Abstract

The versatility to learn from a handful of samples is the hallmark of human intelligence. Few-shot learning is an endeavour to transcend this capability down to machines. Inspired by the promise and power of probabilistic deep learning, we propose a novel variational inference network for few-shot classification (coined as TRIDENT) to decouple the representation of an image into context and label latent variables, and simultaneously infer them in an intertwined fashion. To induce task-awareness, as part of the inference mechanics of TRIDENT, we exploit information across both query and support images of a few-shot task using a novel built-in attention-based transductive feature extraction module (we call AttFEX). Our extensive experimental results corroborate the efficacy of TRIDENT and demonstrate that, using the simplest of backbones and a meta-learning strategy, it sets a new state-of-the-art in the most commonly adopted datasets miniImageNet and tieredImageNet (offering up to 4% and 5% improvements, respectively), as well as for the recent challenging cross-domain miniImagenet → CUB scenario offering a significant margin (up to 20% improvement) beyond the best existing baseline.

1 Introduction

Deep learning algorithms are usually data hungry and require massive amounts of training data to reach a satisfactory level of performance on any task. To tackle this limitation, few-shot classification aims to learn to classify images from various unseen tasks in a data-deficient setting. In this exciting space, metric learning proposes to learn a shared feature extractor to embed the samples into a metric space of aggregated class embeddings (Sung et al., 2018; Vinyals et al., 2016; Snell et al., 2017; Wang et al., 2019; Liu et al., 2020). Due to limited data per class, these embeddings suffer from sample-bias and fail to efficiently represent class characteristics. Furthermore, sharing a feature extractor across tasks implies that the discriminative information learnt from the seen classes are equally effective on any arbitrary unseen classes, which is not true in most cases. Transductive task-aware few-shot learning approaches (Bateni et al., 2022; Ye et al., 2020; Cui & Gue, 2021) address these limitations by exploiting information hidden in the unlabeled data. As a result, the model learns task-specific embeddings by aligning the features of the labelled and unlabelled task instances for optimal distance metric based label assignment. Since the alignment of these embeddings is still subject to the relevance of the characteristics captured by the shared feature extractors, task-aware methods sometimes fail to extract meaningful representations particularly relevant to classification. Probabilistic methods address sample-bias by relaxing the need to find point estimates to approximate data-dependent distributions of either high-dimensional model weights (Nguyen et al., 2019; Ravi & Beatson, 2019; Gordon et al., 2019; Hu et al., 2020) or lower-dimensional class prototypes (Sun et al., 2021; Zhang et al., 2019). However, inferring a high-dimensional posterior of model parameters is inefficient in low-data regimes and estimating distributions of class prototypes involves using hand-crafted non-parametric aggregation techniques which may not be well suited for every unseen task.

1 Codebase available at https://github.com/anujinho/trident
Although fit for purpose, all these approaches seem to overlook an important perspective. An image is composed of different attributes such as style, design, backdrop and setting which are not necessarily relevant discriminative characteristics for classification. Here, we refer to these attributes as contextual information. On the other hand, other class-characterizing attributes (such as wings of a bird, trunk of an elephant, hump on a camel’s back) are critical for classification, irrespective of context. We refer to such attributes as label information. Typically, contextual information is majorly governed by context attributes, whereas the label characteristics are subtly embedded throughout an image. In other words, contextual information can be predominantly present across an image, whereas attending to subtle label information determines how effective a classification algorithm would be. Thus, we argue that attention to label-specific information should be ingrained into the mechanics of the classifier, decoupling it from contextual information. This becomes even more important in a few-shot setting where the network has to quickly learn from little data. Building upon this idea, we propose transductive variational inference of decoupled latent variables (coined as TRIDENT), to simultaneously infer decoupled label and context information using two intertwined variational networks. To induce task-awareness while constructing the variational inference mechanics of TRIDENT, we introduce a novel attention-based transductive feature extraction module (we call AttFEX) which further enhances the discriminative power of the inferred label attributes. This way TRIDENT infers distributions instead of point estimates and injects a handcrafted inductive-bias into the network to guide the classification process. Our main contributions can be summarized as:

1. We propose TRIDENT, a variational inference network to simultaneously infer two salient decoupled attributes of an image (label and context), by inferring these two using two intertwined variational sub-networks (Fig. 1).

2. We introduce an attention-based transductive feature extraction module, AttFEX, to enable TRIDENT see through and compare all images within a task, inducing transductive task-cognizance in the inference of label information.

3. We perform extensive evaluations to demonstrate that TRIDENT sets a new state-of-the-art by outperforming all existing baselines on the most commonly adopted datasets miniImagenet and tieredImagenet (up to 4% and 5%), as well as for the challenging cross-domain scenario of miniImagenet → CUB (up to 20% improvement).

2 Related Work

Metric-based learning. This body of work involves mapping input samples into a lower-dimensional embedding space and then classifying the unlabelled samples based on a distance or similarity metric. By
parameterizing these mappings with neural networks and using differentiable similarity metrics for classification, these networks can be trained in an episodic manner (Vinyals et al., 2016) to perform few-shot classification. Prototypical Nets (Snell et al., 2017), Simple Shot (Wang et al., 2019), FRN (Wertheimer et al., 2021), Relation Networks (Sung et al., 2018), Matching Networks (Vinyals et al., 2016) variants of Graph Neural Nets (Satorras & Estrach, 2018; Yang et al., 2020), are a few examples of seminal ideas here.

**Transductive Feature-Extraction and Inference.** Transductive feature extraction or transductive task-aware learning is a variant of metric-learning with an adaptation mechanism that *aligns* support and query feature vectors in the embedding space for better representation of task-specific discriminative information. This not only improves the discriminative ability of classifiers across tasks, but also alleviates the problem of overfitting on limited support set since information from the query set is also used for extracting features of images in a task. CNAPS (Requeima et al., 2019), Transductive-CNAPS (Bateni et al., 2022), FEAT (Ye et al., 2020), Assoc-Align (Afrasiyabi et al., 2020), TPMN (Wu et al., 2021) and CTM (Li et al., 2019) are prime examples of such methods. Next to transduction for task-aware feature extraction, there are methods that use *transductive inference* to classify all the query samples at once by jointly assigning them labels, as opposed to their inductive counterparts where prediction is done on the samples one at a time. This is either done by iteratively propagating labels from the support to the query samples or by fine-tuning a pre-trained backbone using an additional entropy loss on all query samples, which encourages confident class predictions at query samples. TPN (Liu et al., 2019), Ent-Min (Dhillon et al., 2020), TIM (Boudiaf et al., 2020), Transductive-CNAPS (Bateni et al., 2022), LaplacianShot (Ziko et al., 2020), DPGN (Yang et al., 2020) and ReRank (SHEN et al., 2021) are a few notable examples in this space that usually report state-of-the-art results in certain few-shot classification settings (Liu et al., 2019). That being said, TRIDENT can be regarded as a transductive feature-extraction method, owing to AttFx’s unique ability to see through and compare all images within a task.

**Optimization-based meta-learning.** These methods optimize for model parameters that are sensitive to task objective functions for fast gradient-based adaptation to new tasks. MAML (Finn et al., 2017) and its variants (Rajeswaran et al., 2019; Nichol et al., 2018b; Oh et al., 2021) are a few prominent examples while LEO (Rusu et al., 2019) efficiently meta-updates its parameters in a lower dimensional latent space. Meta-learner LSTM (Ravi & Larochelle, 2017b) uses a separate meta-learner model to learn the exact optimization algorithm used to train another learner neural network classifier.

**Probabilistic learning.** The estimated parameters of typical gradient-based meta-learning methods discussed earlier (Finn et al., 2017; Rusu et al., 2019; Mishra et al., 2018; Nichol et al., 2018b; Rajeswaran et al., 2019) have high variance due to the small task sample size. To deal with this, a natural extension is to model the uncertainty by treating these parameters as latent variables in a Bayesian framework as proposed in Neural Statistician (Edwards & Storkey, 2017), PLATIPUS (Finn et al., 2018), VAMPIRE (Nguyen et al., 2019), ABML (Ravi & Beatson, 2019), VERSA (Gordon et al., 2019), SIB (Hu et al., 2020), SAMOVAR (Iakovleva et al., 2020). Methods like ABPML (Sun et al., 2021) and VariationalFSL (Zhang et al., 2019) infer latent variables of class prototypes to perform classification and avoid inferring high-dimensional model parameters. ABPML (Sun et al., 2021) and VariationalFSL (Zhang et al., 2019) are the closest to our approach. In contrast to these two methods, we avoid hand-crafting class-level aggregations. Additionally, we enhance variational inference by incorporating a classification-relevant inductive bias through decoupling of label and context information.

