On Recent Progress in Few-shot Classification

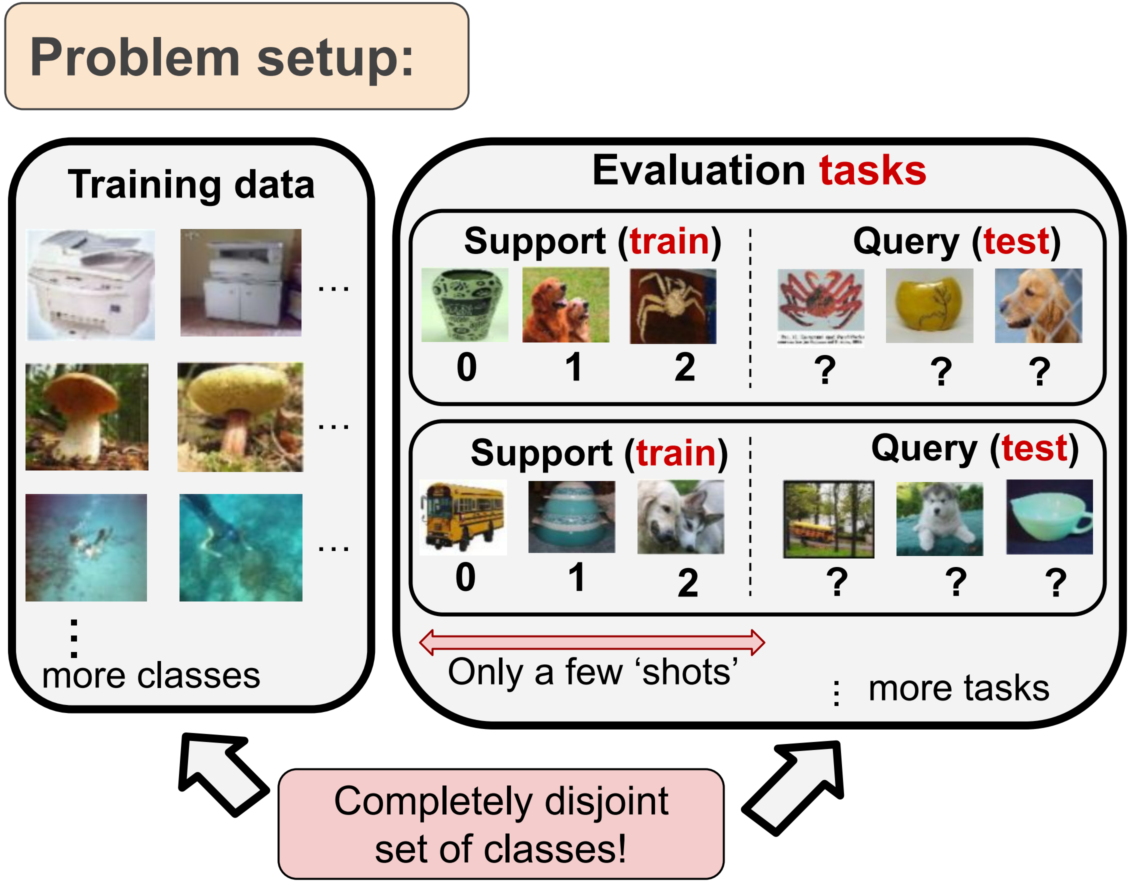
Eleni Triantafillou

Roadmap

- What is few-shot classification?
- Main families of approaches
- Representative meta-learning models
- Meta-Dataset: a more realistic and large-scale benchmark
- Open challenges and next steps

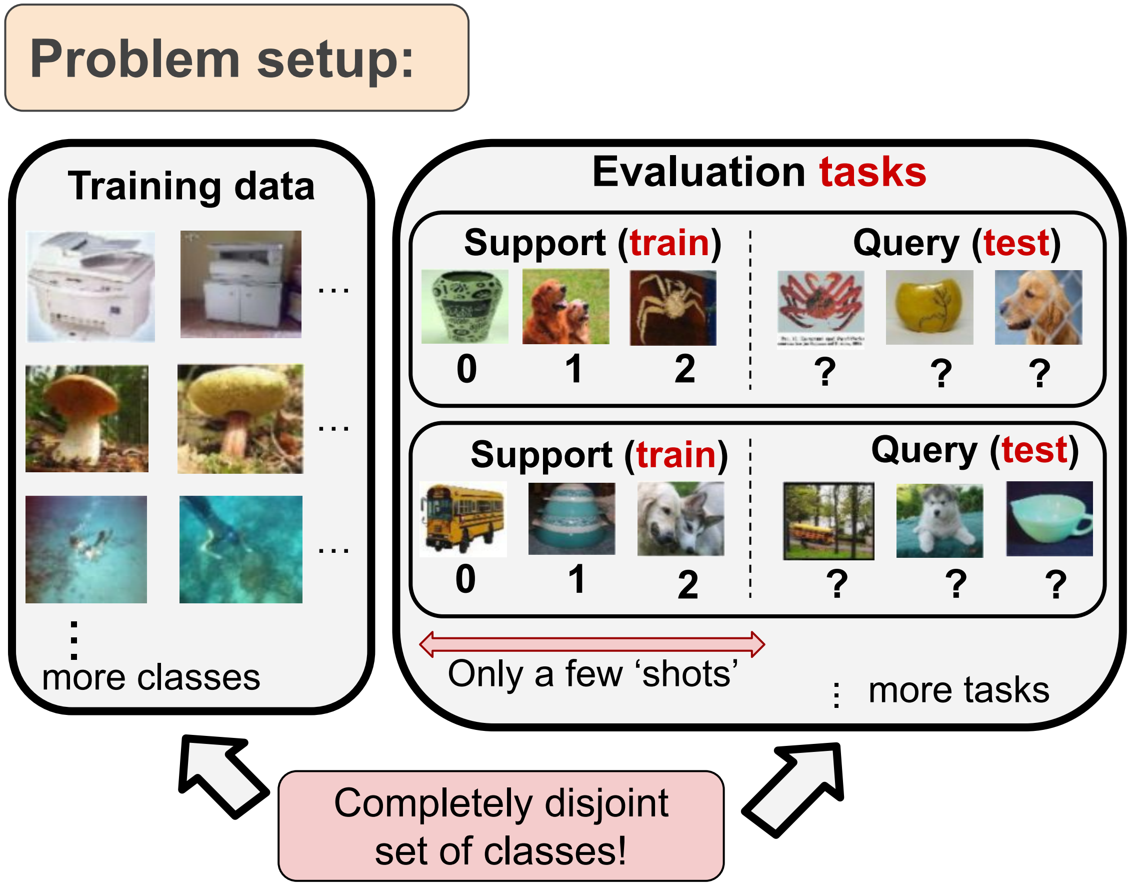
Few-shot Classification

- Learn new classes from few examples
- Practically important and scientifically interesting



Few-shot Classification

- Learn new classes from few examples
- Practically important and scientifically interesting
- Two challenges:
  1. How to use the training data to learn a model that supports rapid learning? ('*training approach*')
  2. How to use the support set of each task to adapt? ('*inference algorithm*')



Families of approaches to few-shot classification

Different approaches differ by their choice of training approach and inference algorithm:

- Generative modeling
- Metric learning
- Transfer learning
- Meta-learning

Disclaimer: this presentation does not thoroughly cover all approaches. Happy to chat offline and point to related papers / more information about any particular approach.

Teaser: Early Generative Approaches (Fei-Fei et al., 2006)

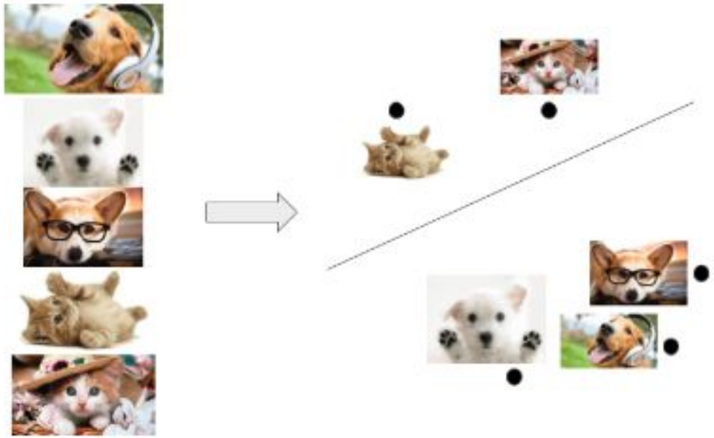
- At test time, we need to estimate parameters θ_c for $p(x|\theta_c)$ for the *test* class c using its **support set** $\mathcal{S}_c$
  - Bayes' rule to the rescue: $p(\theta_c|\mathcal{S}_c) \propto p(\theta_c)p(\mathcal{S}_c|\theta_c)$
  - The prior $p(\theta_c)$ reflects across-class general knowledge
  - A query point x^* then is classified as class c with probability:

$$p(x^*|\mathcal{S}_c) = \int p(x^*|\theta_c)p(\theta_c|\mathcal{S}_c)d\theta_c$$

- **Training approach**: Learn a prior probability density over models of classes
- **Inference algorithm**: Compute the posterior predictive probability of each query example x^* as shown above.

Metric Learning

- Learn an **embedding space** where examples cluster according to class labels



- **Training approach**: learn a *similarity function*.
- **Inference algorithm**: classify examples of new classes based on their *similarity* to the few support examples.

Siamese Networks (Koch et al., 2015)

- Metric learning method: use the training clases to learn a similarity metric.
- Siamese network: two identical branches for predicting similarity of pairs
- Koch et al. (2015) showed that a siamese network is capable of one-shot classification

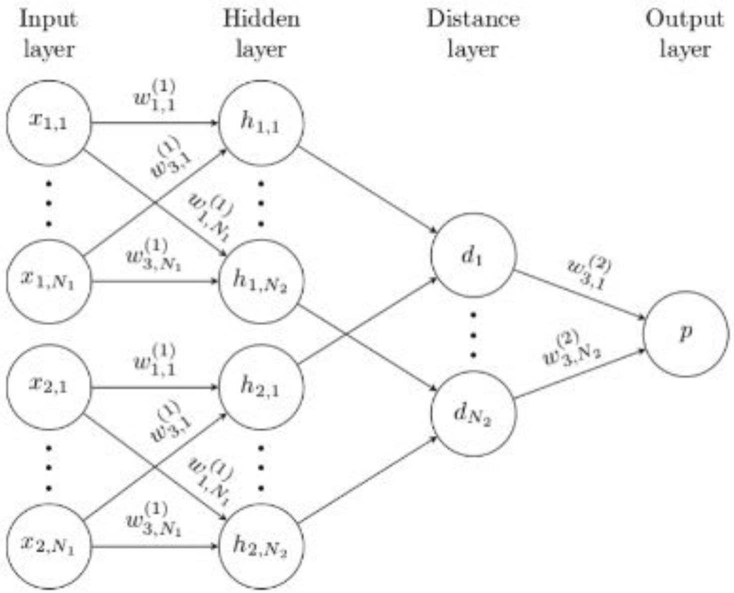
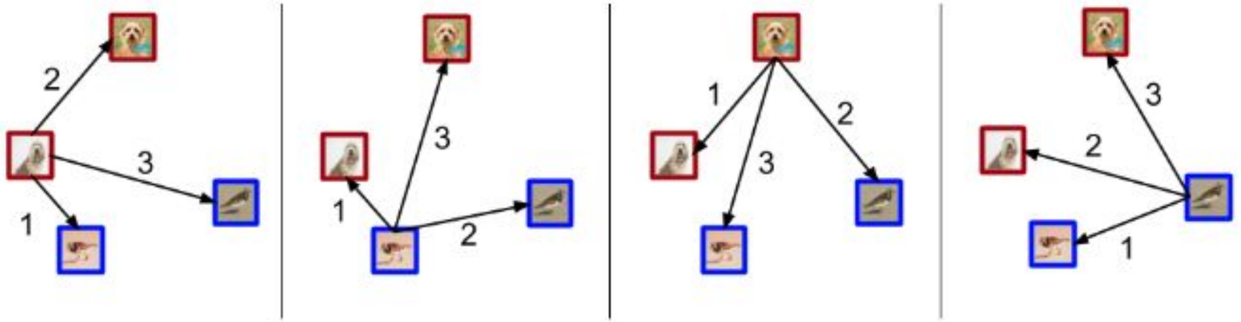


Figure: from (Koch et al., 2015)

Optimizing mean Average Precision (Triantafillou et al., 2017)

- Can we learn a better metric via a more informative objective?
- What do we *want* to hold in the embedding space? **Each point should be closer to *all* similar ones than to *any* dissimilar one.**
- We enforce this via a **structured objective**:
  - Compute ranks of predicted similarity between all examples
  - Maximize the mean Average Precision (mAP) of these rankings



Transfer learning vs Meta-learning

- Arguably the two most popular approaches recently

Transfer learning vs Meta-learning

- Arguably the two most popular approaches recently
- Influential work advocated for meta-learning

Matching Networks for One Shot Learning

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Prototypical Networks for Few-shot Learning

Jake Snell
University of Toronto*

Kevin Swersky
Twitter

Richard S. Zemel
University of Toronto, Vector Institute

Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks

Chelsea Finn [1] **Pieter Abbeel** [1 2] **Sergey Levine** [1]

Transfer learning vs Meta-learning

- Influential work advocated for meta-learning
- Recently, strong transfer learning ‘baselines’ emerged

A CLOSER LOOK AT FEW-SHOT CLASSIFICATION

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A BASELINE FOR FEW-SHOT IMAGE CLASSIFICATION

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Transfer learning vs Meta-learning

- Influential work advocated for meta-learning
- Recently, strong transfer learning 'baselines' emerged
- More recently, hybrid 'pre-training' and meta-learning models achieved better results

META-DATASET: A DATASET OF DATASETS FOR LEARNING TO LEARN FROM FEW EXAMPLES

Eleni Triantafillou[*†], Tyler Zhu[†], Vincent Dumoulin[†], Pascal Lamblin[†], Utku Evci[†], Kelvin Xu[‡†], Ross Goroshin[†], Carles Gelada[†], Kevin Swersky[†], Pierre-Antoine Manzagol[†] & Hugo Larochelle[†]
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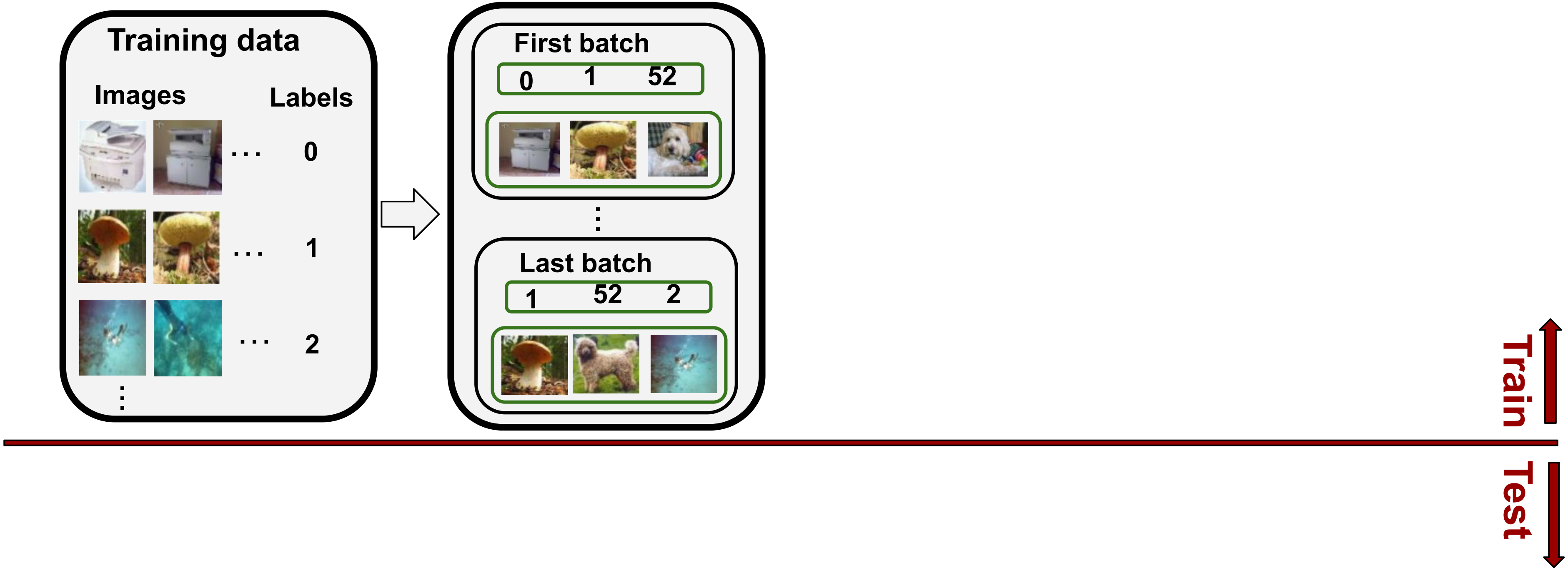
A New Meta-Baseline for Few-Shot Learning

