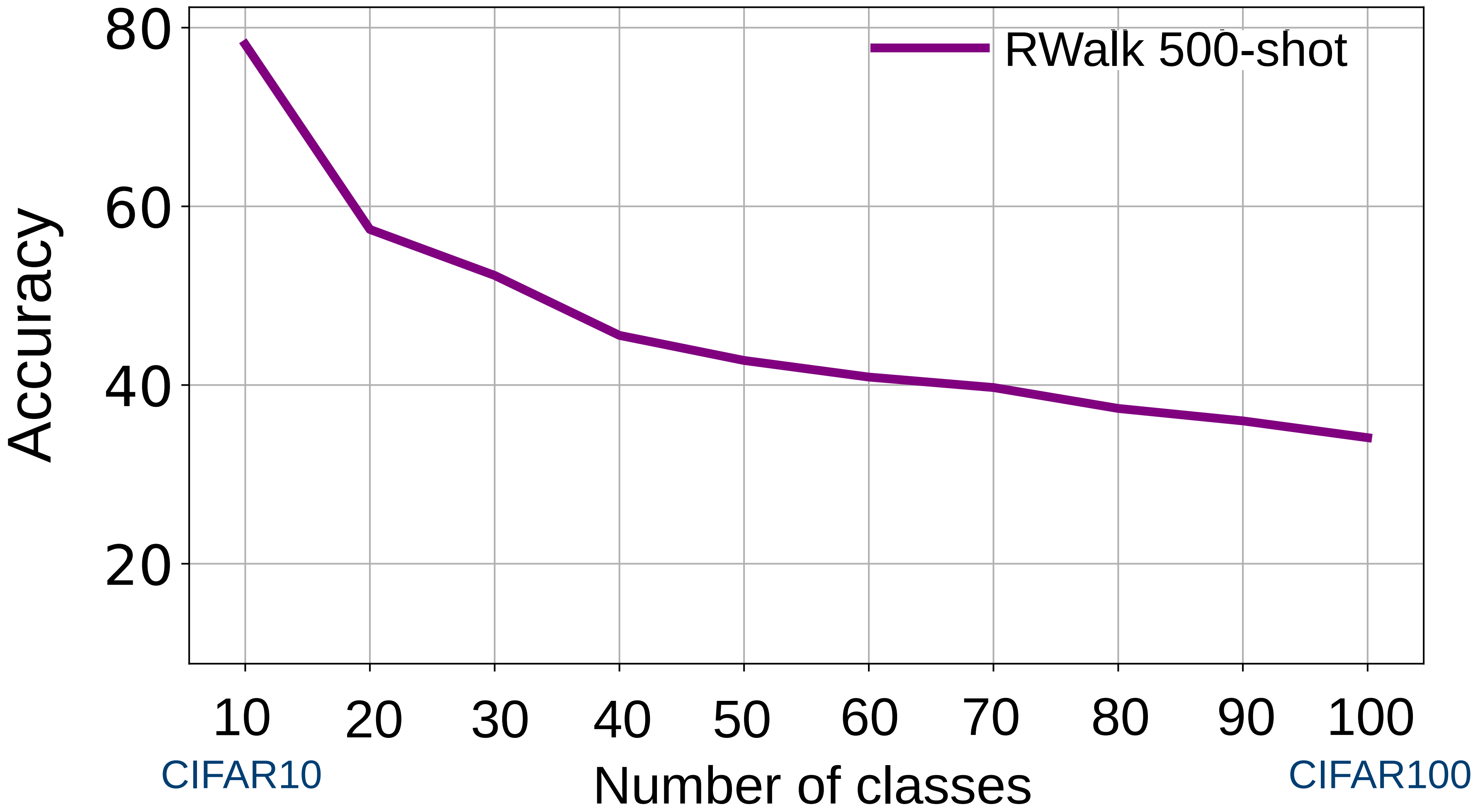