### 3 Problem Definition

Consider a labelled dataset \( D = \{ (x_i, y_i) \mid i \in [1, N] \} \) of images \( x_i \) and class labels \( y_i \). This dataset \( D \) is divided into three disjoint subsets: \( D = \{ D^{tr} \cup D^{val} \cup D^{test} \} \), respectively, referring to the training, validation, and test subsets. The validation dataset \( D^{val} \) is used for model selection and the testing dataset \( D^{test} \) for final evaluation. Following standard few-shot classification settings, as proposed in (Vinyals et al., 2016; Sung et al., 2018; Snell et al., 2017), we use episodic training on a set of tasks \( T \sim p(T) \). The tasks are constructed by drawing \( K \) random samples from \( N \) different classes, which we denote as an \((N\text{-way, } K\text{-shot})\) task. Concretely, each task \( T_k \) is composed of a support and a query set. The support set \( S = \{ (x_{kn}^S, y_{kn}^S) \mid k \in [1, K], n \in [1, N] \} \) contains \( K \) samples per class and the query set \( Q = \{ (x_{kn}^Q, y_{kn}^Q) \mid k \in [1, K], n \in [1, N] \} \).
Let us start with the high-level idea. The proposed approach is devised to learn meaningful representations that capture two pivotal characteristics of an image by modelling them as separate latent variables: (i) $z_c$ representing context, and (ii) $z_l$ embodying class labels. Inferring these two latent variables simultaneously allows $z_l$ to learn meaningful distributions of class-discriminating characteristics *decoupled* from context features represented by $z_c$. We argue that learning $z_l$ as the sole latent variable for classification results in capturing a mixture of true label and other context information. This in turn can lead to sub-optimal classification performance, especially in a few-shot setting where the information per class is scarce and the network has to adapt and generalize quickly. By inferring decoupled label and context latent variables, we inject a handcrafted inductive-bias that incorporates only relevant characteristics, and thus, ameliorates the network’s classification performance.

### 4 The Proposed Method: TRIDENT

The directed graphical model in Fig. 2 illustrates the common underlying generative process $p$ such that $p_i = p(x_i, y_i | z_l, z_c)$. For the sake of brevity, in the following we drop the sample index $i$ as we always refer to terms associated with a single data sample. We work on the logical premise that the label latent variable $z_l$ is responsible for generating class label as well as for image reconstruction, whereas the context latent variable $z_c$ is only responsible for image reconstruction (solid lines in the figure). Formally, the data is explained by the generative processes: $p_{\theta_1}(y | z_l) = \text{Cat}(y | z_l)$ and $p_{\theta_2}(x | z_l, z_c) = g_{\theta_2}(x; z_l, z_c)$, where $\text{Cat}(.)$ refers to a multinomial distribution and $g_{\theta_2}(x; z_l, z_c)$ is a suitable likelihood function such as a Gaussian or Bernoulli distribution. The likelihoods of both these generative processes are parameterized using deep neural networks and the priors of the latent variables are chosen to be standard multivariate Gaussian distributions $\mathcal{N}(z_c | 0, I)$ and $p(z_l) = \mathcal{N}(z_l | 0, I)$.

#### 4.1 Generative Process

The directed graphical model in Fig. 2 illustrates the common underlying generative process $p$ such that $p_i = p(x_i, y_i | z_l, z_c)$. For the sake of brevity, in the following we drop the sample index $i$ as we always refer to terms associated with a single data sample. We work on the logical premise that the label latent variable $z_l$ is responsible for generating class label as well as for image reconstruction, whereas the context latent variable $z_c$ is only responsible for image reconstruction (solid lines in the figure). Formally, the data is explained by the generative processes: $p_{\theta_1}(y | z_l) = \text{Cat}(y | z_l)$ and $p_{\theta_2}(x | z_l, z_c) = g_{\theta_2}(x; z_l, z_c)$, where $\text{Cat}(.)$ refers to a multinomial distribution and $g_{\theta_2}(x; z_l, z_c)$ is a suitable likelihood function such as a Gaussian or Bernoulli distribution. The likelihoods of both these generative processes are parameterized using deep neural networks and the priors of the latent variables are chosen to be standard multivariate Gaussian distributions $\mathcal{N}(z_c | 0, I)$ and $p(z_l) = \mathcal{N}(z_l | 0, I)$.

#### 4.2 Variational Inference of Decoupled $Z_l$ and $Z_c$

Computing exact posterior distributions is intractable due to high dimensionality and non-linearity of the deep neural network parameter space. Following [Kingma & Welling 2014; Kingma et al. 2014], we instead construct an approximate posterior over the latent variables by introducing a fixed-form distribution $q(z_l, z_c | x, y)$ parameterized by $\phi$. By using $q_{\phi}(.)$ as an inference network, the inference is rendered tractable, scalable and amortized since $\phi$ now acts as the global variational parameter. We assume $q_{\phi}$ has a factorized form $q_{\phi}(z_c, z_l | x, y) = q_{\phi_1}(z_l | z_c, x, y) q_{\phi_2}(z_c | x)$, where $q_{\phi_1}(.)$, $q_{\phi_2}(.)$ are assumed to be multivariate Gaussian distributions. As is also depicted in Fig. 2, we use $z_c$ as input to $q_{\phi_1}(.)$ to infer $z_l$ because of their conditional dependence given $x$. This way we forge a path to allow *necessary* context latent information flow through the label inference network. On the other hand, the opposite direction (using $z_l$ to infer $z_c$) is unnecessary,
because label information does not directly contribute to the extraction of context features. We will further reflect on this design choice in the next subsection. Neural networks are then used to parameterize both inference networks as:

\[
\begin{align*}
q_{\phi_2}(z_c | x) &= \mathcal{N}(z_c | \mu_{\phi_2}(x), \text{diag}(\sigma^2_{\phi_2}(x))), \\
q_{\phi_1}(z_l | x, z_c) &= \mathcal{N}(z_l | \mu_{\phi_1}(x, z_c), \text{diag}(\sigma^2_{\phi_1}(x, z_c))).
\end{align*}
\]

(1)

To find the optimal \emph{approximate} posterior, we derive the evidence lower bound (ELBO) on the marginal likelihood of the data to form our objective function:

\[
\begin{align*}
\ln p(x, y) &= \int \int p(x, y | z_c, z_l) p(z_c, z_l) \, dz_c \, dz_l, \\
&= \mathbb{E}_{q(z_c, z_l | x)} \left[ \frac{p(x | z_l, z_c) p(y | z_l) p(z_l) p(z_c)}{q(z_l, z_c | x)} \right], \\
&= \mathbb{E}_{q_{\phi_2}} \left[ \mathbb{E}_{q_{\phi_1}} \left[ \ln \left( \frac{p(x | z_c, z_l) p(y | z_l) p(z_c)}{q(z_c, z_l | x)} \right) \right] \right].
\end{align*}
\]

Denoting \( \Psi = (\theta_1, \theta_2, \phi_1, \phi_2) \), the negative ELBO can be given by

\[
\mathcal{L}(\Psi) = -\mathbb{E}_{q_{\phi_2}} \mathbb{E}_{q_{\phi_1}} [\ln p_{\phi_2}(x | z_c, z_l) + \ln p_{\phi_1}(y | z_l)] + \\
\mathbb{E}_{q_{\phi_2}} [D_{KL}(q_{\phi_1}(z_l | x, z_c) \| p(z_l))] + \\
D_{KL}(q_{\phi_2}(z_c | x) \| p(z_c)),
\]

(2)

where the second line follows the graphical model in Fig 2 and \( \mathbb{E}(\cdot) \) and \( \ln(\cdot) \) denote the expectation operator and the natural logarithm, respectively. We avoid computing biased gradients by following the re-parameterization trick from Kingma & Welling (2014). Note that in equation (1) we deliberately choose to exclude the label information \( y \) as input to \( q_{\phi_2}(\cdot) \) to be able to exploit the associated generative network \( p_{\theta_1}(y | z_l) \) as a classifier. The consequence and the proposed solution to accommodate this design choice are discussed in the next subsection.