Yinbo Chen[1] Xiaolong Wang[2] Zhuang Liu[2] Huijuan Xu[2] Trevor Darrell[2]

Transfer learning ‘baseline’



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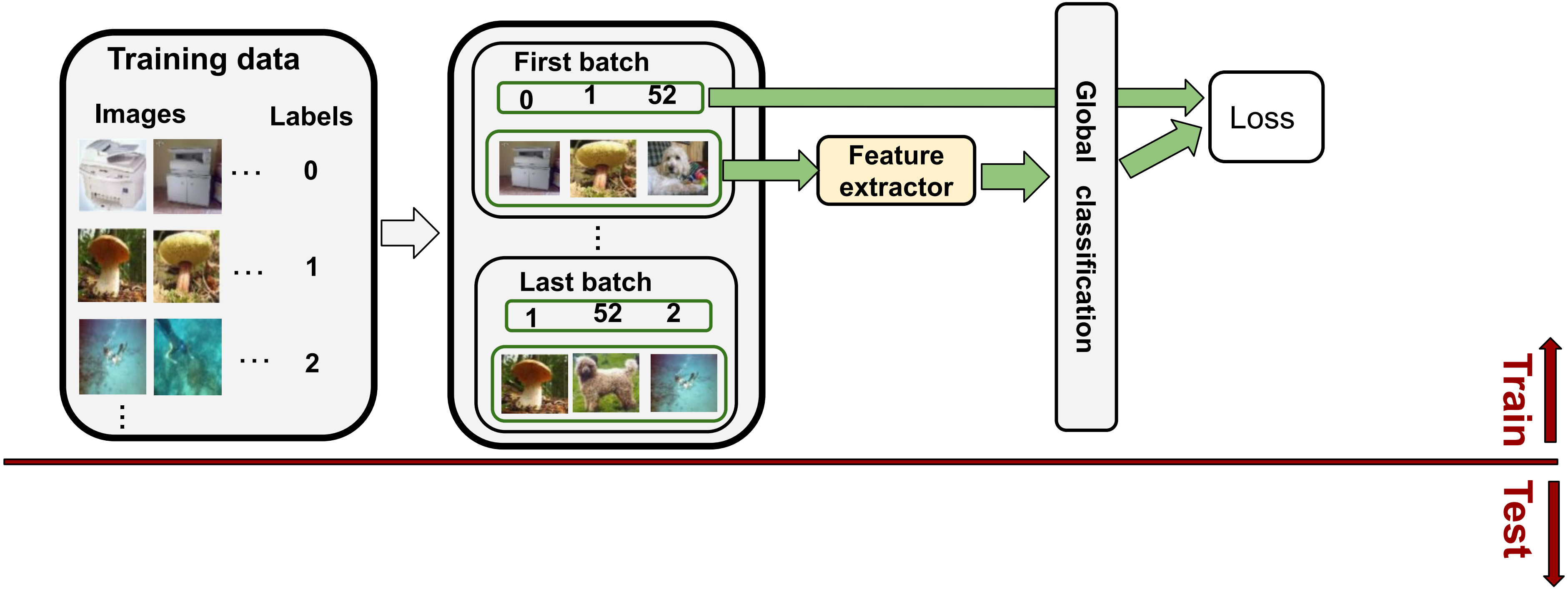

Transfer learning ‘baseline’

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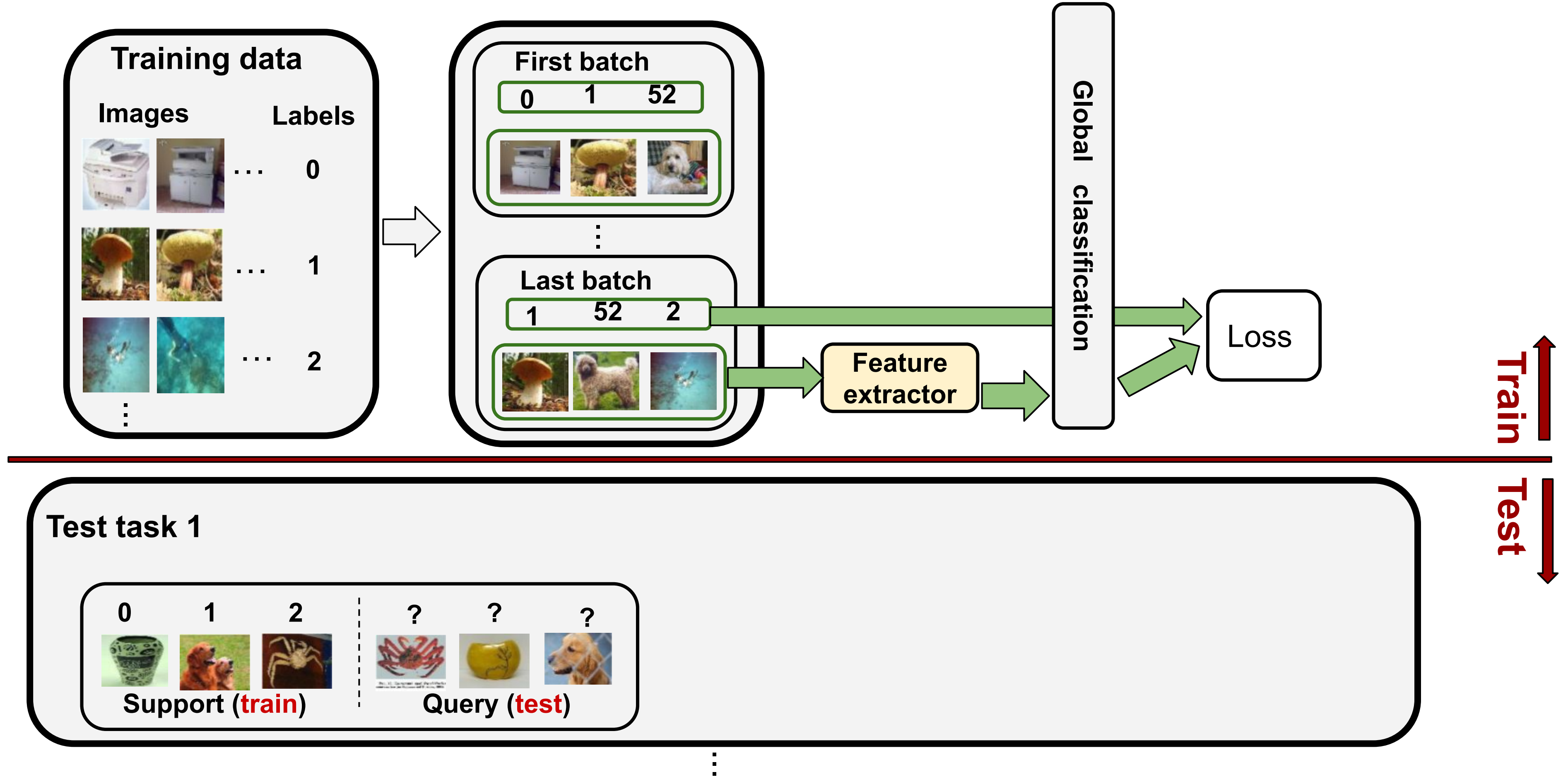

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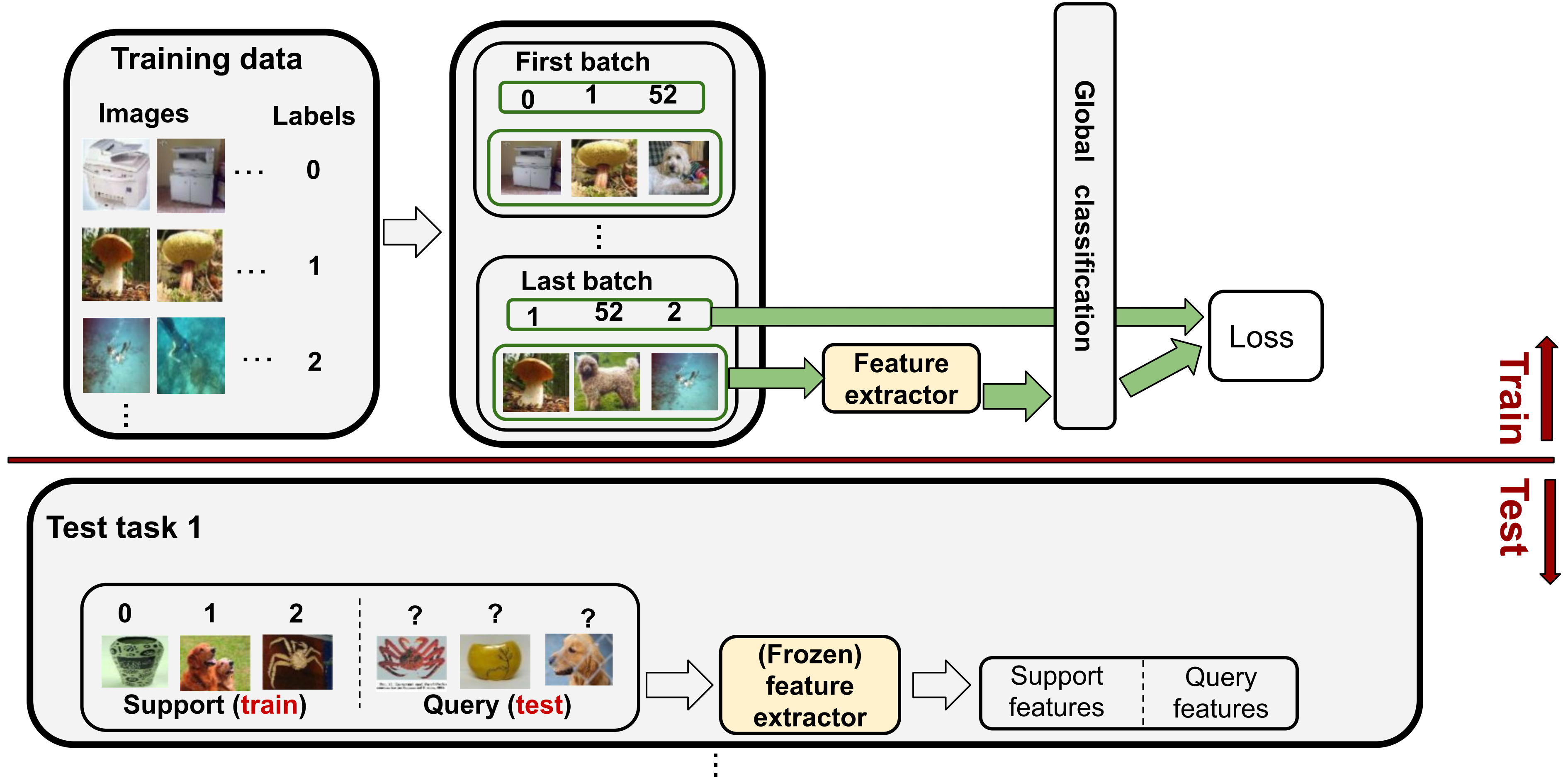

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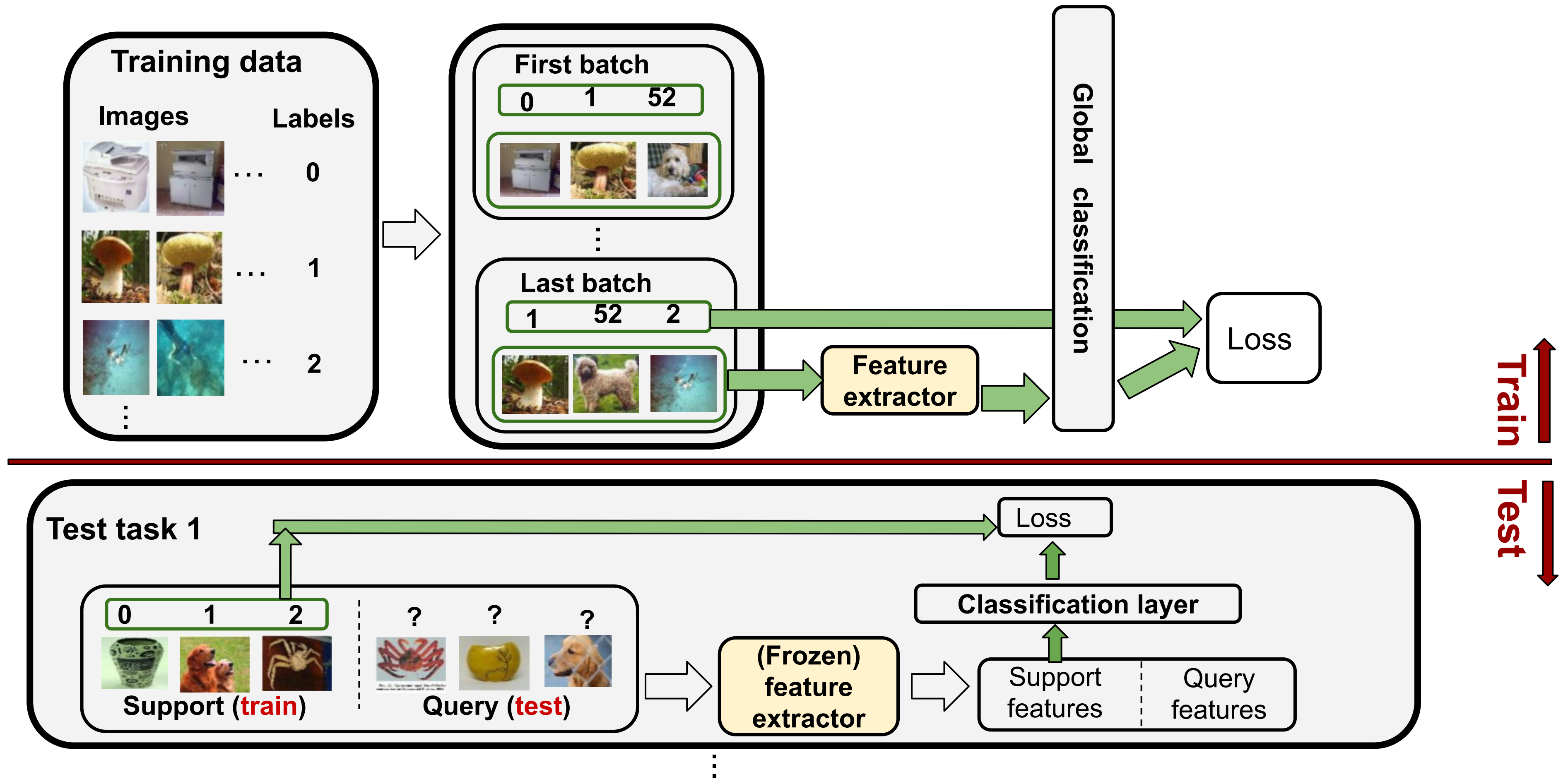