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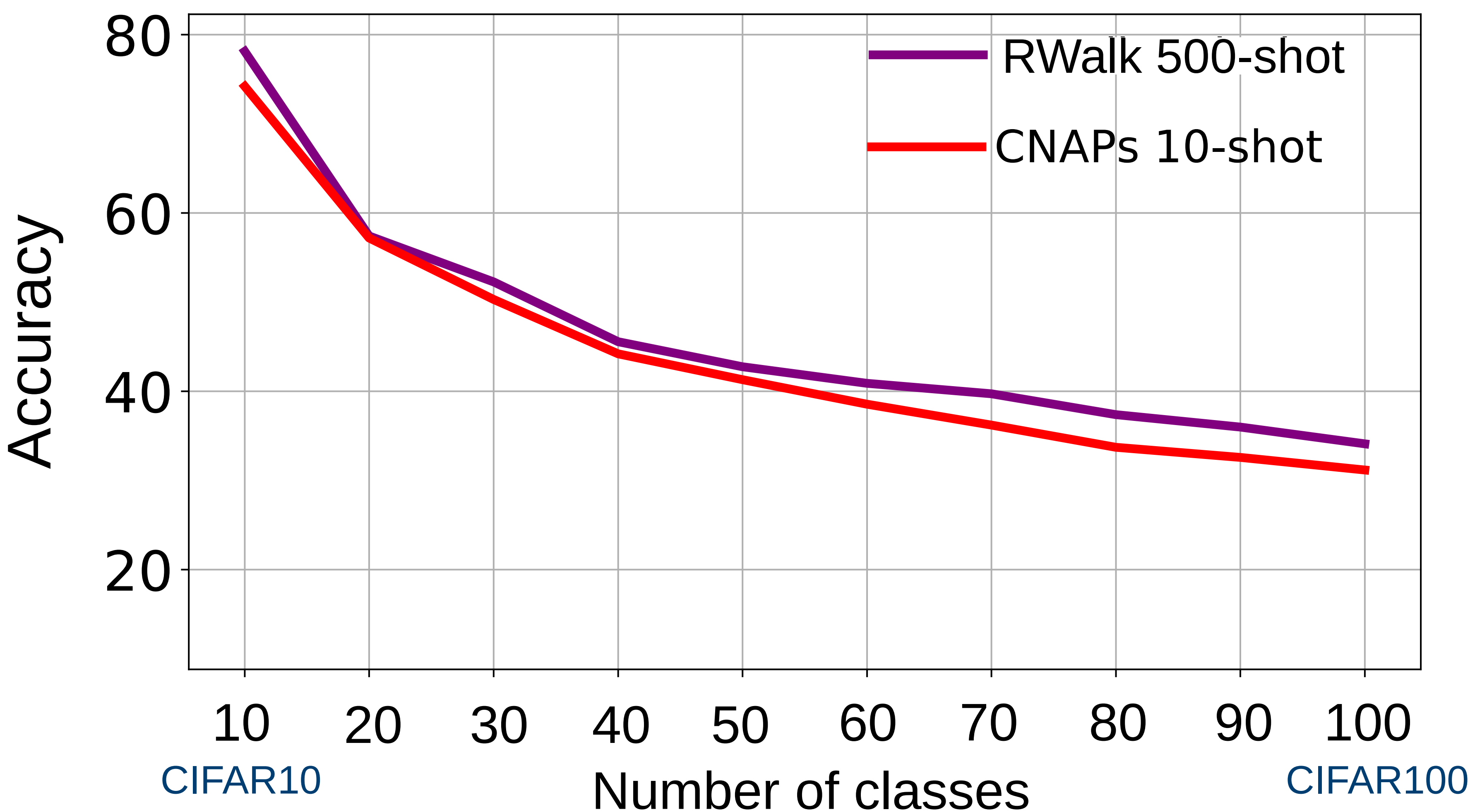