4.3 \textbf{AttFEX for Transductive Feature Extraction}

Our design choice to omit label information \( y \) when inferring \( z_l \) (as discussed for equation (1)) can be an information bottleneck and counter-productive to the discriminative power \( z_l \) holds. However, this allows us to employ \( z_l \) for classification and not reconstruction of the label. To compensate for this bottleneck, we introduce an attention-based transductive feature extractor (\textbf{AttFEX}) module that allows the network \( q_{\phi_2}(z_l | x, z_c) \) see through and compare images across all classes within each task (irrespective of being from the query or support sets), thus, induces \textit{task-cognizance} in the inference network. We first extract the feature maps of all images in the task using a convolutional block \( \mathbf{F} = \text{ConvEnc}(\mathbf{X}) \) where \( \mathbf{X} \in \mathbb{R}^{N(K+Q) \times C \times W \times H} \), \( \mathbf{F} \in \mathbb{R}^{N(K+Q) \times C' \times W' \times H'} \). The feature map tensor \( \mathbf{F} \) is then transposed into \( \mathbf{F}' \in \mathbb{R}^{C' \times N(K+Q) \times W' \times H'} \) and fed into two consecutive \( 1 \times 1 \) convolution blocks. This helps the network utilize information across corresponding pixels of all images in a task \( T_t \), which can be considered as a parametric comparison of classes. We leverage the fact that \textbf{ConvEnc} already extracts local pixel information by using larger kernels, and thus, use parameter-light \( 1 \times 1 \) convolutions subsequently to focus only on individual pixels. Let \( \mathbf{F}'_i \) denote the \( i^{th} \) channel (or feature map layer) out of total of \( C' \) available and \textbf{ReLU} denote the rectified linear unit activation. The \( 1 \times 1 \) convolution block (\textbf{Conv}_{1 \times 1}) is formulated as follows:

\[
\begin{align*}
\mathbf{M}_i &= \text{ReLU}(\text{Conv}_{1 \times 1}(\mathbf{F}'_i, \mathbf{W}_M)), \forall i \in [1, C']; \\
\mathbf{N}_j &= \text{ReLU}(\text{Conv}_{1 \times 1}(\mathbf{M}_j, \mathbf{W}_N)), \forall j \in [1, C'];
\end{align*}
\]

(3)

where \( \mathbf{N} \in \mathbb{R}^{C' \times 32 \times W' \times H'} \) and \( \mathbf{W}_M \in \mathbb{R}^{64 \times N(K+Q) \times 1 \times 1}, \mathbf{W}_N \in \mathbb{R}^{32 \times 64 \times 1 \times 1} \) denote the learnable weights. Next, we want to blend information across feature maps for which we use a self-attention mechanism (Vaswani
Support Set Feature Maps
Query Set Feature Maps

Figure 3: AttFEX module depicting colors as images and shades as feature maps. We illustrate only 3 image feature maps and 3 channels instead of 32 for \( N \), for the sake of simplicity.

Ye et al. (2017) across \( N_j, \forall j \in [1,32] \). To do so, we feed \( N \) to query, key and value extraction networks \( f_q(\cdot; W_Q), f_k(\cdot; W_K), f_v(\cdot; W_V) \) which are also designed to be \( 1 \times 1 \) convolutions as:

\[
Q_i = \text{ReLU}(\text{Conv}_{1 \times 1}(N_i, W_Q)), \quad \forall i \in [1,C'];
\]

\[
K_i = \text{ReLU}(\text{Conv}_{1 \times 1}(N_i, W_K)), \quad \forall i \in [1,C'];
\]

\[
V_i = \text{ReLU}(\text{Conv}_{1 \times 1}(N_i, W_V)), \quad \forall i \in [1,C'];
\]

(4)

where \( W_Q, W_K, W_V \in \mathbb{R}^{1 \times 32 \times 1 \times 1} \) are the learnable weights and \( Q, K, V \in \mathbb{R}^{C' \times 1 \times W' \times H'} \) are the query, key and value tensors. Next, each feature map \( N_j \) is mapped to its output tensor \( G_j \) by computing a weighted sum of the values, where each weight (within parentheses in equation 5) measures the compatibility (or similarity) between the query and its corresponding key tensor using an inner-product:

\[
G_i = \sum_{j=1}^{C'} \left( \frac{\exp(Q_i \cdot K_j)}{\sqrt{d_k} \sum_{k=1}^{C'} \exp(Q_i \cdot K_k)} \right) V_i,
\]

(5)

where \( d_k = W' \times H' \), and \( G_i \in \mathbb{R}^{1 \times C' \times W' \times H'} \), \( \forall i \). Finally, we transform the original feature maps \( F \) by applying a Hadamard product between the feature mask \( G \) and \( F \), thus, rendering the required feature maps transductive:

\[ \tilde{F}^{S} = G \circ F^{S} \quad \text{or} \quad \tilde{F}^{Q} = G \circ F^{Q}. \]

Here, \( F^{S} \) and \( F^{Q} \) represent the feature maps corresponding to the support and query images, respectively. As a result of operating on this channel-pixel distribution across images in a task, \( F^{S} \) and \( F^{Q} \) are rendered transductive. Unlike other attention-based few-shot learning methods (Ye et al. 2020; Vinyals et al. 2016), we do not compute an attention-based transform on the flattened support and query vectors, but rather on the outputs of the \( \text{Conv}_{1 \times 1}(\cdot; W_N) \) to effectively fuse information from multiple class-pixel comparisons.

Note that the query tensor \( Q \) must not be confused with the query set \( Q \) of a task.

4.4 TRIDENT’s Transductive ELBO

AttFEX’s transductive feature extraction process introduces task-level dependencies in the variational formulation of \( q_{\phi_1} \). To incorporate this dependency in equation 2, we now revise the derivation of our negative ELBO to be defined in terms of the entire task set and not individual data points. Let \( X = X^{S} \cup X^{Q} \) denote the tensor containing all images sampled in a task, \( Y = Y^{S} \cup Y^{Q} \) denote all the labels corresponding to the...
images in the task and \( N' = NK + NQ \) be the total number of samples in a task. Considering all samples to be independently and identically distributed (I.I.D.), the likelihood of the entire task can be written as:

\[
p(X, Y) = \prod_{i=1}^{N'} \int \int p(x_i, y_i | z_{ci}, z_{li}) p(z_{ci}, z_{li}) \, dz_{ci} \, dz_{li}.
\]  

(6)

Since the generative networks \( p_{\theta_2}(x | z_c, z_l) \) and \( p_{\theta_1}(y | z_l) \) remain inductive, while the approximate inference network \( q_{\phi_1}(z_l | X, z_c) \) becomes transductive (via AttFEX), the log-likelihood now becomes:

\[
\ln p(X, Y) \geq \sum_{i=1}^{N'} \mathbb{E}_{q_{\theta_2}} \left[ \mathbb{E}_{q_{\phi_1}} \left[ \ln \left( \frac{p(x_i | z_{ci}, z_{li}) p(y | z_{li}) p(z_{ci}) p(z_{li})}{q(z_{ci} | x_i) q(z_{li} | X, z_{ci})} \right) \right] \right].
\]

(7)

Finally, the overall negative ELBO for the entire task can be given by

\[
\mathcal{L}(\Psi) = - \sum_{i=1}^{N'} \mathbb{E}_{q_{\theta_2}} \mathbb{E}_{q_{\phi_1}} \left[ \ln p_{\theta_2}(x_i | z_{ci}, z_{li}) + \ln p_{\theta_1}(y_i | z_{li}) \right] + \mathbb{E}_{q_{\theta_2}} \left[ \mathcal{D}_{KL}(q_{\phi_1}(z_{li} | x) \| p(z_{li})) \right] + \mathbb{E}_{q_{\theta_2}} \left[ \mathcal{D}_{KL}(q_{\phi_1}(z_{ci} | x) \| p(z_{ci})) \right].
\]

(8)

Assuming Gaussian distributions for the priors as well as the variational distributions allows us to compute the KL Divergences of \( z_l \) and \( z_c \) (last two terms in equation 8) analytically \cite{Kingma2014}. By considering a multivariate Gaussian distribution and a multinomial distribution as the likelihood functions for \( p_{\theta_2}(x | z_c, z_l) \) and \( p_{\theta_1}(y | z_l) \), respectively, the negative log-likelihood of \( x \) becomes the mean squared error (MSE) between the reconstructed images \( \tilde{x} \) and the ground-truth images \( x \) while the negative log-likelihood of \( y \) becomes the cross-entropy between the actual labels \( y \) and the predicted labels \( \hat{y} \). After working equation 8 out, we arrive at our overall objective function \( \mathcal{L} = \mathcal{L}_R + \mathcal{L}_C \), where:

\[
\mathcal{L}_R = \alpha_1 \sum_{i=1}^{N'} \| x_i - \tilde{x}_i \|^2 - KL(\mu_{ci}, \sigma_{ci}),
\]

\[
\mathcal{L}_C = -\alpha_2 \sum_{i=1}^{N'} \sum_{n=1}^{N} [y_i]_n \ln p_{\theta_1}(\hat{y}_i = n | z_l) - KL(\mu_{li}, \sigma_{li}).
\]

(9)

where \( KL(\mu, \sigma) = \frac{1}{2} \sum_{i=1}^{D} \left( 1 + 2 \ln(\sigma^d) - (\mu^d)^2 - (\sigma^d)^2 \right) \), \([y_i]_n\) denotes the \( n \)-th dimension of the \( i \)-th one-hot encoded ground-truth vector \( y \), \( D \) denotes the dimension of the latent space, \( N \) is the total number of classes in an \((N\text{-way, } K\text{-shot})\) task, \( \alpha_1, \alpha_2 \) are constant scaling factors, \( \mu_c \) and \( \sigma_c^2 \) denote the mean and variance vectors of context latent distribution, and \( \mu_l \) and \( \sigma_l^2 \) denote the mean and variance vectors of label latent distribution. The hyper-parameters \( \alpha_1, \alpha_2 \) only scale the evidence lower-bound appropriately, since the reconstruction loss is in practice three orders of magnitude greater than the cross-entropy loss. Moreover, these scaling factors can be understood as gradient-scaling parameters which help improve training in heterogeneous likelihoods (Gaussian and Categorical in our case) \cite{Javaloy2022}.