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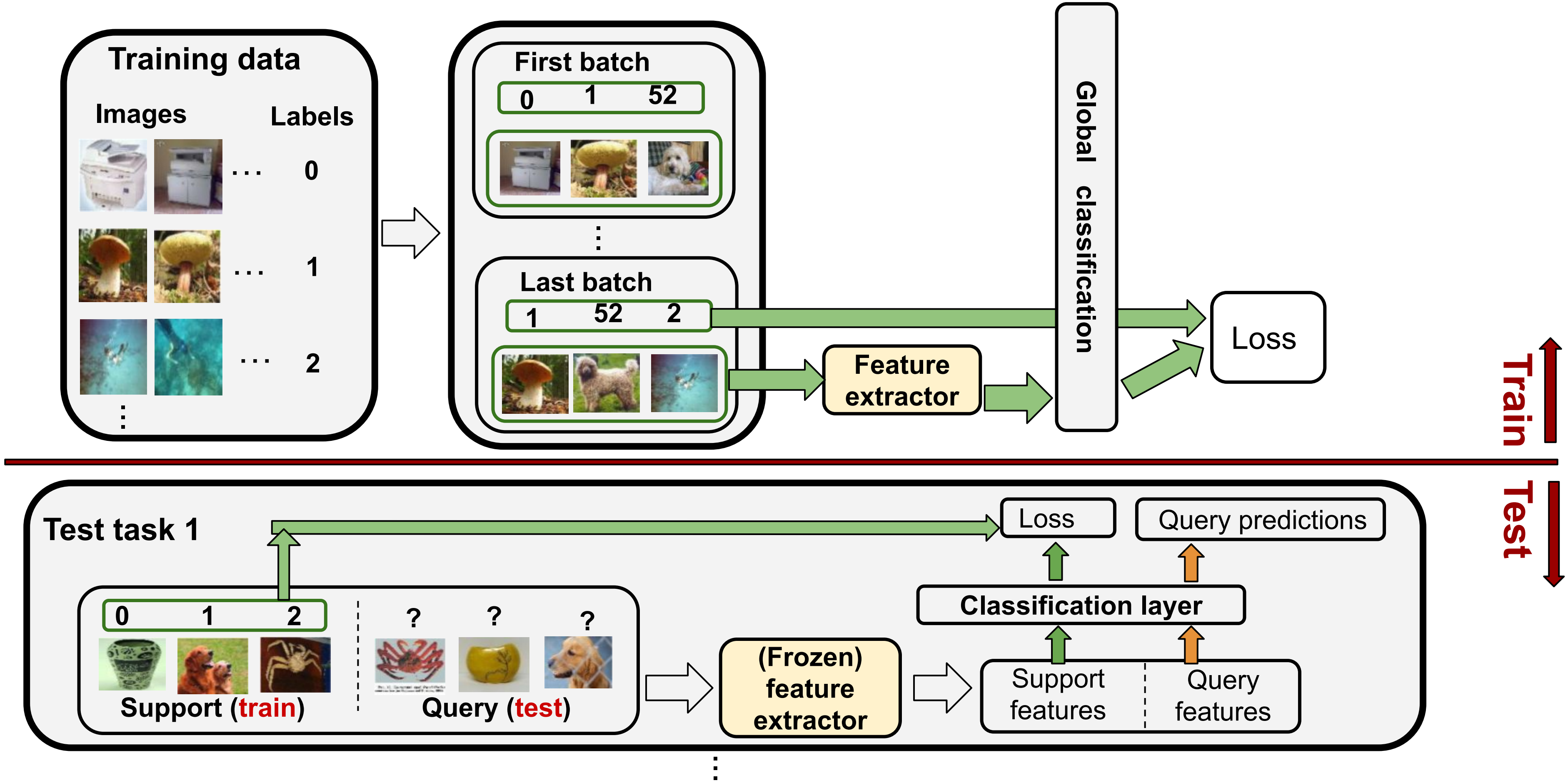

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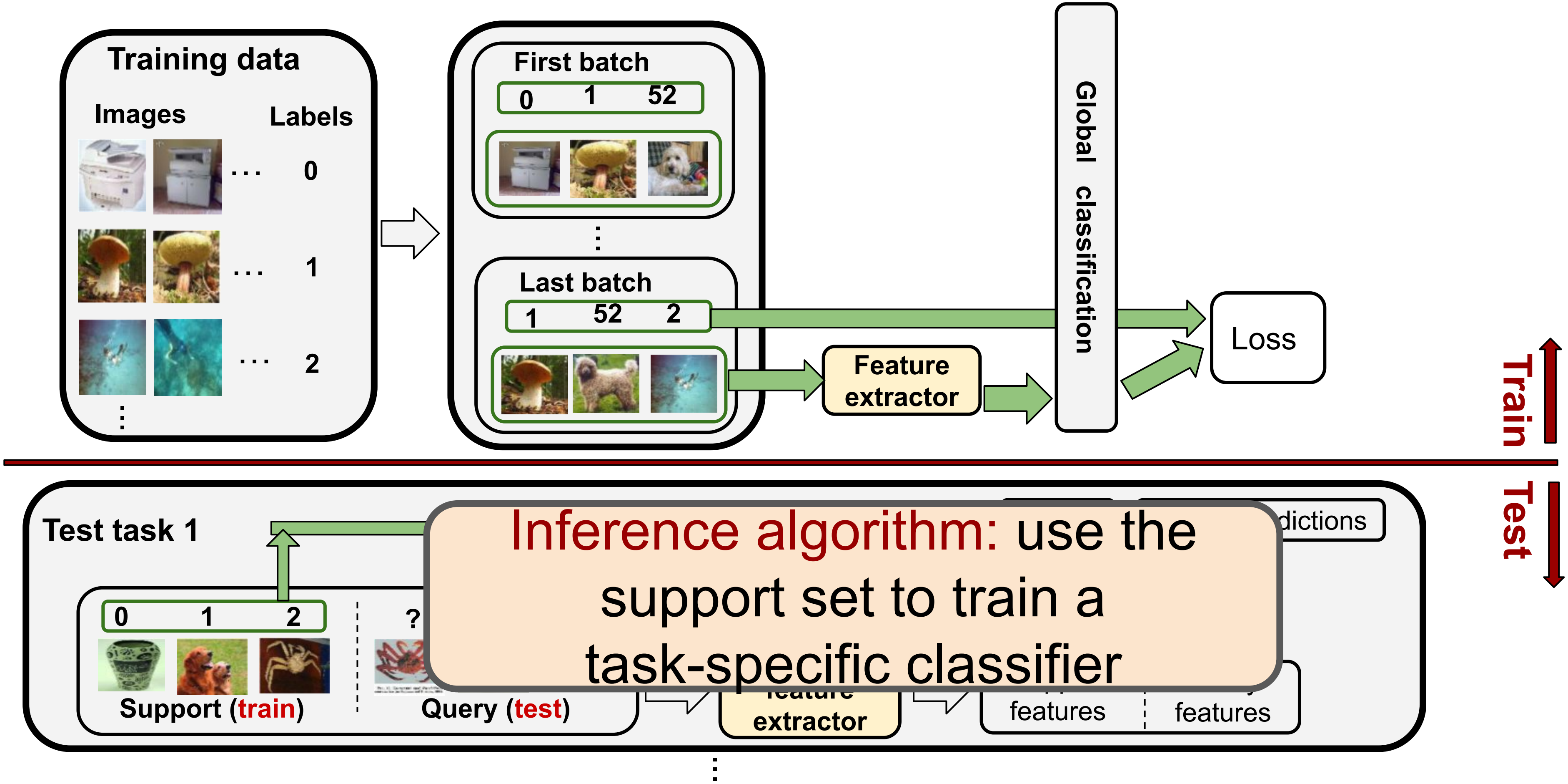

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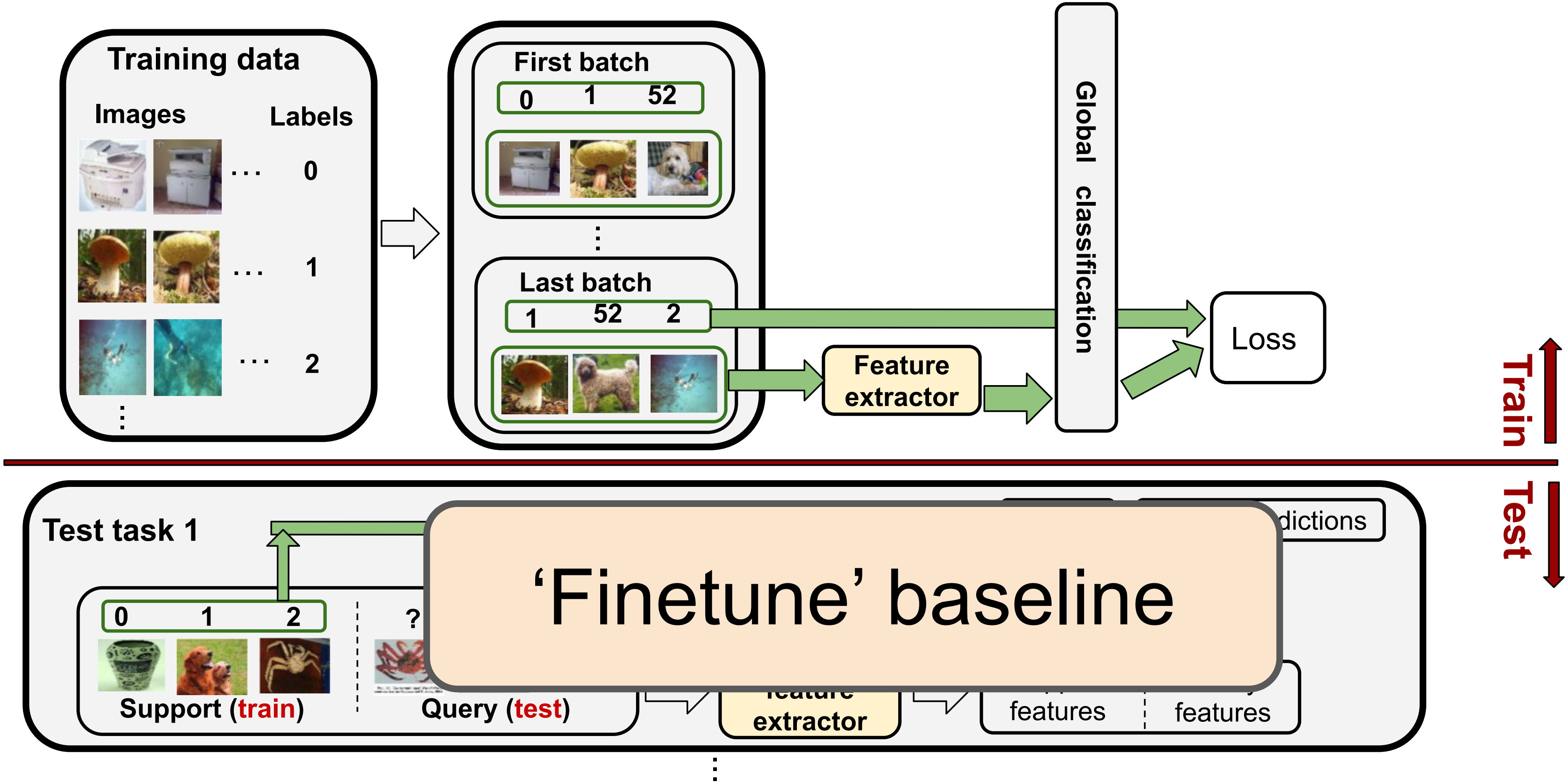

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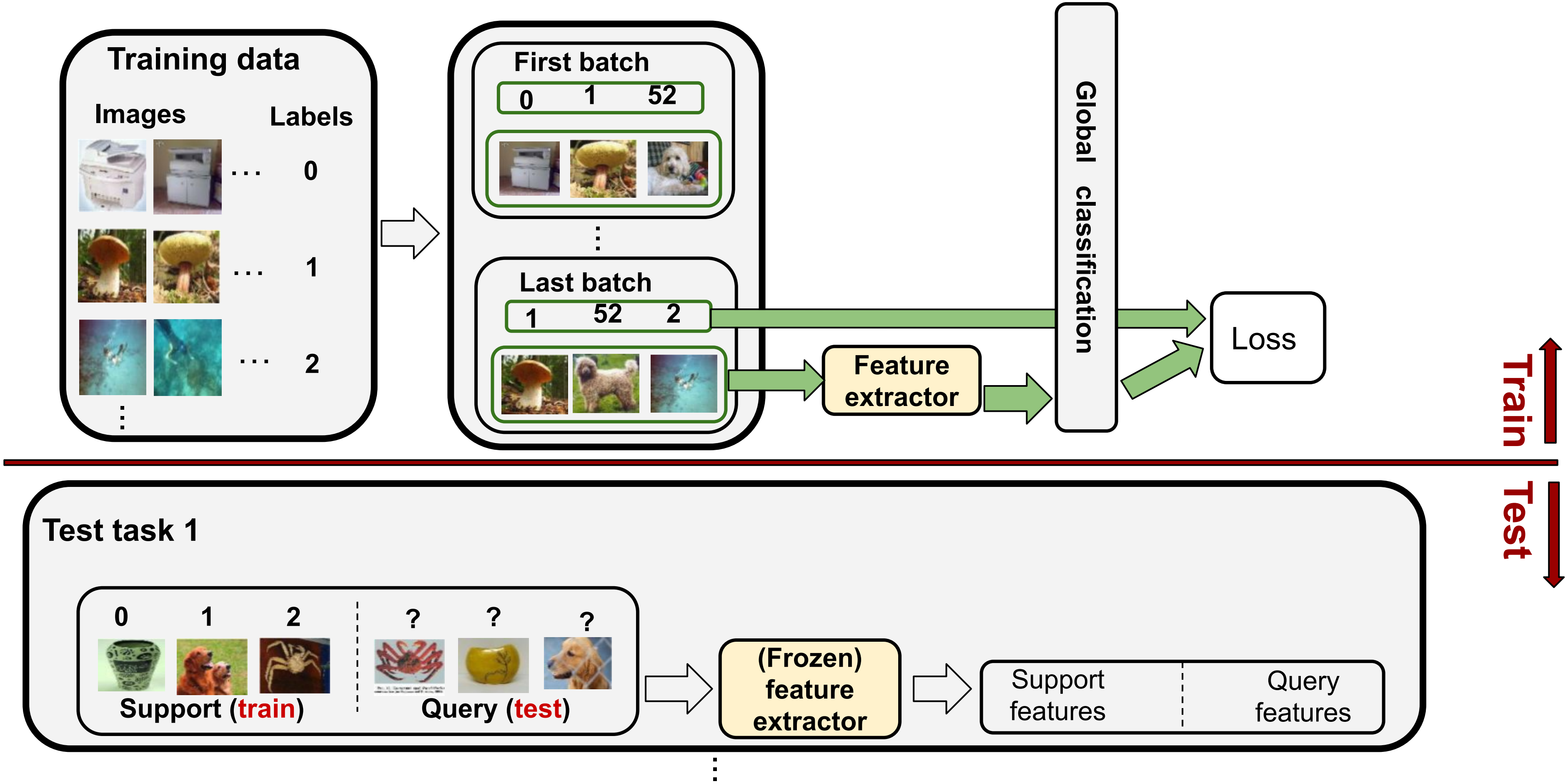

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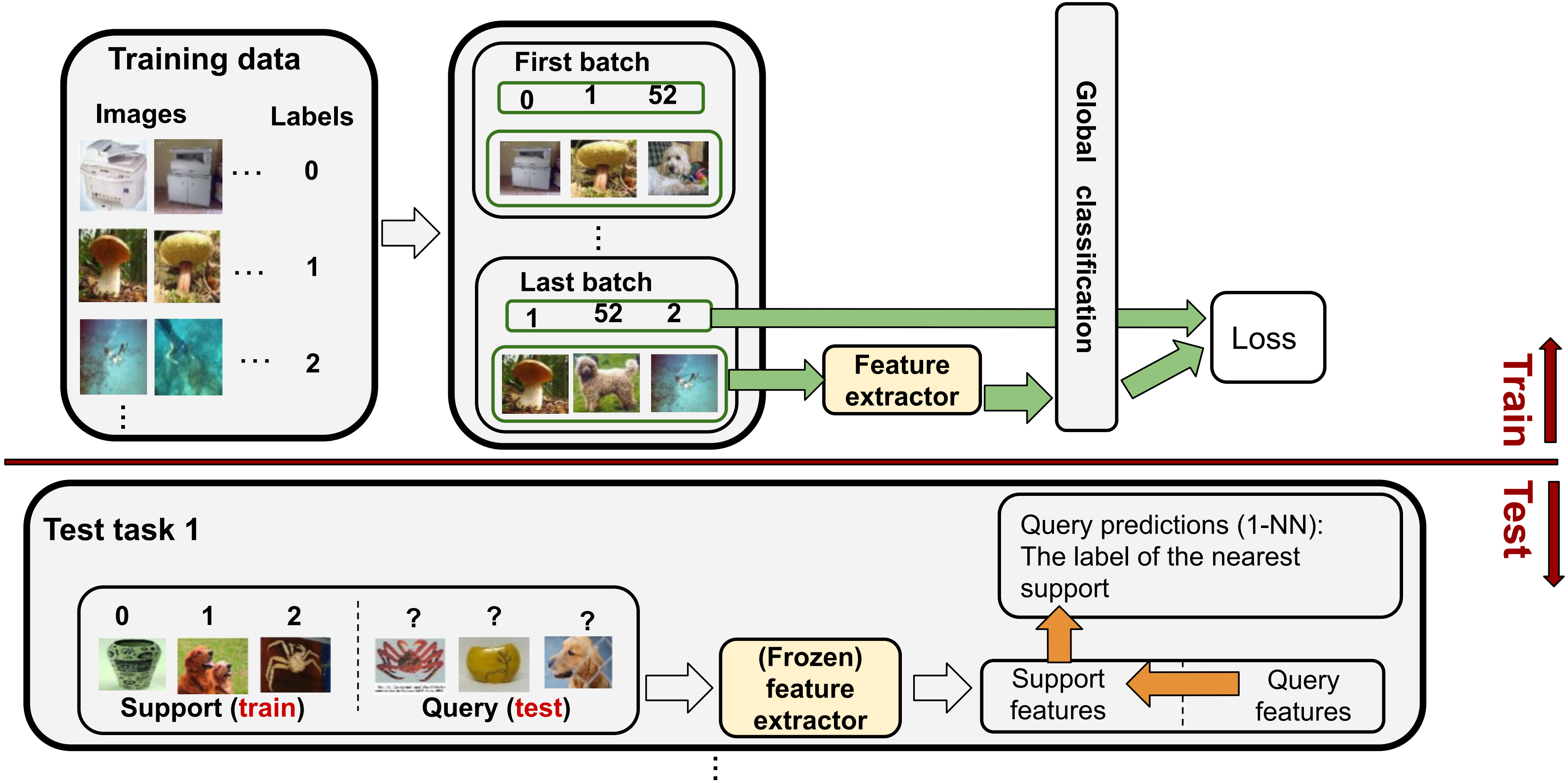