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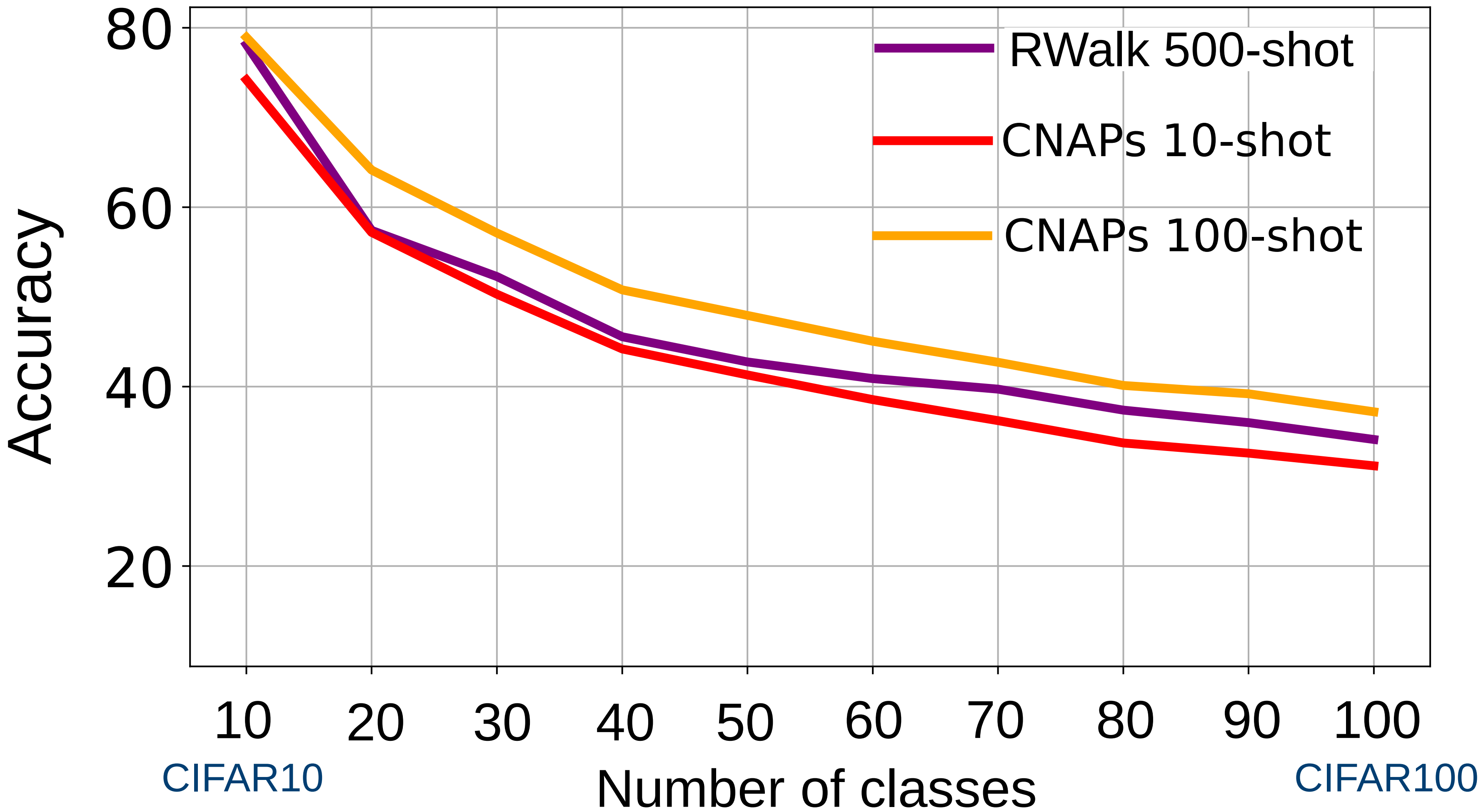

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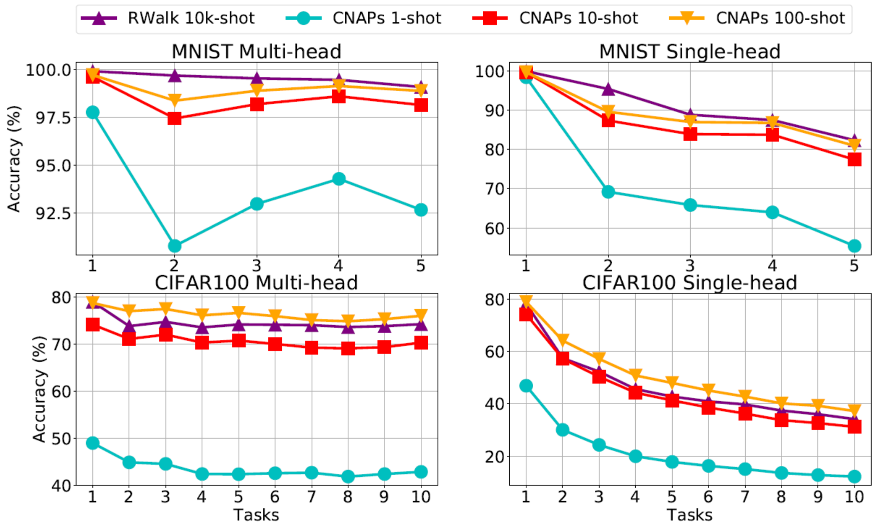

	MNIST		*CIFAR100*	
Method	Multi	Single	Multi	Single
SI [41]	99.3	57.6	73.2	22.8
EWC [43]	99.3	55.8	72.8	23.1
VCL [44]	98.5 $\pm$ 0.4	-	-	-
RWalk [42]	99.3	82.5	74.2	34.0
CNAPs	98.9 $\pm$ 0.2	80.9 $\pm$ 0.9	76.0 $\pm$ 0.5	37.2 $\pm$ 0.6

- Results are competitive with or better than state of the art baselines. Despite:
  - Not being trained to do continual learning.
  - Not exposed to these datasets during meta-training.
  - Observing orders of magnitude fewer examples.

Thanks for listening!

- Any questions?
- Paper: https://arxiv.org/pdf/1906.07697.pdf
- Code: https://github.com/cambridge-mlg/cnaps