### 4.5 Algorithmic Overview and Training Strategy

**Overview of TRIDENT.** The complete architecture of TRIDENT is illustrated in Fig. 4. The ConvEnc feature extractor and the linear layers \( \mu_{\phi_2}(.) \) and \( \sigma_{\phi_2}^2(.) \) constitute the inference network \( q_{\phi_2} \) of the context latent variable (bottom row of Fig. 4). The AttFEX module, another ConvEnc, and linear layers \( \mu_{\phi_1}(.) \) and \( \sigma_{\phi_1}^2(.) \) make up the inference network \( q_{\phi_1} \) of the label latent variable (top row of Fig. 4). The proposed approach, TRIDENT, is described in Algorithm 1. Note that TRIDENT is trained in a MAML \cite{Finn2017} fashion, where depending on the inner or outer loop, the support or query set \((g \in \{S, Q\})\) will be the reference, respectively. First, the lower ConvEnc block extracts feature maps \( X_{\text{CE}}^g = \text{ConvEnc}(X^g) \). \( X_{\text{CE}}^g \)'s are then flattened and passed onto \( \mu_{\phi_2}(.) \) and \( \sigma_{\phi_2}^2(.) \), which respectively output the mean and variance vectors of the
Figure 4: TRIDENT is comprised of two intertwined variational networks. $Z^g_c$ is concatenated with the output of AttFEX, and used for inferring $Z^l_i$, where $g \in \{S,Q\}$. Next, both $Z^l_i$ and $Z^g_c$ are used to reconstruct images $X^q$ while $Z^g_c$ is used to extract $Y^g$.

Algorithm 1: TRIDENT

**Require:** $X^S$, $X^Q$, $Y^q$, $X^q_{g\in}$, where $g \in \{S,Q\}$

1. Sample: $Z^g_c \sim q_{\phi_2}(Z_c | \mu_{\phi_2}(X^q_{g\in}), \text{diag}(\sigma^2_{\phi_2}(X^q_{g\in}))$)

2. Compute task-cognizant embeddings: $[\tilde{F}^S, \tilde{F}^Q] = \text{AttFEX(ConvEnc(X))}; X = X^S \cup X^Q$

3. Concatenate $Z^g_c$ and $\tilde{F}^g$ into $[\tilde{F}^g, Z^g_c]$ and sample: $Z^l_i \sim q_{\phi_1}(Z_i | \mu_{\phi_1}([\tilde{F}^g, Z^g_c]), \text{diag}(\sigma^2_{\phi_1}([\tilde{F}^g, Z^g_c])))$

4. Reconstruct $X^q$ using $\hat{X}^q = p_{\theta_1}(X | Z^l_i, Z^g_c)$

5. Extract class-conditional probabilities using: $p(Y^q | Z^l_i) = \text{softmax}(p_{\theta_1}(Y^q | Z^l_i))$

6. Compute $L^q = L_R^q + L_C^q$ using equation [8]

**Return:** $L^q$

The context latent distribution, as discussed in equation [4]. This is done either for the entire support or the query images $X^q$, where $g \in \{S,Q\}$ for a given task $T_i$. We then sample a set of vectors $Z^g_c$ (subscript $c$ for context) from their corresponding Gaussian distributions using the re-parameterization trick (line 1, Algorithm 1). Upon passing $X = X^S \cup X^Q$ through the upper ConvEnc, the AttFEX module of $q_{\phi_2}$ comes into play to create task-cognizant feature maps $\tilde{F}^g$ for either $S$ or $Q$ (line 2). $Z^g_c$ together with $\tilde{F}^g$ are passed onto the linear layers $\mu_{\phi_1}()$, $\sigma^2_{\phi_1}()$ to generate the mean and variance vectors of the label latent Gaussian distributions (line 3). After sampling the set of vectors $Z^l_i$ (subscript $l$ for label) from their corresponding distributions, we use $Z^l_i$ and $Z^g_c$ to reconstruct images $\tilde{X}^q$ using the generative network $p_{\theta_1}$ (line 4). Next, $Z^l_i$’s are input to the classifier network $p_{\theta_1}$ to generate the class logits, which are normalized using a $\text{softmax}(.)$, resulting in class-conditional probabilities $p(Y^q | Z^l_i)$ (line 5). Finally (in line 6), using the outputs of all the components discussed earlier, we calculate the loss $L^q$ as formulated in equation [8].

**Training strategy.** An important aspect of the training procedure of TRIDENT is that its set of parameters $\Psi = (\theta_1, \theta_2, \phi_1, \phi_2)$ are meta-learnt by back-propagating through the adaptation procedure on the support set, as proposed in MAML [Finn et al., 2017] and illustrated here in Algorithm 2. This increases the sensitivity of the parameters $\Psi$ towards the loss function for fast adaptation to unseen tasks and reduces generalization errors on the query set $Q$, as discussed from a dynamical systems standpoint in [Finn et al., 2017]. First, we randomly initialize the parameters $\Psi$ (line 1, Algorithm 2) to compute the objective function over the support set $L^{S_i}(\Psi)$ using equation [5] and perform a number of gradient descent steps on the parameters $\Psi$ to adapt them to the support set (lines 5 to 9). This is called the inner-update and is done separately for all the support sets corresponding to their $B$ different tasks (line 3). Once the inner-update is computed for each of the $B$ parameter sets, the loss is evaluated on the query set $L^Q_i(\Psi_i)$ (line 12), following
Algorithm 2: End to End Meta-Training of TRIDENT

Require: $D^{tr}, \alpha, \beta, B$
1 Randomly initialise $\Psi = (\phi_1, \phi_2, \theta_1, \theta_2)$
2 while not converged do
3     Sample $B$ tasks $T_i = S_i \cup Q_i$ from $D^{tr}$
4         for each task $T_i$ do
5             for number of adaptation steps do
6                 Compute $\mathcal{L}^{S_i}(\Psi) = \text{TRIDENT}(T_i - \{Y_i\})$
7                 Evaluate $\nabla_{\Psi} \mathcal{L}^{S_i}(\Psi)$
8                 $\Psi \leftarrow \Psi - \alpha \nabla_{\Psi} \mathcal{L}^{S_i}(\Psi)$
9             end
10            $(\Psi_i') = \Psi$
11        end
12        Compute $\mathcal{L}^{Q_i}(\Psi_i') = \text{TRIDENT}(T_i - \{Y_i\}); \forall i \in [1, B]$
13        Meta-update on $Q_i$: $\Psi \leftarrow \Psi - \beta \nabla_{\Psi} \sum_{i=1}^{B} \mathcal{L}^{Q_i}(\Psi_i')$
14 end

which a meta-update is conducted over all the corresponding query sets, which involves computing a gradient through a gradient procedure as described in [Finn et al., 2017] (line 13).

5 Experimental Evaluation

The goal of this section is to address the following four questions: (i) How well does TRIDENT perform when compared against the state-of-the-art methods for few-shot classification? (ii) How reliable is TRIDENT in terms of the confidence and uncertainty metrics? (iii) How well does TRIDENT perform in a cross-domain setting where there is a domain shift between the training and testing datasets? (iv) Does TRIDENT actually decouple latent variables?

Benchmark Datasets. We evaluate TRIDENT on the three most commonly adopted datasets: miniImagenet [Ravi & Larochelle, 2017a], tieredImagenet [Ren et al., 2018] and CUB [Welinder et al., 2010]. miniImagenet [Vinyals et al., 2016] is a subset of ImageNet [Deng et al., 2009] for few-shot classification. It contains 100 classes with 600 samples each. We follow the predominantly adopted settings of [Ravi & Larochelle, 2017a; Chen et al., 2019] where we split the entire dataset into 64 classes for training, 16 for validation and 20 for testing. tieredImagenet is a larger subset of ImageNet with 608 classes and 779,165 total images, which are grouped into 34 higher-level nodes in the ImageNet human-curated hierarchy. This set of nodes is partitioned into 20, 6, and 8 disjoint sets of training, validation, and testing nodes, and the corresponding classes form the respective meta-sets. CUB [Welinder et al., 2010] dataset has a total of 200 classes, split into training, validation and test sets following [Chen et al., 2019]. We use this dataset to simulate the effect of a domain shift where the model is first trained on a (5-way, 1 or 5-shot) configuration of miniImagenet and then tested on the test classes of CUB, as used in [Chen et al., 2019; Boudiaf et al., 2020; Ziko et al., 2020; Long et al., 2018].