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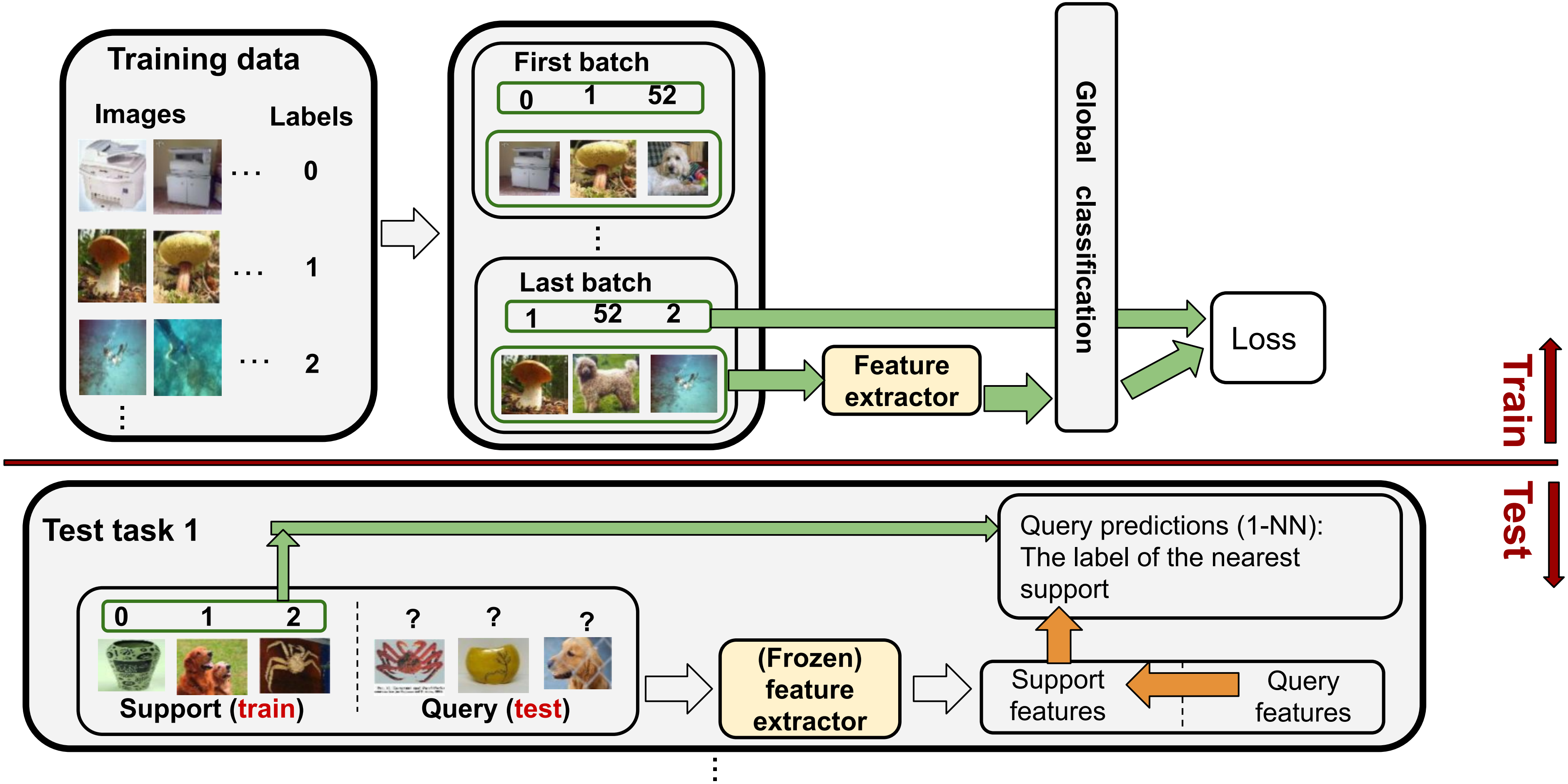

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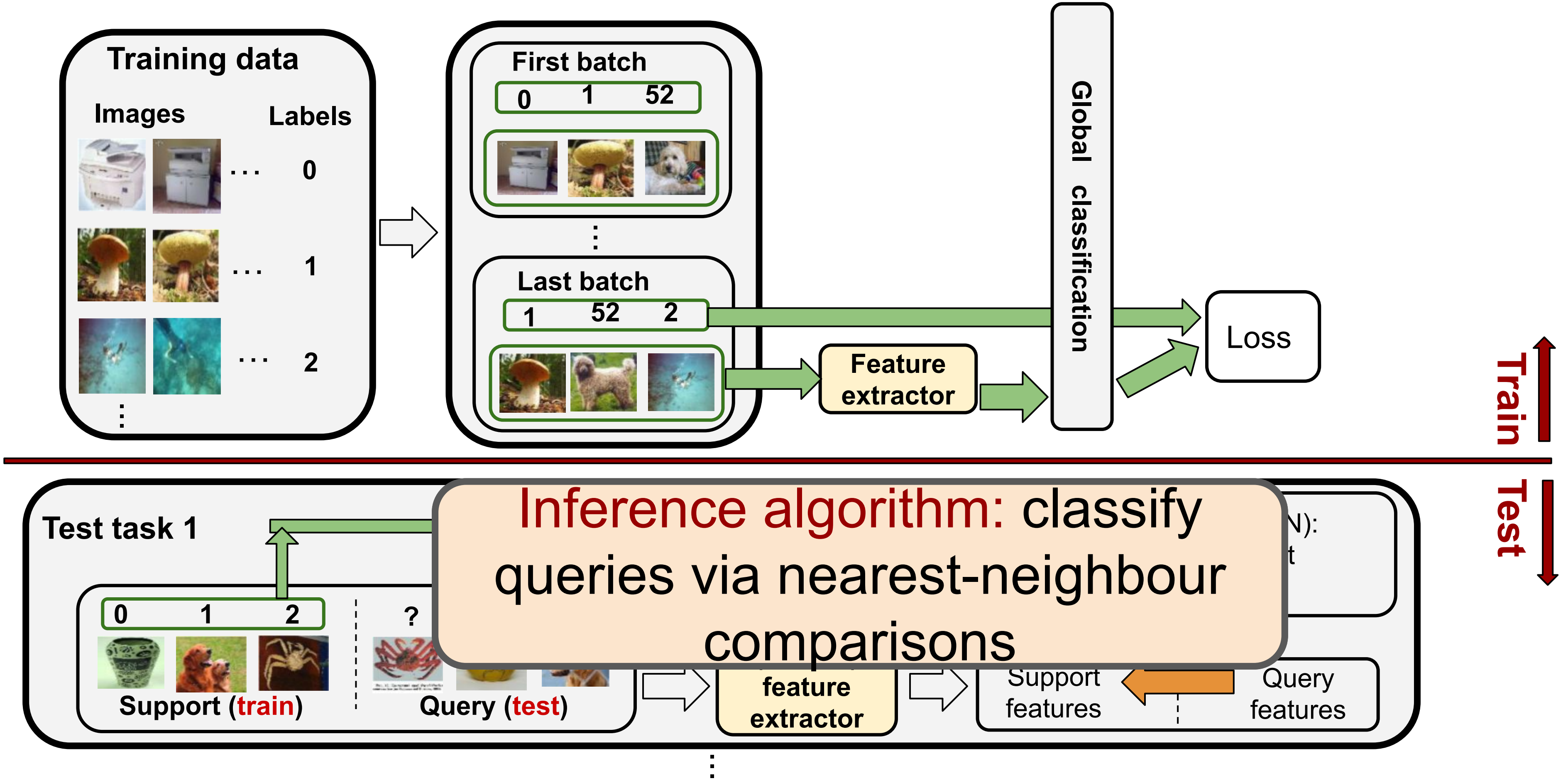
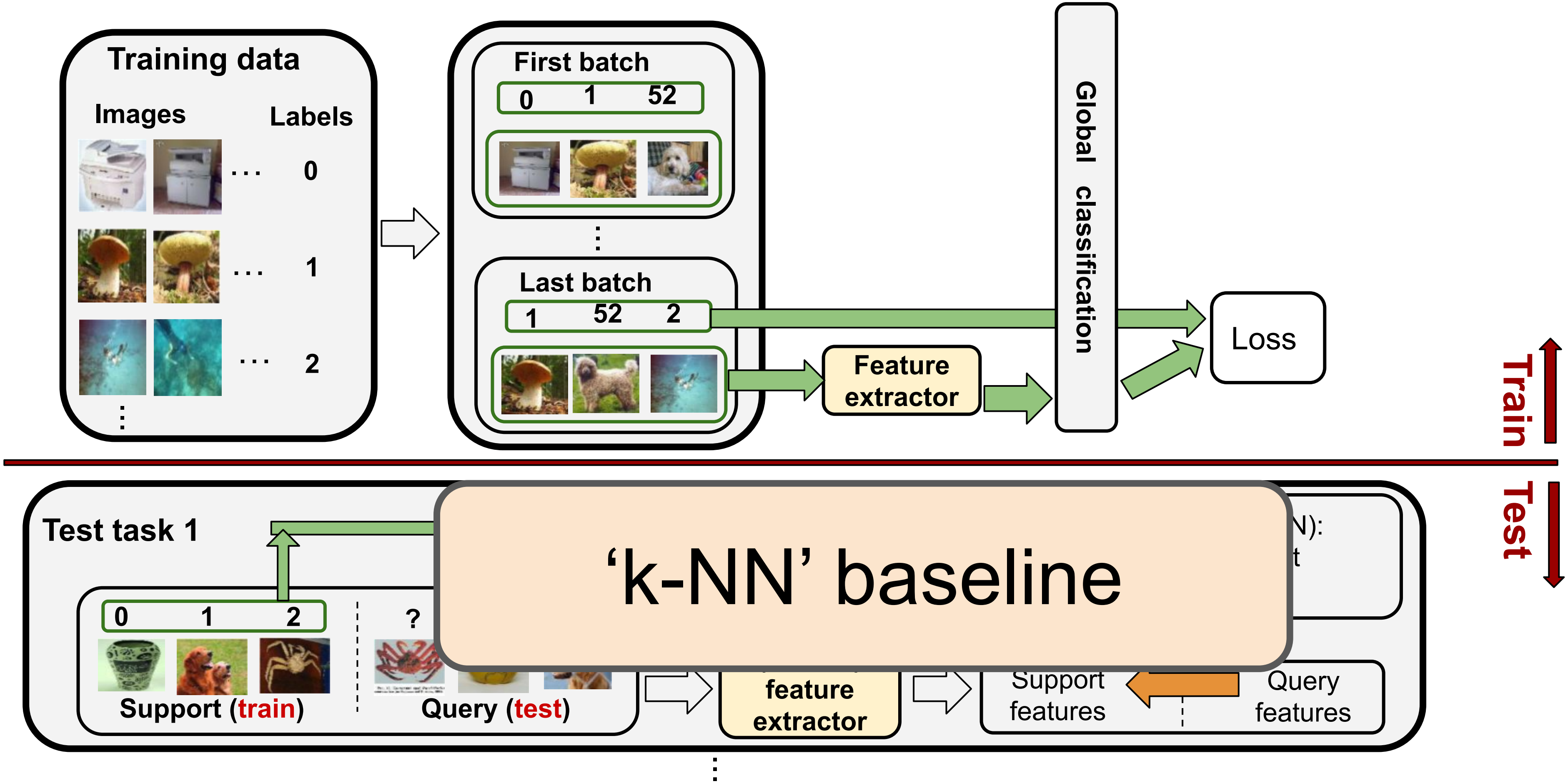
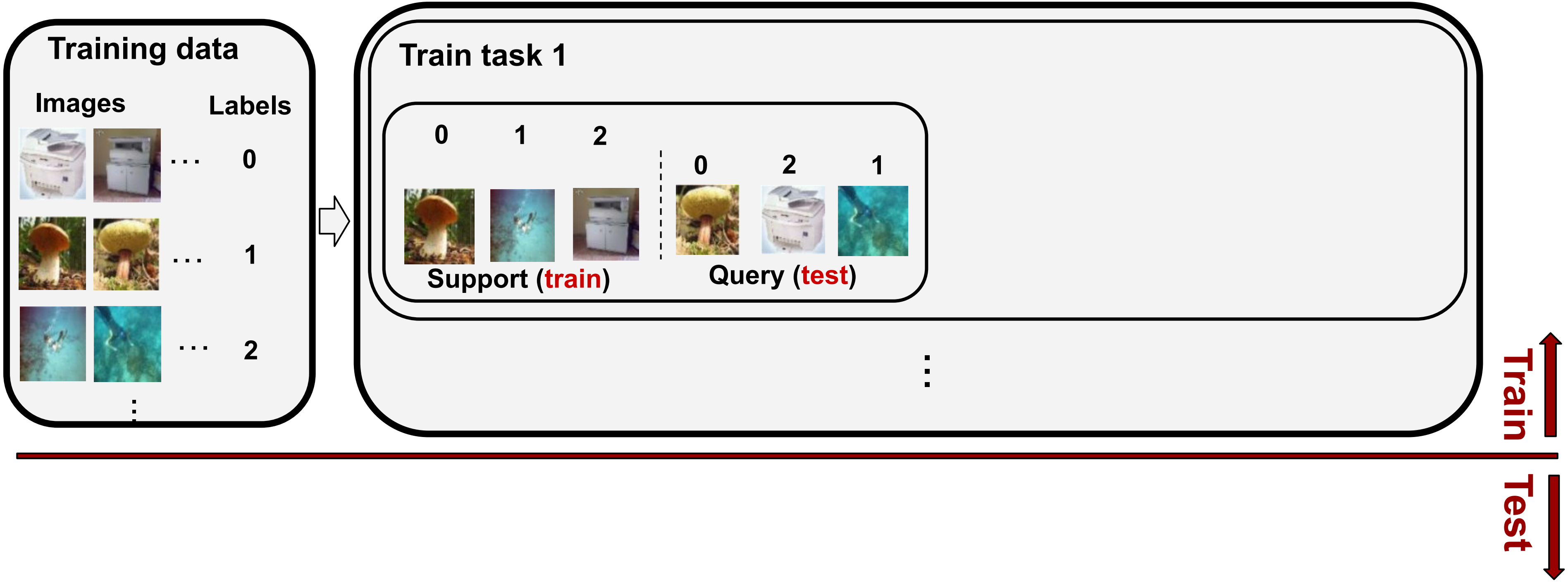


Inference algorithm: classify queries via nearest-neighbour comparisons

Transfer learning ‘baseline’