Implementational Details. We use PyTorch [Paszke et al., 2019] and learn2learn [Arnold et al., 2020] for all our implementations. We use a commonly adopted Conv4 architecture [Ravi & Larochelle, 2017a; Finn et al., 2017; Patacchiola et al., 2020; Afrasiyabi et al., 2020; Wang et al., 2019; Boudiaf et al., 2020] as ConvEnc to obtain the generic feature maps. Following the standard setting in the literature [Finn et al., 2017; Ravi & Larochelle, 2017a], the Conv4 has four convolutional blocks where each block has a 3 × 3 convolution layer with 32 feature maps, followed by a batch normalization (BN) [Ioffe & Szegedy, 2015] layer, a 2 × 2 max-pooling layer and a LeakyReLU(0.2) activation. The generative network $p_{\theta_1}$ for $z_i$ is a classifier with two linear layers and a LeakyReLU(0.2) activation in between, while $p_{\theta_2}$ for $z_c$ consists of four blocks of a 2-D upsampling layer, followed by a 3 × 3 convolution and LeakyReLU(0.2) activation. Both latent variables $z_i$ and $z_c$ have a dimensionality of 64.
Following [Nichol et al. (2018a); Liu et al. (2019); Vaswani et al. (2017)], images are resized to 84 × 84 for all configurations and we train and report test accuracy of (5-way, 1 and 5-shot) settings with 10 query images per class for all datasets. The hyper-parameter values (H.P.) used for training TRIDENT on miniImagenet and tieredImagenet are shown in Table 1. We apply the same hyperparameters for the cross-domain testing scenario of miniImagenet → CUB used for training TRIDENT on miniImagenet, for the given (N-way, K-shot) configuration. Hyperparameters are kept fixed throughout training, validation and testing for a given configuration. Adam [Kingma & Ba (2015)] optimizer is used for inner and meta-updates. Finally, the query, key and value extraction networks \( f_q(); W_Q \), \( f_k(); W_K \), \( f_v(); W_V \) of the AttFEX module only use \( \text{Conv}_{1 \times 1}(.) \) and not the \( \text{LeakyReLU}(0.2) \) activation function for (5-way, 1-shot) tasks, irrespective of the dataset. We observed that utilizing BatchNorm [Ioffe & Szegedy (2015)] in the decoder of \( z_c(p) \) to train TRIDENT on (5-way, 5-shot) tasks of miniImagenet and on (5-way, 1-shot) tasks of tieredImagenet leads to better scores and improved stability during training. We used the ReLU activation function instead of \( \text{LeakyReLU}(0.2) \) to carry out training on (5-way, 1-shot) tasks of tieredImagenet. Meta-learning objectives can lead to unstable optimization processes in practice, especially when coupled with stochastic sampling in latent spaces, as also previously observed in [Antreas Antoniou et al. (2019); Rusu et al. (2019)]. For ease of experimentation, we clip the meta-gradient norm at an absolute value of 1. Since AttFEX operates on all samples available in a task, scaling to a larger number of ways and shots per task requires more computational resources. TRIDENT converges in 82,000 and 22,500 epochs for (5-way, 1-shot) and (5-way, 5-shot) tasks of miniImagenet, respectively and takes 67,500 and 48,000 epochs for convergence on (5-way, 1-shot) and (5-way, 5-shot) tasks of tieredImagenet, respectively. This translates to an average training time of 110 hours on an 11GB NVIDIA 1080Ti GPU. Note that we did not employ any data augmentation, feature averaging or any other data apart from the corresponding training subset \( D^t \), during training.

### 5.1 Evaluation Results

We report test accuracies indicating 95% confidence intervals over 600 tasks for miniImagenet, and 2000 tasks for both tieredImagenet and CUB, as is customary across the literature (Chen et al. [2019]; Dhillon et al. [2020]; Bateni et al. [2022]). We compare our performance against a wide variety of state-of-the-art few-shot classification methods such as: (i) metric-learning [Wang et al. (2019); Bateni et al. (2020); Afrasiyabi et al. (2020); Yang et al. (2020); Li et al. (2019); Xu et al. (2021)], (ii) transductive feature-extraction based [Oreshkin et al. (2018); Ye et al. (2020); Lee et al. (2019); Rusu et al. (2019)], (iii) optimization-based [Finn et al. (2017); Mishra et al. (2018); Oh et al. (2021); Hu et al. (2022); Patacchiola et al. (2020); Ravi & Beaston (2019)], (iv) transductive inference-based [Bateni et al. (2022); Bouidadi et al. (2020); Ziko et al. (2020); Liu et al. (2019)], and (v) Bayesian [Iakovleva et al. (2020); Zhang et al. (2019); Hu et al. (2020); Liu et al. (2019), and [Hou et al. (2019)] have demonstrated the superiority of transductive inference methods over their inductive counterparts. In this light, we compare against a larger number of transductive (18 baselines) rather than inductive (7 baselines) methods for a fair comparison. It is important to note that TRIDENT is only a transductive feature-extraction based method as we utilize the query set images to extract task-aware feature embeddings; it is not a transductive inference based method since we perform inference of class-labels over the entire domain of definition and not just for the selected query samples (Vapnik 2000; Gammerman et al. (1998)). The results on miniImagenet and tieredImagenet for both (5-way, 1 and 5-shot) settings are summarized in Table 2. We accentuate on the fact that we also compare against Trans-CNAPS+FETI [Bateni et al. (2022)], where the authors pre-train the ResNet-18 backbone on the entire train split of Imagenet. We, however, avoid training on additional datasets, in favor of fair comparison with the rest of literature. Regardless of the choice of backbone (simplest in our case), TRIDENT sets a new state-of-the-art on miniImagenet and tieredImagenet for both (5-way, 1 and 5-shot) settings, offering up to 5% gain over the prior art. Recently, a more challenging cross-domain setting has been proposed for few-shot classification to assess its generalization capabilities to unseen datasets. The commonly adopted setting is

| H.P. | 5-way, 1-shot | 5-way, 5-shot | 5-way, 1-shot | 5-way, 5-shot |
|------|--------------|--------------|--------------|--------------|
| \( \alpha_1 \) | 1e-2 | 1e-2 | 1e-2 | 1e-2 |
| \( \alpha_2 \) | 100 | 100 | 150 | 150 |
| \( \alpha_3 \) | 1e-3 | 1e-3 | 1.5e-3 | 1.7e-3 |
| \( \beta \) | 1e-4 | 1e-4 | 1.5e-4 | 1.7e-4 |
| \( \gamma \) | 5 | 5 | 5 | 5 |
Table 2: Accuracies in (\% ± std). The predominant methodology of the baselines: \textbf{Ind.}: inductive feature, \textbf{TF}: transductive feature extraction methods, \textbf{TI}: transductive feature extraction methods. \textbf{Conv}: convolutional blocks, \textbf{RN}: ResNet backbone, \(|\): extra data. Style: \textbf{best} and \textbf{second best}. \textbf{TRIDENT} employs a transductive feature extraction module (\textbf{TF}), and the simplest of backbones (\textbf{Conv4}).