The meta-learning approach



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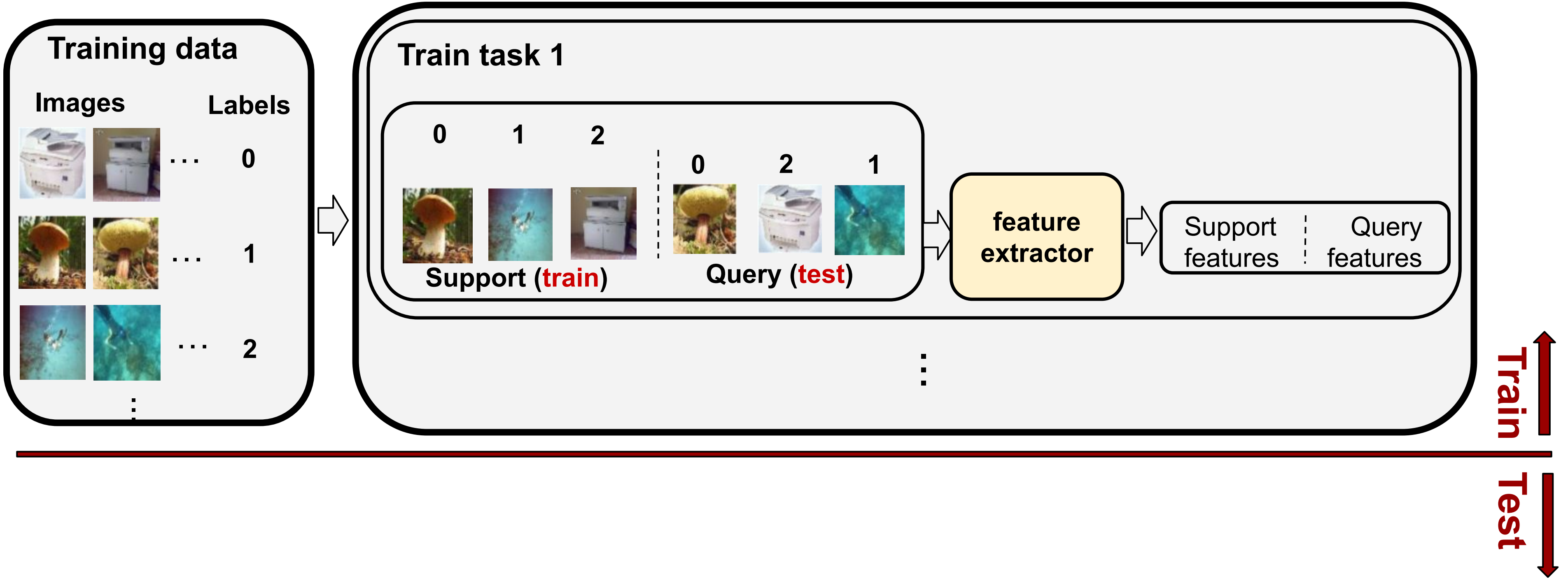

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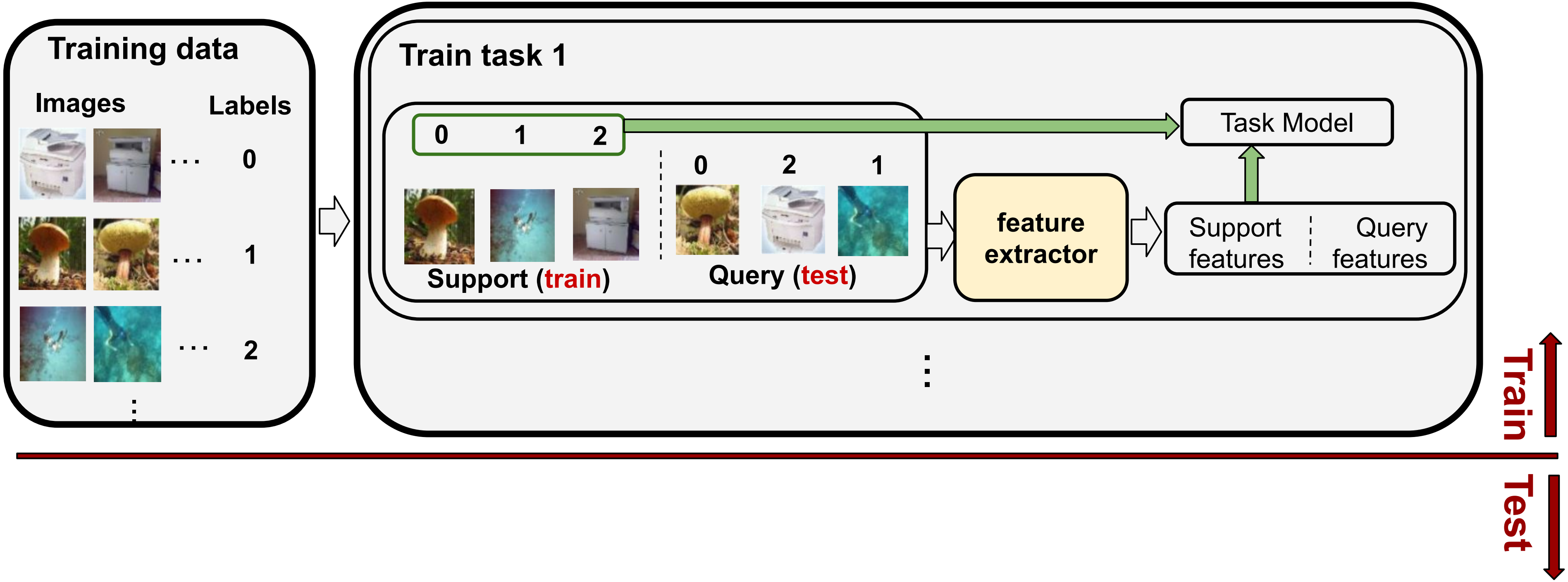

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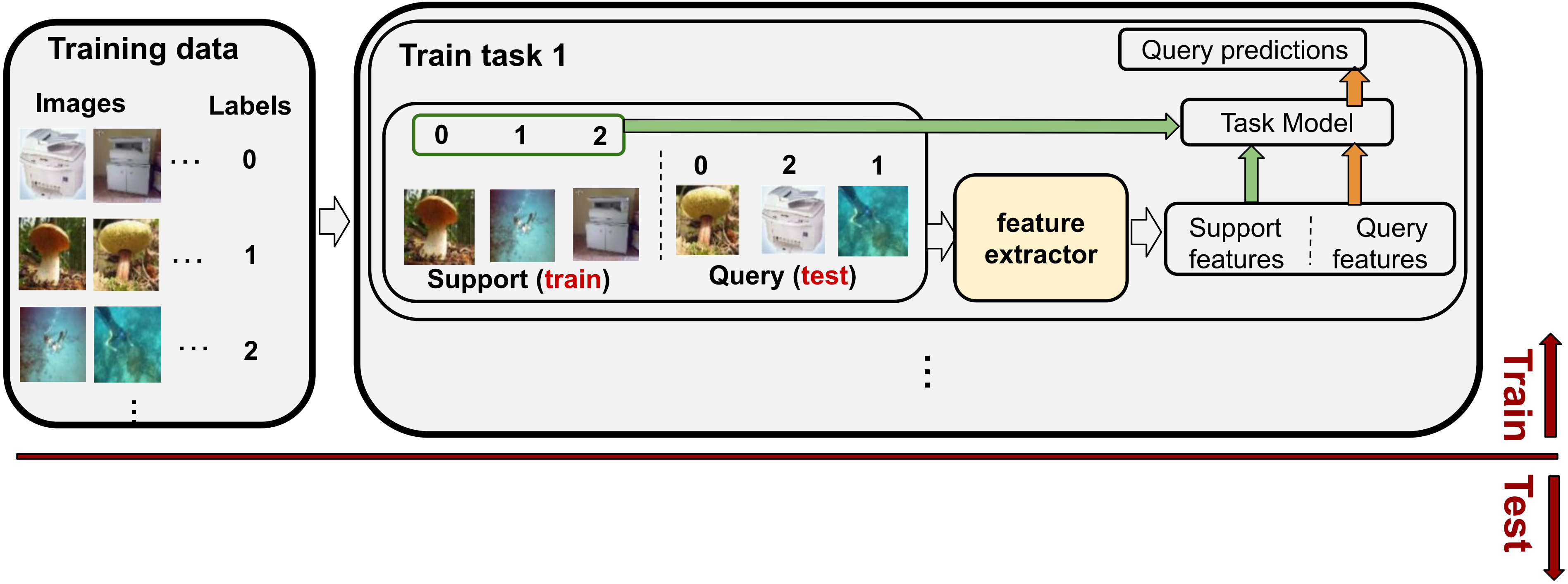

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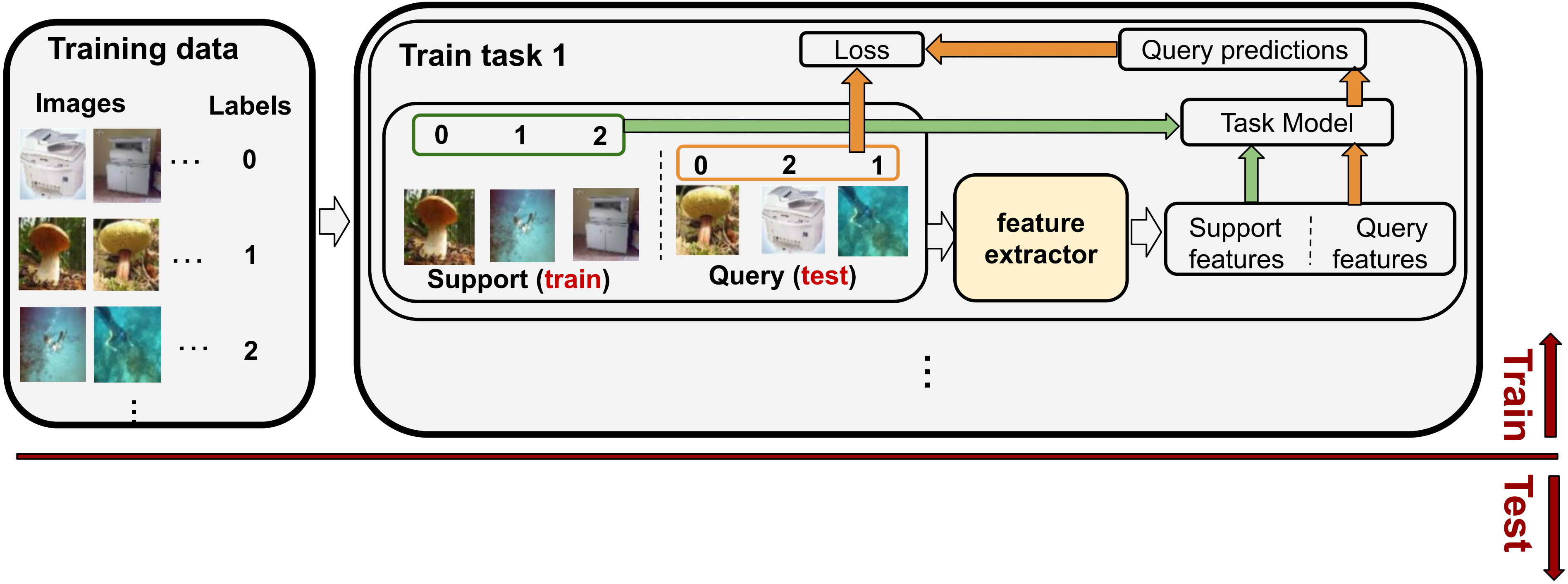

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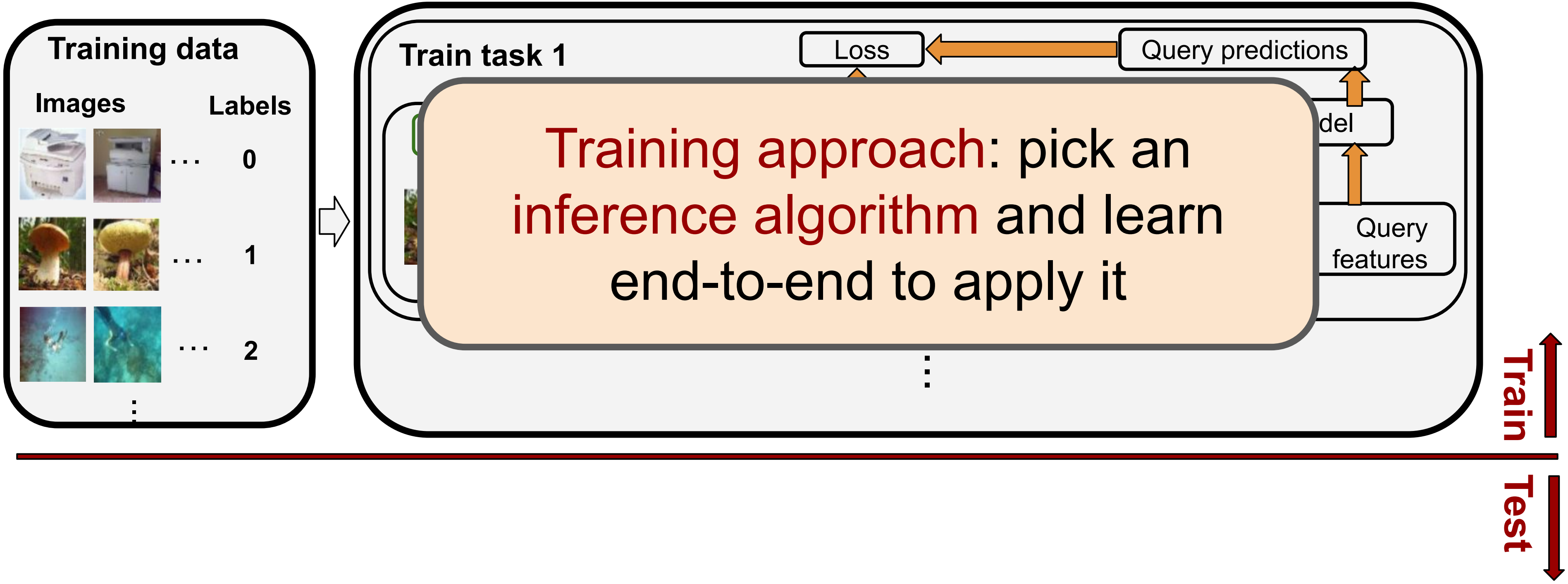
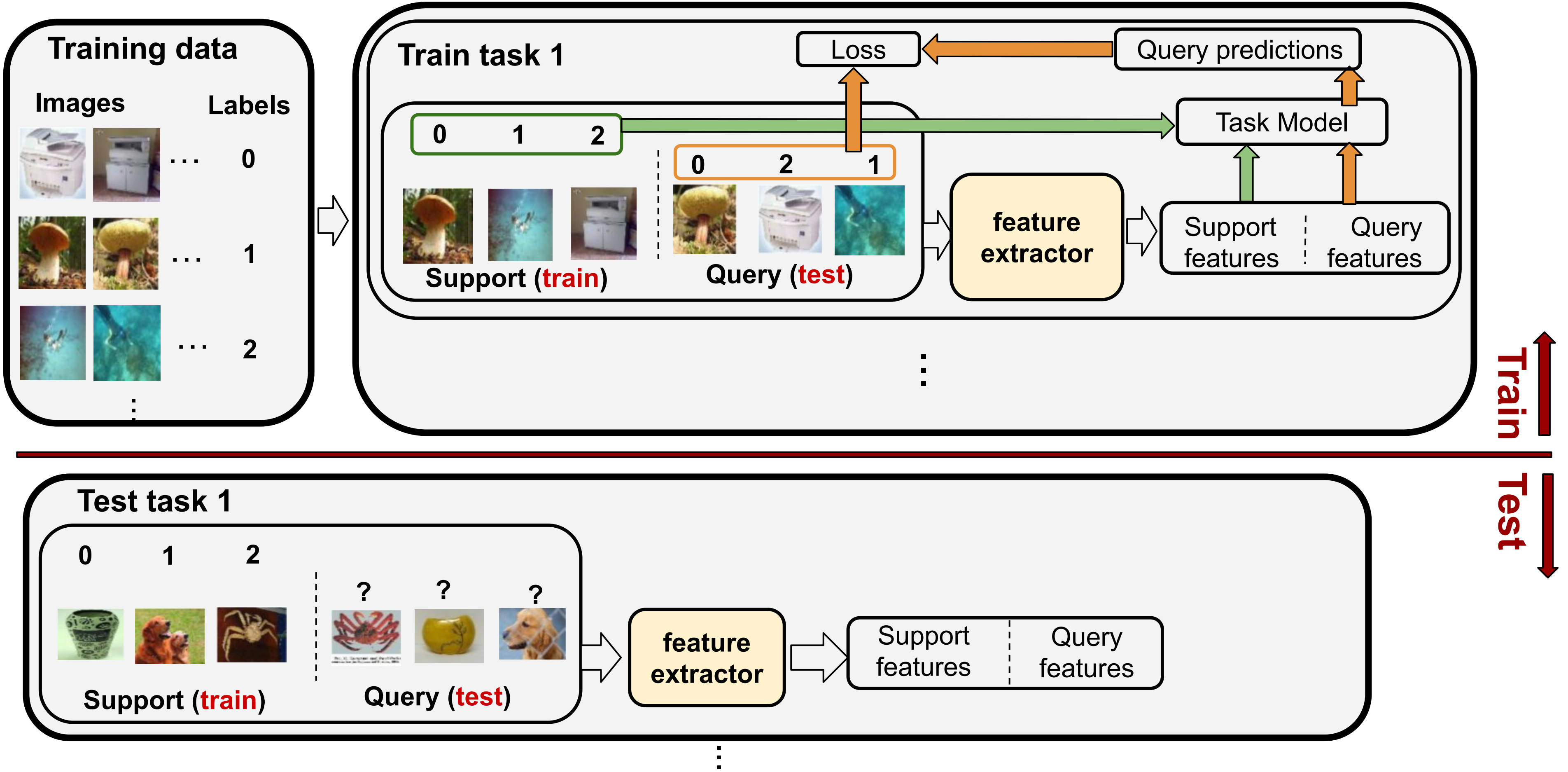