| Methods             | Backbone | Approach | 5-way 1-shot | 5-way 5-shot | 5-way 1-shot | 5-way 5-shot | 5-way 1-shot | 5-way 5-shot |
|---------------------|----------|----------|--------------|--------------|--------------|--------------|--------------|--------------|
| MAML (Finn et al., 2017) | Conv4     | Ind.     | 48.70 ± 1.86 | 63.11 ± 0.92 | 51.67 ± 1.81 | 70.30 ± 0.08 | 40.01 ± 1.25 | 49.83 ± 0.62 |
| ABML (Yang et al., 2019) | Conv4     | Ind.     | 40.88 ± 0.25 | 58.19 ± 0.17 | -            | -            | 31.51 ± 0.32 | 47.90 ± 0.51 |
| GVE(T) (Patacchino et al., 2020) | Conv4     | Ind.     | 48.09 ± 0.24 | 67.14 ± 0.23 | -            | -            | 37.49 ± 0.11 | 57.23 ± 0.31 |
| DKT+Cos (Patacchino et al., 2020) | Conv4     | Ind.     | 48.64 ± 0.15 | 62.85 ± 0.37 | -            | -            | 40.22 ± 0.54 | 53.65 ± 0.05 |
| BOIL (Gu et al., 2020) | Conv4     | Ind.     | 49.61 ± 0.16 | 48.58 ± 0.27 | 66.45 ± 0.37 | 69.37 ± 0.12 | -            | -            |
| LFVT (Ge et al., 2020)  | R810      | TF+TI    | 66.32 ± 0.80 | 81.98 ± 0.55 | -            | -            | 47.47 ± 0.75 | 66.98 ± 0.68 |
| FRN (Afrasiyabi et al., 2020) | Conv4     | Ind.     | 66.45 ± 0.19 | 82.83 ± 0.13 | 71.16 ± 0.22 | 86.01 ± 0.15 | 54.11 ± 0.19 | 77.09 ± 0.15 |
| RFOA (Yang et al., 2021) | Conv4     | TF+TI    | 67.71 ± 0.46 | 84.64 ± 0.67 | 72.45 ± 0.74 | 87.24 ± 0.74 | -            | -            |
| PAL (He et al., 2021)   | R812      | TF+TI    | 63.97 ± 0.64 | 84.40 ± 0.44 | 72.25 ± 0.72 | 86.95 ± 0.47 | -            | -            |
| Proto-Complementary (Ong et al., 2021) | R812  | TF+TI    | 73.13 ± 0.83 | 82.06 ± 0.54 | 81.04 ± 0.89 | 87.42 ± 0.57 | -            | -            |
| TPMN (He et al., 2021)  | R812      | TF+TI    | 67.64 ± 0.63 | 83.44 ± 0.43 | 72.24 ± 0.70 | 86.55 ± 0.61 | -            | -            |
| LIF-EMT (Ye et al., 2022) | R812      | TF+TI    | 68.94 ± 0.28 | 85.07 ± 0.30 | 73.76 ± 0.32 | 87.83 ± 0.59 | -            | -            |
| Trans-CNAPS-EasiLin et al., 2022 | R818  | TF+TI    | 55.6 ± 0.9   | 74.1 ± 0.7   | 65.9 ± 1.0   | 81.8 ± 0.7   | -            | -            |
| Baseline++ (Chen et al., 2020) | R818      | TF       | 51.7 ± 0.77 | 75.68 ± 0.63 | -            | -            | 42.85 ± 0.69 | 62.04 ± 0.74 |
| FEAT (Ye et al., 2020)  | R818      | TF       | 66.78 ± 0.82 | 82.05 ± 0.78 | 70.80 ± 0.79 | 84.79 ± 0.78 | 50.67 ± 0.78 | 71.08 ± 0.73 |
| SimpleShot (Wang et al., 2019) | WRN      | Ind.     | 63.32       | 80.28       | 69.98       | 85.45       | 48.56       | 65.63       |
| Assoc-Align (Ye et al., 2020) | WRN56    | TF       | 65.92 ± 0.60 | 82.95 ± 0.55 | 74.40 ± 0.68 | 86.61 ± 0.59 | 47.29 ± 0.76 | 72.37 ± 0.89 |
| ReRank (SHEN et al., 2021) | WRN      | TF       | 74.03 ± 0.66 | 82.84 ± 0.54 | 79.5 ± 0.6   | 84.8 ± 0.4   | -            | -            |
| TRIDENT (Ours)        | Conv4     | TF       | 86.11 ± 0.59 | 95.95 ± 0.28 | 86.97 ± 0.50 | 96.57 ± 0.17 | 84.61 ± 0.33 | 80.74 ± 0.35 |

where one trains on miniImagenet and tests on CUB (Chen et al., 2019). The results of this experiment are also presented in Table 2. We compare against any existing baselines for which this cross-domain experiment has been conducted. As can be seen, and to the best of our knowledge, TRIDENT again sets a new state-of-the-art by a significant margin of 20% (5-way, 1-shot) setting, and 1.5% for (5-way, 5-shot) setting.

**Computational Complexity.** Most of the reported baselines in Table 2 use stronger backbones such as ResNet12, ResNet18 and WRN which contain 11.5, 12.4 and 36.4 millions of parameters respectively. On the other hand, we use three Conv4s along with two fully connected layers and an AttFEX module which accounts for 410,958 and 412,238 parameters in the (5-way, 1-shot) and (5-way, 5-shot) scenarios, respectively. This is summarized in details in Table 3. Even though we are more parameter heavy than approaches that use a single Conv4 as feature extractor, TRIDENT’s total parameters still lies in the same order of magnitude as these approaches. In summary, when it comes to complexity in parameter space, we are considerably more efficient than the vast majority of the cited competitors.

**Reliability Metrics.** A complementary set of metrics is typically used in probabilistic settings to measure the uncertainty and reliability of predictions. More specifically, expected calibration error (ECE) and maximum calibration error (MCE) respectively measure the expected and maximum binned difference between confidence and accuracy (Guo et al., 2017). This is illustrated in Table 4 where TRIDENT offers superior calibration on miniImagenet (5-way, 1 and 5-shot) as compared to other

| Methods          | ECE  | MCE  |
|------------------|------|------|
| Feature Transfer | 0.055| 0.185|
| Baseline         | 0.052| 0.182|
| Proto Nets       | 0.050| 0.175|
| DKT+Cos          | 0.048| 0.172|
| BMAML+Chaser     | 0.046| 0.169|
| LogSoftGP        | 0.044| 0.166|
| CVE              | 0.042| 0.163|
| TRIDENT (Ours)   | 0.039| 0.159|

Table 3: Parameter count of TRIDENT against competitors.

| Methods | ECE    | MCE    |
|---------|--------|--------|
| Conv4   | 0.040  | 0.060  |
| Ave     | 0.045  | 0.064  |
| TRIDENT | 0.042  | 0.063  |

Table 4: Calibration errors of TRIDENT. Style: \textbf{best} and \textbf{second best}.

| Methods          | ECE  | MCE  |
|------------------|------|------|
| Feature Transfer | 0.055| 0.185|
| Baseline         | 0.052| 0.182|
| Proto Nets       | 0.050| 0.175|
| DKT+Cos          | 0.048| 0.172|
| BMAML+Chaser     | 0.046| 0.169|
| LogSoftGP        | 0.044| 0.166|
| CVE              | 0.042| 0.163|
| TRIDENT (Ours)   | 0.039| 0.159|

Table 5: Style: \textbf{best} and \textbf{second best}.

| Methods          | ECE    | MCE    |
|------------------|--------|--------|
| Conv4             | 0.040  | 0.060  |
| Ave               | 0.045  | 0.064  |
| TRIDENT (Ours)    | 0.042  | 0.063  |

Table 6: Accuracy on miniImagenet (5-way, 1 and 5-shot) as compared to other
Table 6: Ablation study for miniImagenet (5-way, 1-shot) tasks. Accuracies in (% ± std.).

| (B, n) | (5, 3) | (5, 5) | (10, 3) | (10, 5) | (20, 3) | (20, 5) |
|--------|--------|--------|--------|--------|--------|--------|
|        | 67.43 ± 0.75 | 69.21 ± 0.66 | 74.6 ± 0.84 | 80.82 ± 0.68 | 86.11 ± 0.59 |
| (dim(z_l), dim(z_c)) |  | | | | | |
| (32, 32) | 76.29 ± 0.72 | 75.44 ± 0.81 | 79.1 ± 0.57 | 82.93 ± 0.8 | 86.11 ± 0.59 | 85.62 ± 0.52 | 82.89 ± 0.48 | 84.42 ± 0.59 |
| (32, 64) | 78.4 ± 0.23 | 77.89 ± 0.39 | 79.55 ± 0.87 | 86.11 ± 0.59 | 84.87 ± 0.45 | 82.11 ± 0.35 | 84.67 ± 0.7 | 85.8 ± 0.58 | 83.92 ± 0.63 |
| (32, 128) | | | | | | | |
| (64, 32) | | | | | | | |
| (64, 64) | | | | | | | |
| (64, 128) | | | | | | | |
| (128, 32) | | | | | | | |
| (128, 64) | | | | | | | |
| (128, 128) | | | | | | | |

probabilistic approaches, and MAML (Finn et al. 2017). To further examine the reliability and calibration of our method, we assess the ECE, MCE (Guo et al. 2017) and Brier scores (BRIER 1950) of TRIDENT on the challenging cross-domain scenario of miniImagenet → CUB for (5-way, 5-shot) tasks. When compared against other baselines that report these metrics on the aforementioned scenario, TRIDENT proves to be the most calibrated with the best reliability scores. This is shown in Table 5.

5.2 Decoupling Analysis

As a qualitative demonstration, we visualize the label and context latent means (µ_l and µ_c) of query images for a randomly selected (5-way, 5-shot) task from the test split of miniImagenet, before and after the MAML meta-update procedure. The UMAP plots in Fig. 5 illustrate significant improvement in class-conditional separation of query samples for label latent space upon meta-update, whereas negligible improvement is visible on the context latent space. This is qualitative evidence that Z_l captures more class-discriminating information as compared to Z_c. To substantiate this quantitatively, the clustering capacity of these latent spaces is also measured by the Davies-Bouldin score (DBI) (Davies & Bouldin 1979), where, the lower the DBI score, the better both the inter-cluster separation and intra-cluster “tightness”. Fig. 5 shows that the DBI score drops significantly more after meta-update in the case of Z_l as compared to Z_c, indicating better clustering of features in the former than the latter. This aligns with the proposed decoupling strategy of TRIDENT and corroborates the validity of our proposition to put an emphasis on label latent information for the downstream few-shot tasks.