Training approach: pick an inference algorithm and learn end-to-end to apply it

The meta-learning approach



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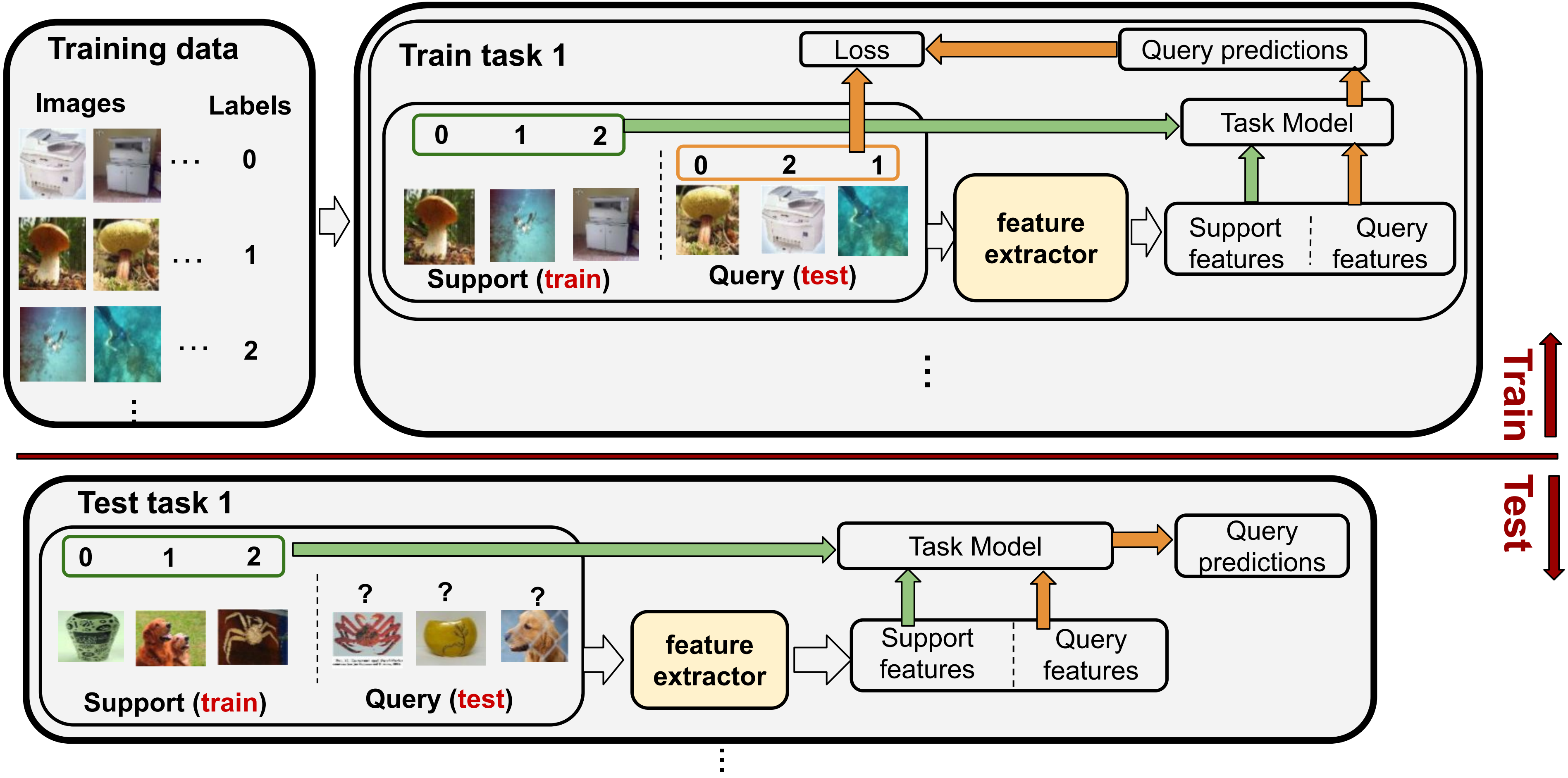

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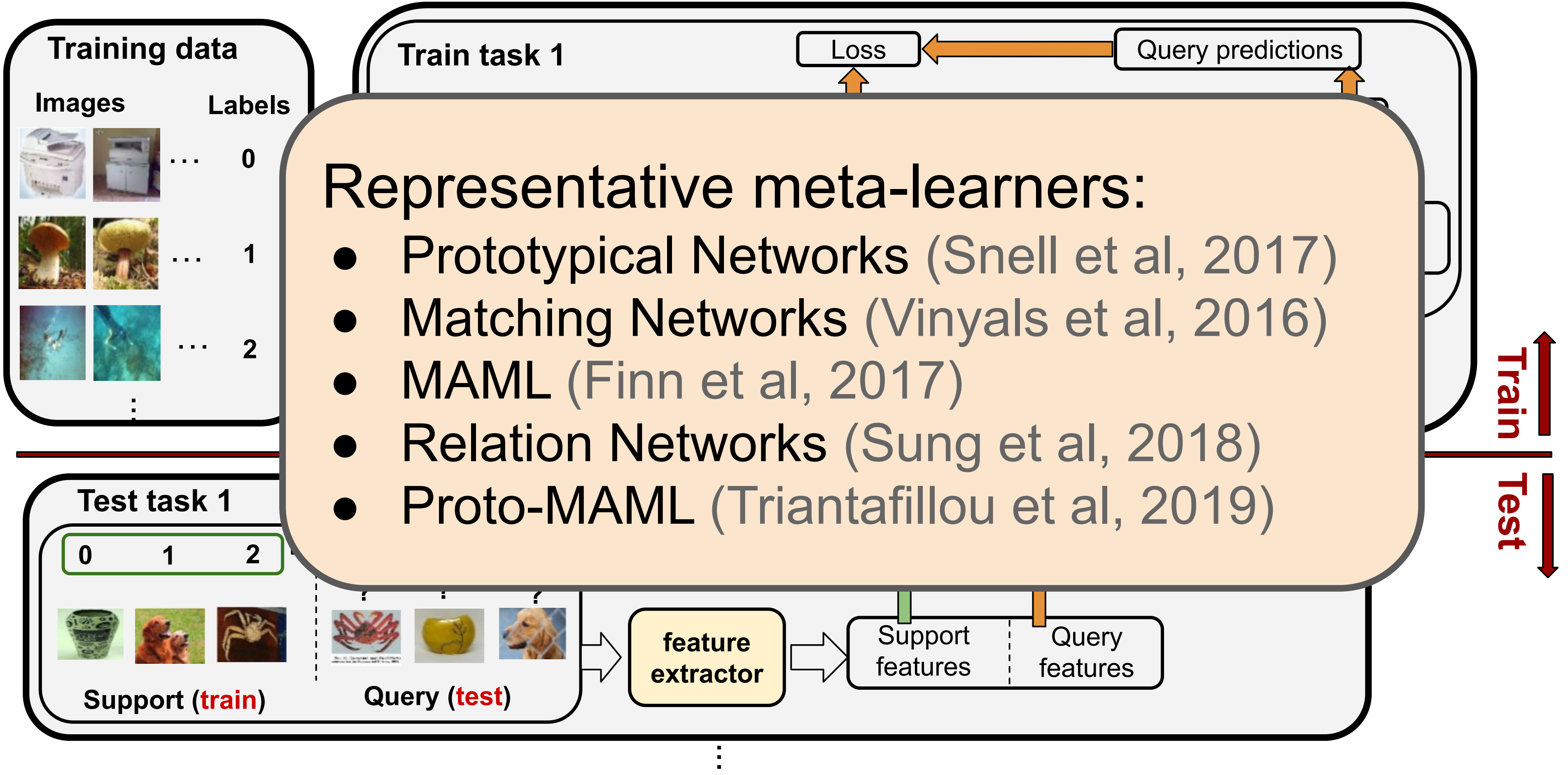


Representative meta-learners:

- Prototypical Networks (Snell et al, 2017)
- Matching Networks (Vinyals et al, 2016)
- MAML (Finn et al, 2017)
- Relation Networks (Sung et al, 2018)
- Proto-MAML (Triantafillou et al, 2019)

Matching Networks (Vinyals et al., 2016)

Defines an inference algorithm for computing $p(y^*|\mathcal{S}, x^*)$ that labels query points x^* *conditioned on a support set* $\mathcal{S}$.

$$p(y^*|\mathcal{S}, x^*) = \sum_{i=1}^{|\mathcal{S}|} \alpha(x^*, x_i) y_i$$

where $\alpha(x^*, x_i) = softmax(\frac{f(x^*) \cdot f(x_i)}{||f(x^*)|| \cdot ||f(x_i)||})$ with f denoting the embedding function

Episodic Training Objective

$$\theta = \arg\max_{\theta} \mathop{\mathbb{E}}_{L} \mathop{\mathbb{E}}_{\mathcal{S},\mathcal{Q}\sim L} \sum_{(x^*,y^*)\in\mathcal{Q}} \log p_\theta(y^*|x^*, \mathcal{S})$$

where L denotes a label set e.g. $\{cat, dog\}$ sampled from **training classes** and $\mathcal{Q}$ is the query set.

Prototypical Networks (Snell et al., 2017)

- Follows episodic training
- But defines a different inference algorithm for computing $p(y^*|\mathcal{S}, x^*)$

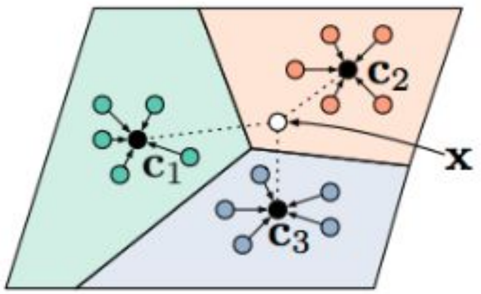


Figure: from (Snell et al., 2017)

Prototypical Network Classifier:

$$p_\theta(y^* = k|\mathcal{S}) = \frac{\exp(-d(f(x^*), c_k))}{\sum_{k' \in \{1,\dots,N\}} \exp(-d(f(x^*), c_{k'}))}$$

where c_k is the prototype for class k computed as: $c_k = \frac{1}{|\mathcal{S}_k|} \sum_{x_i \in \mathcal{S}_k} f(x_i)$ where $\mathcal{S}_k$ is the support points for class k and f is the embedding function.

Model-Agnostic Meta-Learning (MAML) (Finn et al., 2017)

- MAML offers another way of meta-learning the learner parameters θ
- It learns a **common initialization** across tasks that is easily adaptable for each new task

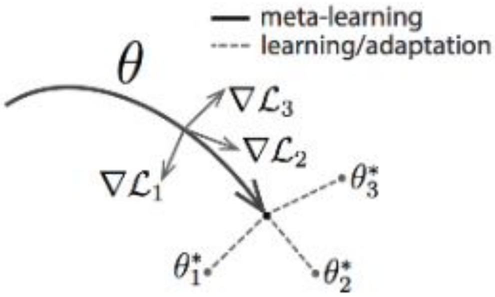


Figure: (Finn et al., 2017)

Model-Agnostic Meta-Learning (MAML) (Finn et al., 2017)

Let $\mathcal{L}_\theta(S)$ denote the loss on set S using parameters θ.

MAML's training objective

In each training episode with support / query sets $\mathcal{S}, \mathcal{Q}$:

$$\min \mathop{\mathbb{E}}_{L} \mathop{\mathbb{E}}_{\mathcal{S},\mathcal{Q} \sim L} \mathcal{L}_{\theta - \alpha \nabla \mathcal{L}_\theta(\mathcal{S})}(\mathcal{Q})$$

As before L is a label set of training classes, e.g. $\{cat, dog\}$

This suggests a simple algorithm...

In each training episode with support / query sets $\mathcal{S}, \mathcal{Q}$:

1. **Learning:** Fine-tune θ for the episode's task via 1 step of SGD for the support loss: $\theta' = \theta - \alpha \nabla \mathcal{L}_\theta(\mathcal{S})$
2. **Meta-Learning:** Update θ (by SGD) to minimize the loss on the query set $\mathcal{L}_{\theta'}(\mathcal{Q})$, computed using the updated θ'

Proto-MAML (Triantafillou et al., 2019)

Aims to capture the best of Prototypical Nets and MAML: inductive bias of the former and flexibility of the latter.

Re-interpreting Prototypical Networks as a linear classifier

Let c_k be the prototype of class k, f the embedding function and x^* a query. The 'logit' for x^* being classified as k is:

$$\begin{aligned} -||f(x^*) - c_k||^2 &= -f(x^*)^T f(x^*) + 2c_k^T f(x^*) - c_k^T c_k = \\ &= 2c_k^T f(x^*) - ||c_k||^2 + constant \end{aligned}$$

which defines a linear layer: $w_k = 2c_k$ and $b_k = -||c_k||^2$, as also shown in (Snell et al., 2017).

Proto-MAML: For each task, initialize MAML's linear layer from the above prototypical classifier, then do task adaptaton as usual.

Relation Networks (Sung et al., 2018)

The inference algorithm is:

- Concatenate the query with each class prototype, and feed each such pair through a *relation module*
- The relation module predicts how likely the given query belongs to the given prototype (binary classification)
- Uses mean square error as the loss

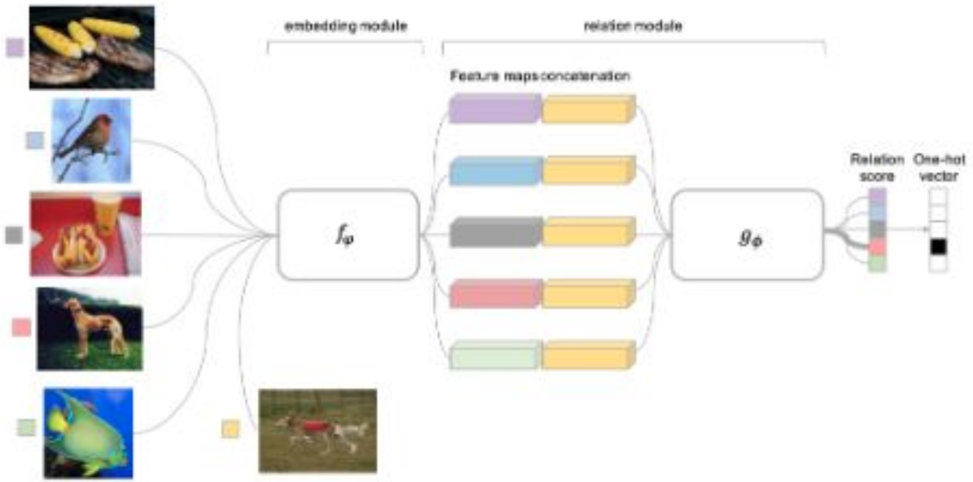


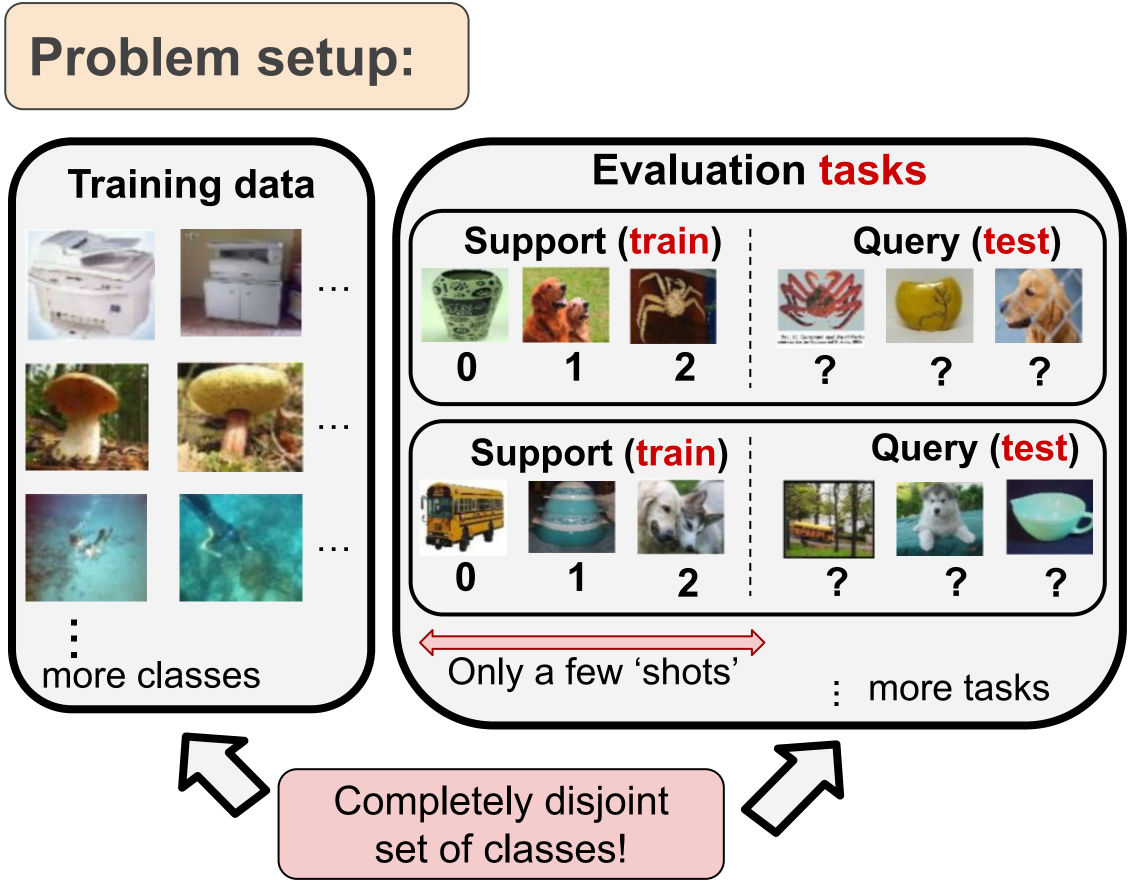
Figure: Figure from (Sung et al., 2018)