5.3 Ablation Study

We analyze the classification performance of TRIDENT across various parameters and hyper-parameters, as is summarized in Table 5. We use miniImagenet (5-way, 1-shot) setting to carry out ablation study experiments. To cover different design perspectives, we carry out ablation on: (i) MAML-style training parameters: meta-batch size B and number of inner adaption steps n, (ii) latent space dimensionality: z_l and z_c to assess the impact of their size, (iii) AttFEX features: number of features extracted by W_M, W_N. Looking at the results, TRIDENT’s performance is directly proportional to the number of tasks and inner-adaptation steps, as is previously demonstrated in Antreas Antoniou et al. (2019); Finn et al. (2017) for MAML based training. Regarding latent space dimensions, a correlation between a higher dimension of z_l and z_c and a better performance can be observed. Even though, the results show that increasing both dimensions beyond 64...
leads to performance degradation. As such, \((64, 64)\) seems to be the sweet spot. Finally, on feature space dimensions of \(\text{AttFEX}\), the performance improves when \(W_M > W_N\), and the best performance is achieved when the parameters are set to \((64, 32)\). Notably, the exact set of parameters return the best performance for \((5\text{-way}, 5\text{-shot})\) setting. To sum up, \((B, n, \dim(z_l), \dim(z_i), \dim(W_M), \dim(W_N)) = (20, 5, 64, 64, 32)\) turns out to be the best setting for \((5\text{-way}, 1\text{-shot})\), consistently the same for \((5\text{-way}, 5\text{-shot})\).

### 5.4 Impact of \(\text{AttFEX}\) and the Decoupled Inference Strategy

In order to study the impact of the transductive feature extractor \(\text{AttFEX}\), we exclude it during training and train the remaining architecture. Training proceeds exactly as mentioned in Algorithm 2. As can be seen in Table 7, the exclusion of \(\text{AttFEX}\) from \(\text{TRIDENT (AttFEX OFF)}\) results in a substantial drop in classification performance across both datasets and task settings. Empirically, this further substantiates the importance of \(\text{AttFEX}\)'s ability to render the feature maps transductive/task-aware. As explained earlier in section 4.3, the derivation of \(\text{TRIDENT}\)'s ELBO implies that \(y\) should be included as an input to \(q_{\phi_y}\) due to its dependence on \(z_l\). However, in order to utilize \(\text{TRIDENT}\) as a classification and not a label reconstruction network, we choose not to input \(y\) to \(q_{\phi_y}(\cdot)\), but rather do so indirectly by inducing a semblance of label characteristics in the features extracted from the images in a task. Thus, it is important to realize that this ability of \(\text{AttFEX}\) to render feature maps transductive is not just an adhoc performance enhancer, but rather an essential part of \(\text{TRIDENT}\). To further understand the impact of \(\text{AttFEX}\) on \(\text{TRIDENT}\), we train \(\text{TRIDENT}\) with a transductive feature extraction module different from \(\text{AttFEX}\). The three modules that we replace \(\text{AttFEX}\) with are:

(i) Embedding propagation module (EP): This has been adapted from Embedding Propagation Networks (Rodríguez et al. 2020). Here, a non-parametric graph-based propagation matrix helps smoothen the embedding manifold to remove undesirable noise from the support and query feature vectors;

(ii) Attention-based feature adaption module (FEAT): This has been adapted from FEAT (Ye et al. 2020). A self-attention module is used to transform the support and query set by computing a weighted average of the embedding manifold to remove undesirable noise from the support and query feature vectors;

(iii) LSTM-based feature adaption module (LSTM): We introduce the LSTM-based transductive task-encoding procedure from Transductive CNAPS (Bateni et al. 2022) in place of \(\text{AttFEX}\) and carry out the same training procedure. The results for each of these experiments, when trained with \(\text{TRIDENT}\) on \(\text{miniImageNet}\) and \(\text{tieredImageNet}\), are shown in Table 7.

|          | miniImageNet | tieredImageNet |
|----------|--------------|----------------|
|          | (5-way, 1-shot) | (5-way, 5-shot) | (5-way, 1-shot) | (5-way, 5-shot) |
| \(\text{AttFEX OFF}\) | 67.08 ± 0.14 | 79.53 ± 0.21 | 69.32 ± 0.76 | 79.52 ± 0.76 |
| \(\text{TRIDENT (EP)}\) | 69.54 ± 0.75 | 80.15 ± 0.87 | 71.53 ± 0.46 | 82.17 ± 0.65 |
| \(\text{TRIDENT (FEAT)}\) | 80.11 ± 0.45 | 82.61 ± 0.42 | 82.39 ± 0.45 | 84.78 ± 0.39 |
| \(\text{TRIDENT (LSTM)}\) | 75.41 ± 0.45 | 83.89 ± 0.46 | 75.72 ± 0.52 | 86.20 ± 0.92 |
| \(\text{ConvFEX}\) | 51.49 ± 0.91 | 62.56 ± 0.72 | 55.80 ± 0.31 | 64.56 ± 0.29 |
| \(\text{TRIDENT (ours)}\) | 80.11 ± 0.50 | 95.95 ± 0.28 | 86.97 ± 0.50 | 96.57 ± 0.17 |

\(\text{TRIDENT}\)'s superior results corroborate the importance of our design choices in \(\text{AttFEX}\). Furthermore, to empirically verify the contribution of the decoupled variational inference \(\text{vs. AttFEX}\), we trained a simplified network \(\text{ConvFEX} = \text{Conv4} + \text{AttFEX}\) as the inference network \(q(z | x)\) to generate class labels \(y\) using an MLP \(p(y | z)\). \(\text{ConvFEX}\) embodies the inference and generative mechanics of \(z_l\) while omitting the second latent variable \(z_c\), thus dropping the decoupled inference strategy. As shown in Table 7, the classification accuracies across both datasets and task settings for \(\text{ConvFEX}\) corroborate that when label-specific and context information are coupled, we observe a significant performance degradation as compared to \(\text{TRIDENT}\), thus reaffirming the importance of our \textit{decoupled} variational inference strategy.

### 5.5 Impact of End-to-End Meta-Learning

To understand the importance of end-to-end meta-training of the entire network architecture, we train parts of \(\text{TRIDENT}\) in different steps. More specifically, we pre-train a \(\text{ConvEnc}\) on the training split of \(\text{miniImageNet}\) to perform 64-way classification. Note that during this pre-training phase, training proceeds by sampling random batches from the entire training split without defin-
ing support or query sets. We use the pre-trained feature extractors in TRIDENT’s inference networks $q_{\phi_1}$ and $q_{\phi_2}$ for fine-tuning. We then conduct three different experiments for fine-tuning the network: (i) freeze both the ConvEnc’s and fine-tune episodically without any MAML-style meta-learning; (ii) fine-tune the entire architecture episodically without any MAML-style meta-learning; (iii) freeze both the ConvEnc’s and fine-tune using MAML-style meta-learning. Fine-tuning proceeds by sampling $(N$-way, $K$-shot) tasks from the training split of miniImagenet. Notably, in (i) and (ii), we do not have separate updates for the support and query sets following simple episodic training. Therefore, employing an MLP for classification is a suboptimal utilization of the labelled samples. To address this, we use a prototypical classification framework as proposed in Prototypical Networks (Snell et al., 2017). The results of all the experimentation is illustrated in Table 8. It can be observed that episodic fine-tuning is not as effective as meta-learning the entire network architecture. This can be attributed to the ability of MAML-style meta-learning to render the network’s weights sensitive to the loss function, thus enabling quicker generalization to unseen tasks (Finn et al., 2017).

### Table 8: Impact of meta-learning on accuracies.

|                      | miniImagenet  |                |
|----------------------|---------------|---------------|
|                      | (5-way, 1-shot) | (5-way, 5-shot) |
| Frozen ConvEnc (Episodic) | 67.68 ± 0.55 | 78.53 ± 0.21 |
| Fine-tune ConvEnc (Episodic) | 69.84 ± 0.5   | 80.15 ± 0.67 |
| Frozen ConvEnc (Meta-Learn) | 80.11 ± 0.43 | 87.61 ± 0.12 |
| TRIDENT(Ours)        | 86.11 ± 0.59  | 95.95 ± 0.28  |

### 6 Concluding Remarks

We introduce a novel variational inference network (coined as TRIDENT) that simultaneously infers decoupled latent variables representing context and label information of an image. The proposed network is comprised of two intertwined variational sub-networks responsible for inferring the context and label information separately, the latter being enhanced using an attention-based transductive feature extraction module (AttFEX). Our extensive experimental results corroborate the efficacy of this transductive decoupling strategy on a variety of few-shot classification settings demonstrating superior performance and setting a new state-of-the-art for the most commonly adopted datasets mini and tieredImagenet as well as for the recent challenging cross-domain scenario of miniImagenet $\rightarrow$ CUB. As future work, we plan to demonstrate the applicability of TRIDENT in semi-supervised and unsupervised settings by including the likelihood of unlabelled samples derived from the graphical model. This would render TRIDENT as an all-inclusive holistic approach towards solving few-shot classification.