Revisiting the setup for few-shot classification

- The de facto evaluation involves benchmarks that:
  - Are comprised of a single dataset, so training and testing classes aren’t too different visually
  - Are class balanced
  - Have homogeneous tasks

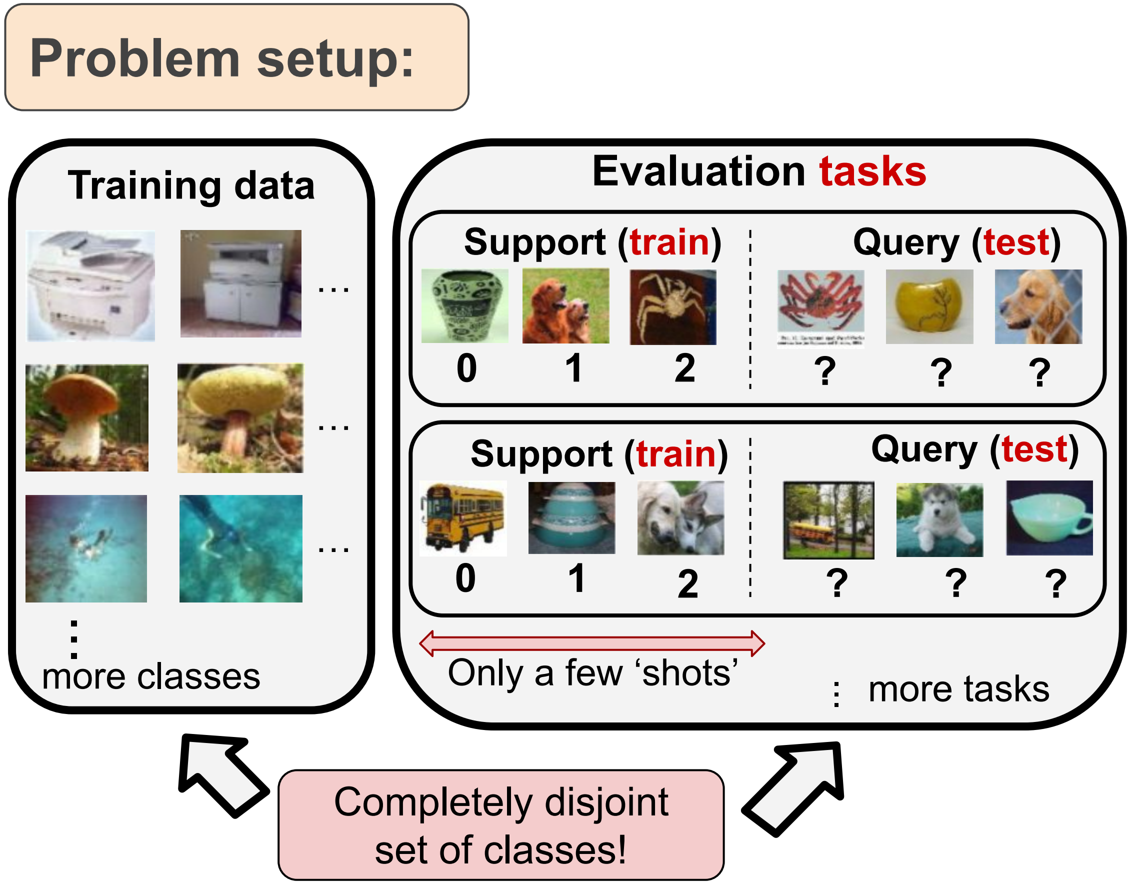
Few-shot Classification

- Learn new classes from few examples
- Practically important and scientifically interesting

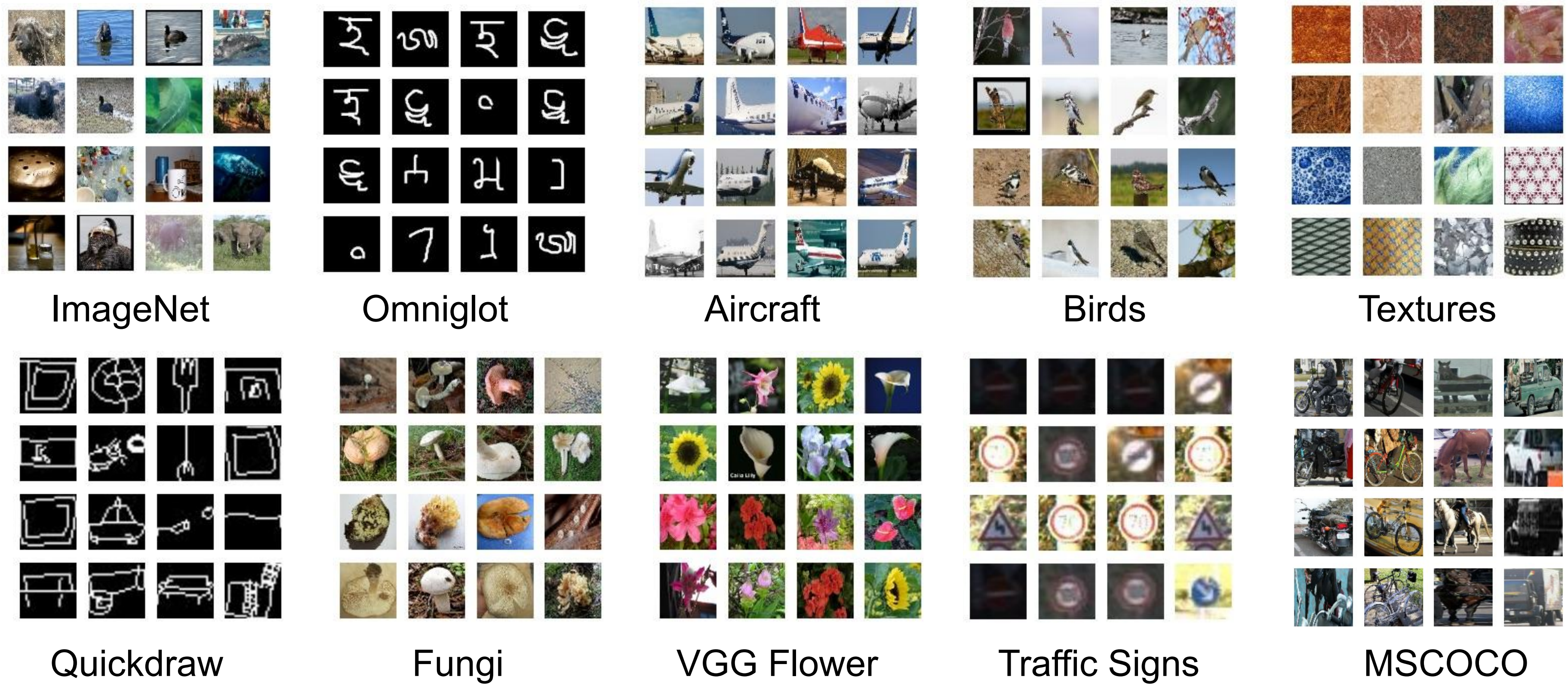


Few-shot Classification

- Learn new classes from few examples
- Practically important and scientifically interesting
- Previous datasets (e.g. mini-ImageNet) don't evaluate on substantially different classes
- We propose a benchmark to address this



Introducing Meta-Dataset



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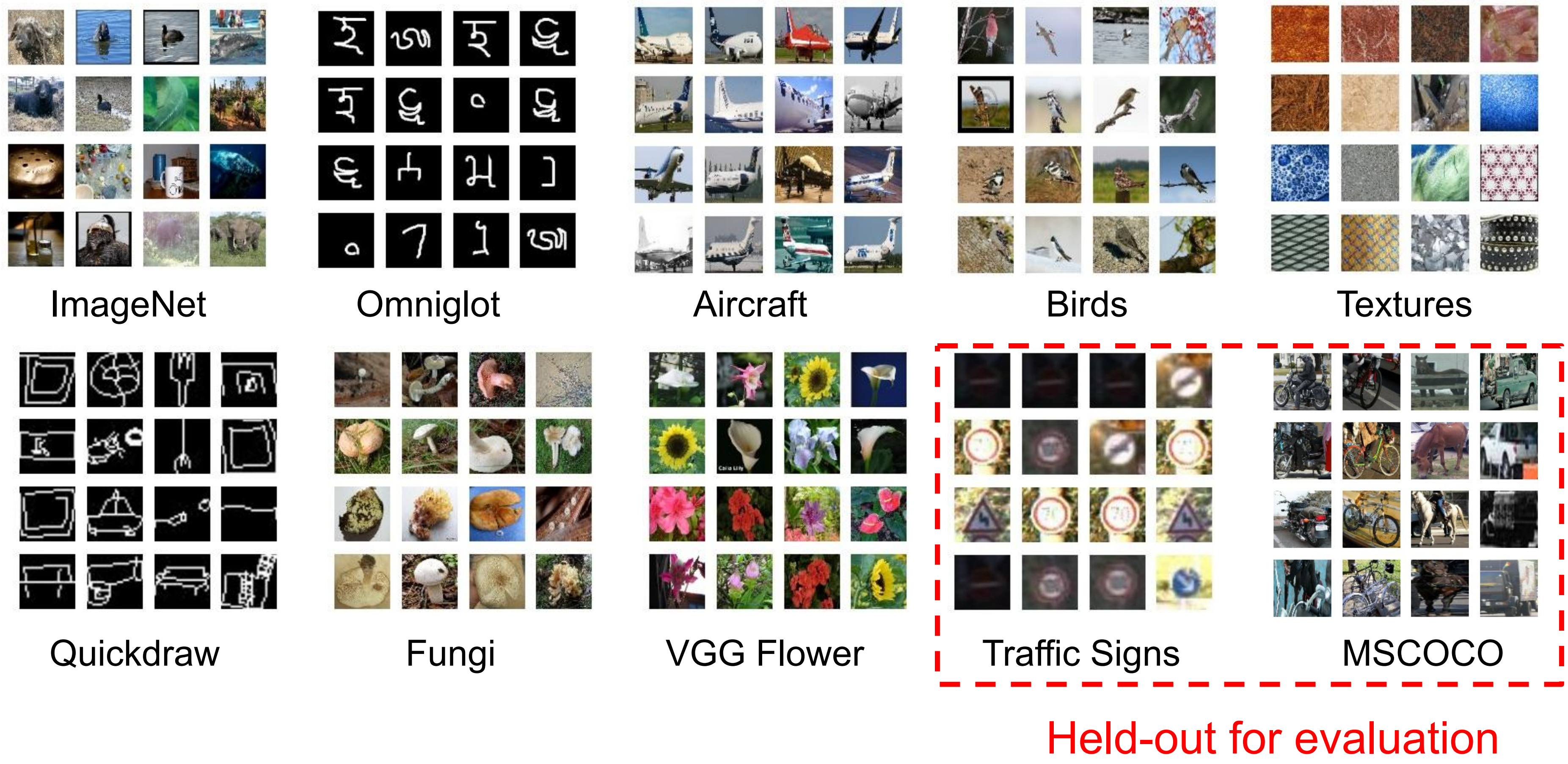
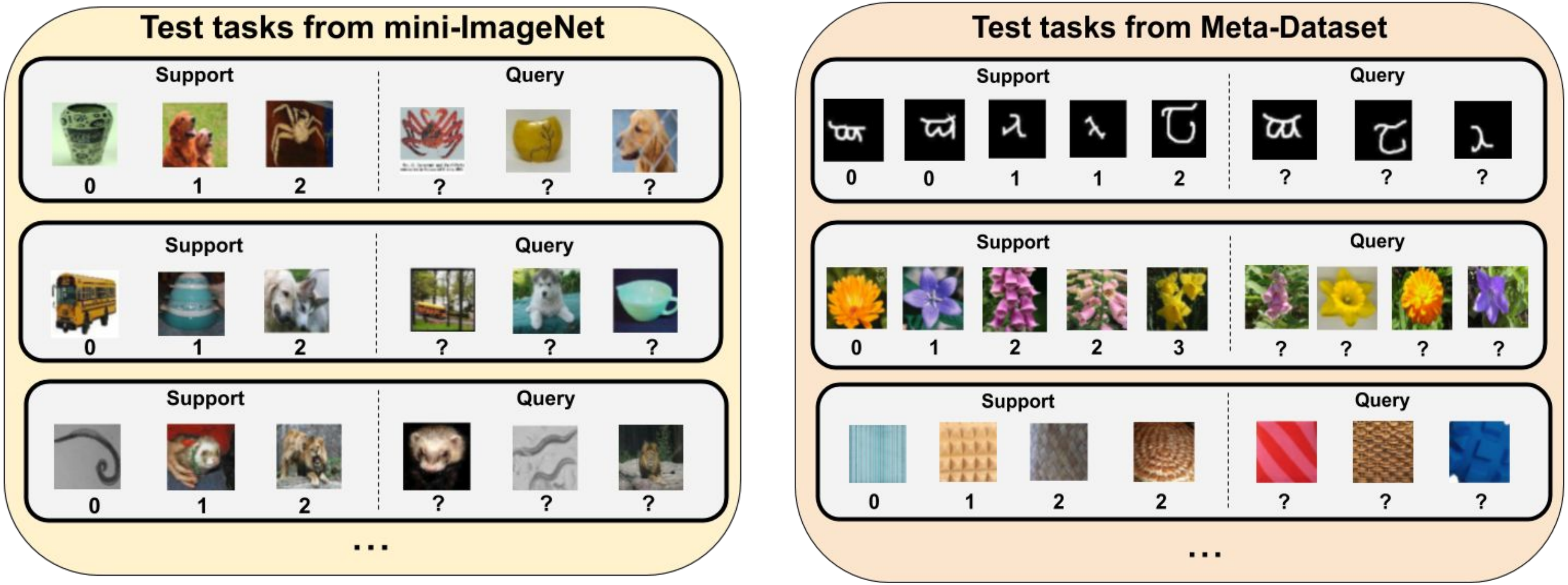


What's new in Meta-Dataset?



Meta-Dataset is much larger scale (larger image resolution and > 5K classes in total) than previous benchmarks (e.g. mini-ImageNet has 100 classes), and its tasks:

1. Are diverse: originate from 10 datasets.
2. Have variable ways and shots, imbalance and degrees of fine-grainedness.

Research Investigation

We investigate several important questions:

- Do we generalize better when training on more datasets?
- Can we benefit from increasing numbers of ‘shots’ at test time?
- Non-meta-learning ‘baselines’ are gaining popularity. Are these sufficient for performing well on Meta-Dataset?

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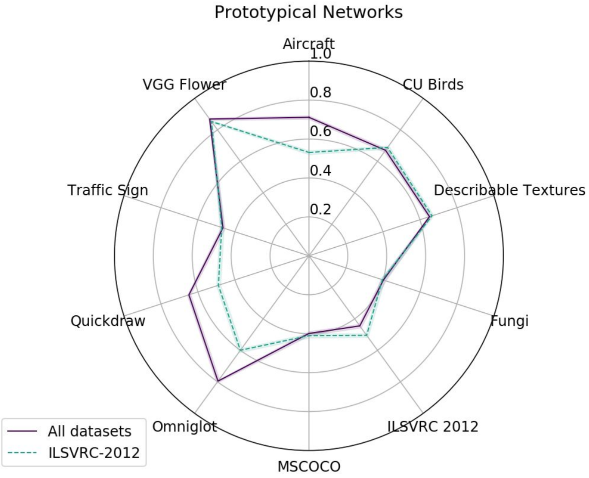
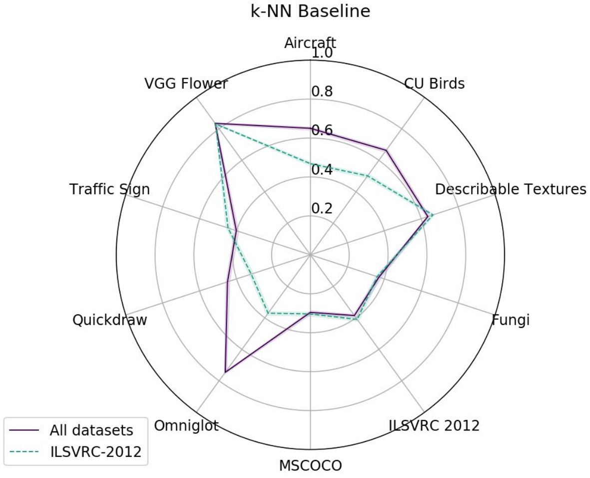
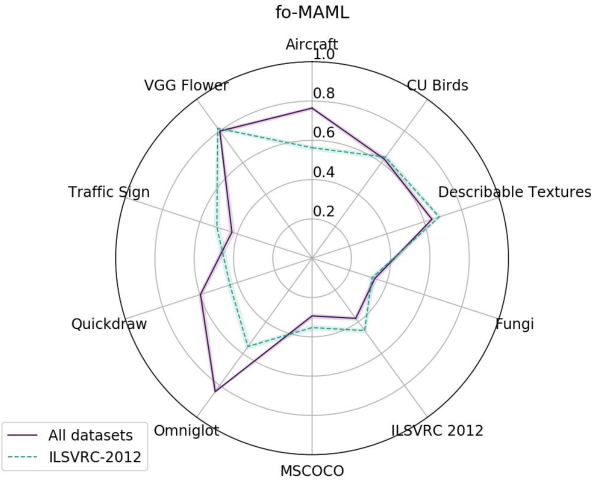
Effect of training on all datasets versus ImageNet only

- Training on (the train classes of) all datasets instead of (the train classes of) ImageNet only is not helpful for all evaluation datasets.
- Further work is needed to better absorb diverse training information.







Visualization technique inspired by [Dvornik et al]() (arXiv:2003.09338)

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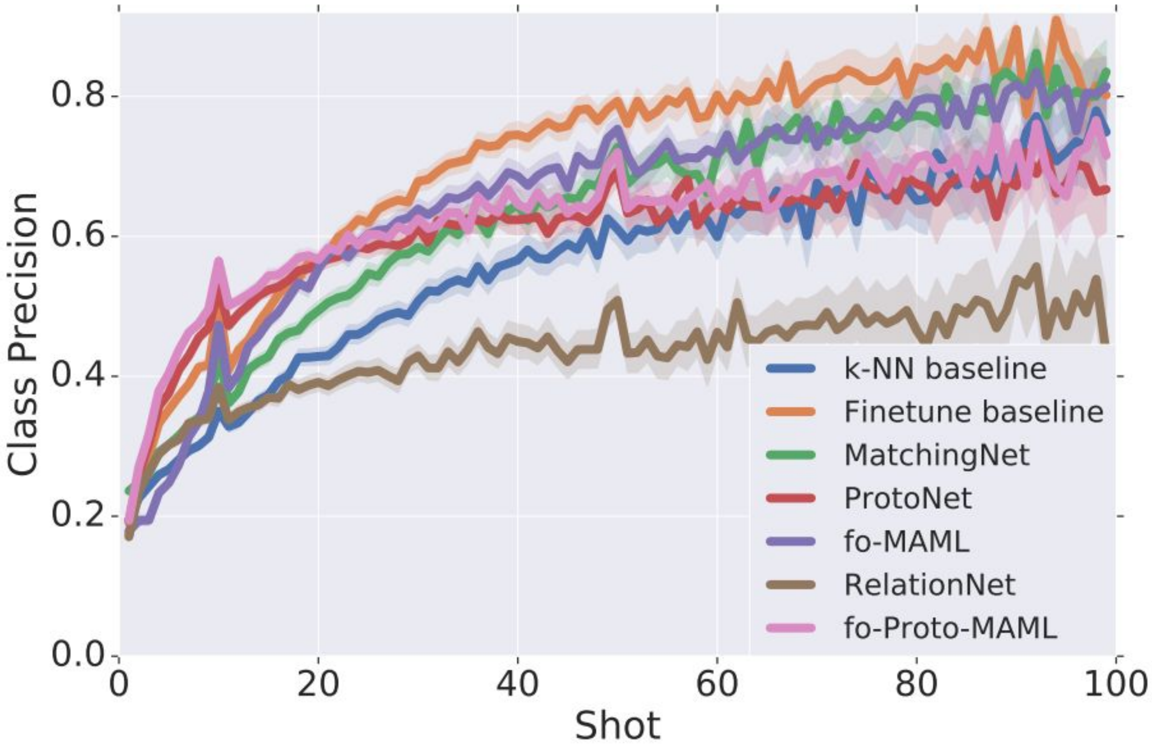
Test-time performance as a function of ‘shots’

- Trade-off: different models do better on different ‘shot’ settings at test time
- **Unmet desideratum**: optimally leverage any number of shots at test time



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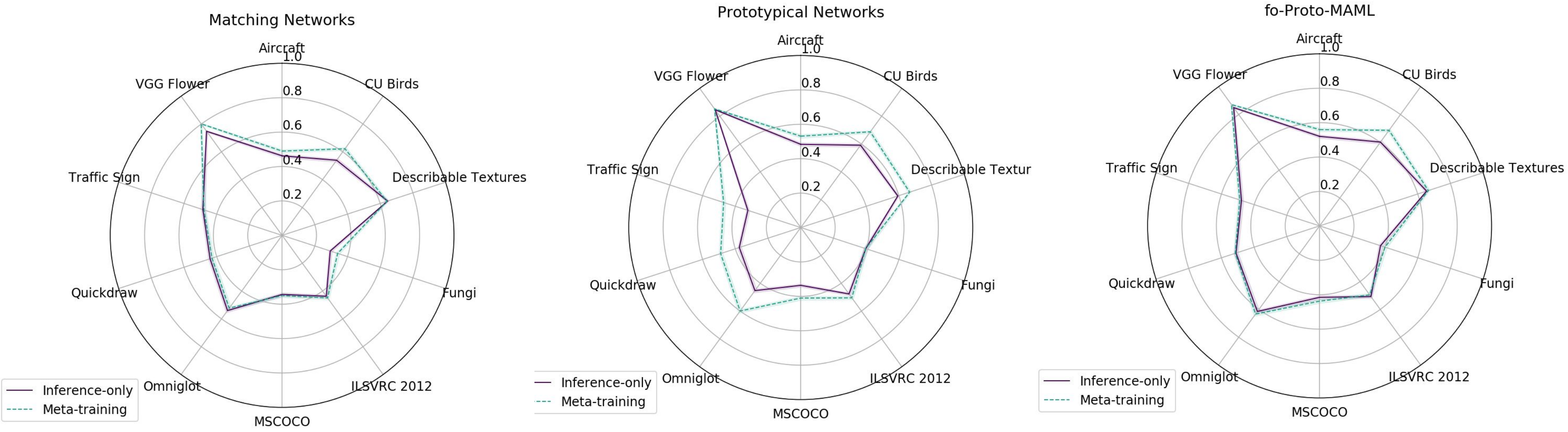
Does meta-learning improve over pre-training?

- 'Inference-only' version of each meta-learner: pre-trains a feature extractor and **at evaluation time** applies the inference algorithm of the corresponding meta-learner.



Training source: ImageNet only

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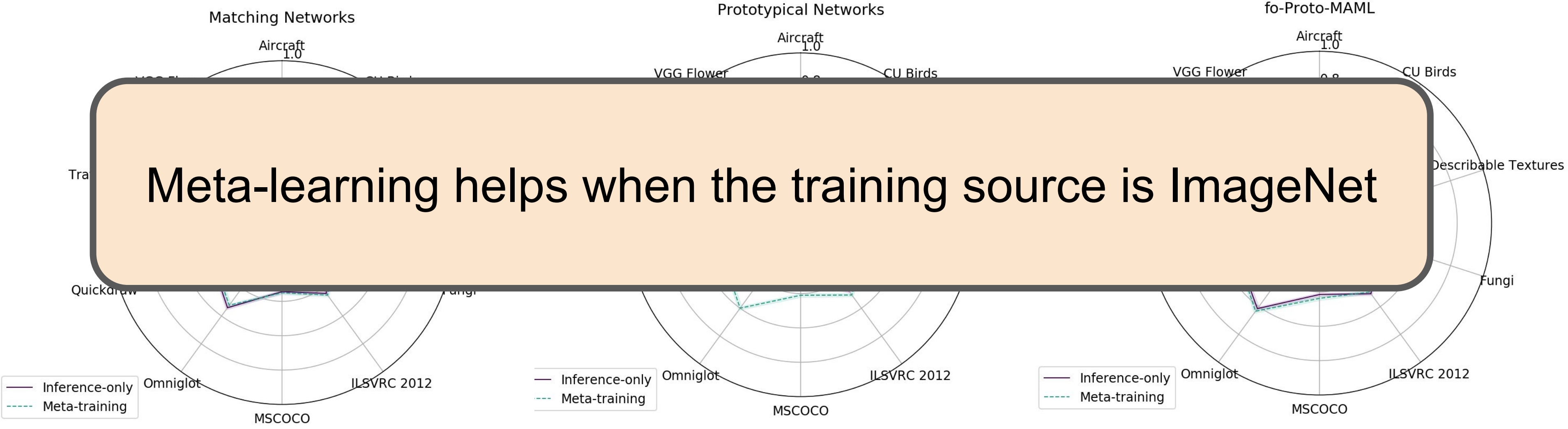
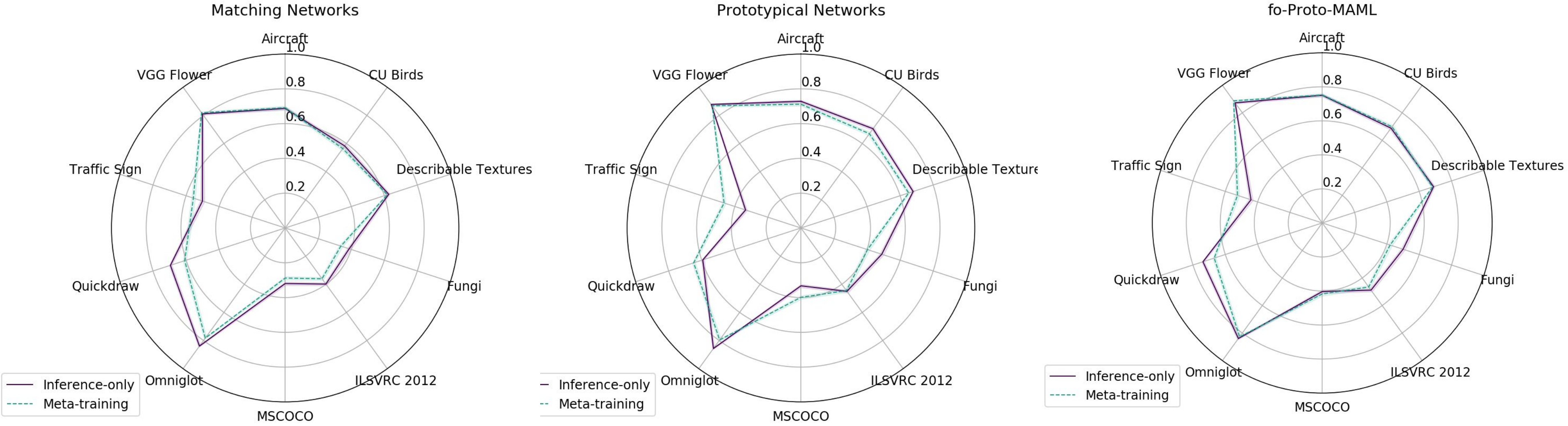


Meta-learning helps when the training source is ImageNet

Training source: ImageNet only

Does meta-learning improve over pre-training?

- ‘Inference-only’ version of each meta-learner: pre-trains a feature extractor and **at evaluation time** applies the inference algorithm of the corresponding meta-learner.



Training source: All datasets

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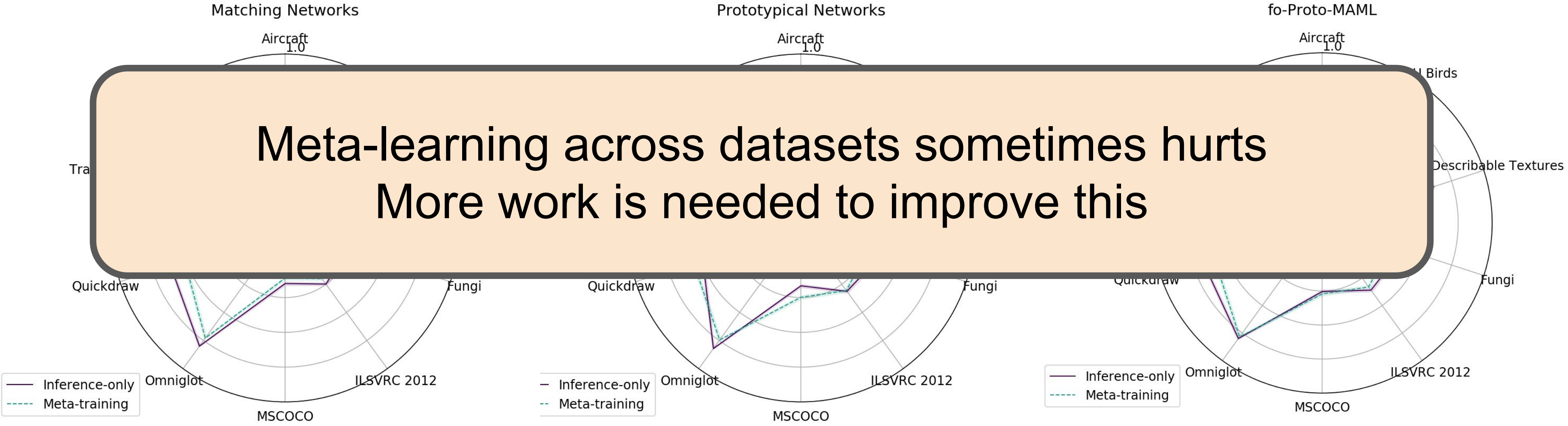

Meta-learning across datasets sometimes hurts
More work is needed to improve this

Training source: All datasets

Progress on Meta-Dataset

Shout out to recent papers reporting results on Meta-Dataset:

- **Requeima et al, 2019.** Fast and Flexible Multi-Task Classification Using Conditional Neural Adaptive Processes.
- **Bateni et al, 2020.** Improved Few-Shot Visual Classification.
- **Saikia et al, 2020.** Optimized Generic Feature Learning for Few-shot Classification across Domains.
- **Yinbo et al, 2020.** A New Meta-Baseline for Few-Shot Learning.
- **Dvornik et al, 2020.** Selecting Relevant Features from a Universal Representation for Few-shot Classification.

Our code is public: https://github.com/google-research/meta-dataset.

More realistic forms of few-shot learning

Interesting directions that study less artificial few-shot classification tasks:

- **Semi-supervised few-shot learning**: in addition to the small labeled support set, there is a pool of possibly relevant unlabeled examples available.
    - Meta-Learning for Semi-Supervised Few-shot Classification (Ren et al, 2018)
    - Learning to Self-Train for Semi-Supervised Few-shot Classification (Li et al, 2019)
- **Incremental few-shot learning:** retain the ability to remember the train classes while learning about test classes
    - Dynamic Few-Shot Visual Learning without Forgetting (Gidaris et al, 2018)
    - Incremental Few-Shot Learning with Attention Attractor Networks (Ren et al, 2018)
- **Continual learning**: does not consider each task as an isolated learning problem.
    - Meta-Learning Representations for Continual Learning (Javed and White, 2019)
    - Learning to Continually Learn (Beaulieu et al, 2019)

Thank you for listening!