### References

Arman Afrasiyabi, Jean-François Lalonde, and Christian Gagné. Associative alignment for few-shot image classification. In European Conference on Computer Vision, pp. 18–35. Springer, 2020.

Antreas Antoniou, Harrison Edwards, and Amos J. Storkey. How to train your maml. In ICLR (Poster). OpenReview.net, 2019.

Sébastien M R Arnold, Praateek Mahajan, Debjyoti Datta, Ian Bunner, and Konstantinos Saitas Zarkias. learn2learn: A library for Meta-Learning research. August 2020. URL [http://arxiv.org/abs/2008.12284](http://arxiv.org/abs/2008.12284).

Peyman Bateni, Raghav Goyal, Vaden Masrani, Frank Wood, and Leonid Sigal. Improved few-shot visual classification. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 2020.

Peyman Bateni, Jarred Barber, Jan-Willem van de Meent, and Frank Wood. Enhancing few-shot image classification with unlabelled examples. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV), pp. 2796–2805, January 2022.

Yassir Bendou, Yuqing Hu, Raphael Lafargue, Giulia Lioi, Bastien Pasdeloup, Stéphane Pateau, and Vincent Gripon. Easy: Ensemble augmented-shot y-shaped learning: State-of-the-art few-shot classification with simple ingredients, 2022. URL [https://arxiv.org/abs/2201.09699](https://arxiv.org/abs/2201.09699).
Malik Boudiaf, Inttaz Ziko, Jérôme Rony, Jose Dolz, Pablo Piantanida, and Ismail Ben Ayed. Information maximization for few-shot learning. In H. Larochelle, M. Ranzato, R. Hadsell, M. F. Balcan, and H. Lin (eds.), Advances in Neural Information Processing Systems, volume 33, pp. 2445–2457. Curran Associates, Inc., 2020. URL https://proceedings.neurips.cc/paper/2020/file/196f5641aa9d87067da4ff90f381e7b-Paper.pdf

GLENN W. BRIER. Verification of forecasts expressed in terms of probability. Monthly Weather Review, 78(1):1 – 3, 1950. doi: 10.1175/1520-0493(1950)078<0001:VOFEIT>2.0.CO;2. URL https://journals.ametsoc.org/view/journals/mwre/78/1/1520-0493_1950_078_0001_vofeit_2_0_co_2.xml

Wei-Yu Chen, Yen-Cheng Liu, Zsolt Kira, Yu-Chiang Wang, and Jia-Bin Huang. A closer look at few-shot classification. In International Conference on Learning Representations, 2019.

Wentao Cui and Yuhong Guo. Parameterless transductive feature re-representation for few-shot learning. In Marina Meila and Tong Zhang (eds.), Proceedings of the 38th International Conference on Machine Learning, volume 139 of Proceedings of Machine Learning Research, pp. 2212–2221. PMLR, 18–24 Jul 2021. URL https://proceedings.mlr.press/v139/cui21a.html

David L. Davies and Donald W. Bouldin. A cluster separation measure. IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMI-1(2):224–227, 1979. doi: 10.1109/TPAMI.1979.4766909.

Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In 2009 IEEE conference on computer vision and pattern recognition, pp. 248–255. Ieee, 2009.

Guneet Singh Dhillon, Pratik Chaudhari, Avinash Ravichandran, and Stefano Soatto. A baseline for few-shot image classification. In International Conference on Learning Representations, 2020.

Harrison Edwards and Amos J. Storkey. Towards a neural statistician. ArXiv, abs/1606.02185, 2017.

Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In Proceedings of the 34th International Conference on Machine Learning, volume 70 of Proceedings of Machine Learning Research, pp. 1126–1135, 2017.

Chelsea Finn, Kelvin Xu, and Sergey Levine. Probabilistic model-agnostic meta-learning. In S. Bengio, H. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett (eds.), Advances in Neural Information Processing Systems, volume 31. Curran Associates, Inc., 2018. URL https://proceedings.neurips.cc/paper/2018/file/8e2c381d4dd04f1c55093f22c59c3a08-Paper.pdf

Théo Galy-Fajou, Florian Wenzel, Christian Donner, and Manfred Opper. Multi-class gaussian process classification made conjugate: Efficient inference via data augmentation. In Ryan P. Adams and Vibhav Gogate (eds.), Proceedings of The 35th Uncertainty in Artificial Intelligence Conference, volume 115 of Proceedings of Machine Learning Research, pp. 755–765. PMLR, 22–25 Jul 2020. URL https://proceedings.mlr.press/v115/galy-fajou20a.html

A Gammerman, V Vovk, and V Vapnik. Learning by transduction, vol uai’98, 1998.

Jonathan Gordon, John Bronskill, Matthias Bauer, Sebastian Nowozin, and Richard Turner. Meta-learning probabilistic inference for prediction. In International Conference on Learning Representations, 2019. URL https://openreview.net/forum?id=HkxStoC5F7

Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q. Weinberger. On calibration of modern neural networks. In Proceedings of the 34th International Conference on Machine Learning, volume 70 of Proceedings of Machine Learning Research, pp. 1321–1330. PMLR, 06–11 Aug 2017.

Ruibing Hou, Hong Chang, Bingpeng MA, Shiguang Shan, and Xilin Chen. Cross attention network for few-shot classification. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d’Alché-Buc, E. Fox, and R. Garnett (eds.), Advances in Neural Information Processing Systems, volume 32. Curran Associates, Inc., 2019. URL https://proceedings.neurips.cc/paper/2019/file/01894d6f048493d2cacde3c579c315a3-Paper.pdf
Shell Xu Hu, Pablo Moreno, Yang Xiao, Xi Shen, Guillaume Obozinski, Neil Lawrence, and Andreas Damianou. Empirical bayes transductive meta-learning with synthetic gradients. In International Conference on Learning Representations (ICLR), 2020. URL https://openreview.net/forum?id=Hkg-xgrYvH.

Yuqing Hu, Vincent Gripon, and Stéphane Pateux. Leveraging the feature distribution in transfer-based few-shot learning. In International Conference on Artificial Neural Networks, pp. 487–499. Springer, 2021.

Yuqing Hu, Stéphane Pateux, and Vincent Gripon. Squeezing backbone feature distributions to the max for efficient few-shot learning. Algorithms, 15(5):147, 2022a.

Yuqing Hu, Stéphane Pateux, and Vincent Gripon. Adaptive dimension reduction and variational inference for transductive few-shot classification, 2022b. URL https://arxiv.org/abs/2209.08527.

Ekaterina Iakovleva, Jakob Verbeek, and Karteek Alahari. Meta-learning with shared amortized variational inference. In Proceedings of the 37th International Conference on Machine Learning, Proceedings of Machine Learning Research. PMLR, 13–18 Jul 2020.

Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In Proceedings of the 32nd International Conference on Machine Learning, volume 37 of Proceedings of Machine Learning Research, pp. 448–456. PMLR, 07–09 Jul 2015.

Adrian Javaloy, Maryam Mehdadi, and Isabel Valera. Mitigating modality collapse in multimodal VAEs via impartial optimization. In Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvari, Gang Niu, and Sivan Sabato (eds.), Proceedings of the 39th International Conference on Machine Learning, volume 162 of Proceedings of Machine Learning Research, pp. 9938–9964. PMLR, 17–23 Jul 2022. URL https://proceedings.mlr.press/v162/javaloy22a.html.

Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In ICLR (Poster), 2015. URL http://arxiv.org/abs/1412.6980.

Diederik P Kingma and Max Welling. Auto-encoding variational bayes, 2014.

Durk P Kingma, Shakir Mohamed, Danilo Jimenez Rezende, and Max Welling. Semi-supervised learning with deep generative models. In Advances in Neural Information Processing Systems, volume 27, 2014.

Kwonjoon Lee, Subhransu Maji, Avinash Ravichandran, and Stefano Soatto. Meta-learning with differentiable convex optimization. In CVPR, 2019.

Hongyang Li, David Eigen, Samuel Dodge, Matthew Zeiler, and Xiaogang Wang. Finding Task-Relevant Features for Few-Shot Learning by Category Traversal. In CVPR, 2019.

Junjie Li, Zilei Wang, and Xiaoming Hu. Learning intact features by erasing-inpainting for few-shot classification. Proceedings of the AAAI Conference on Artificial Intelligence, 35(9):8401–8409, May 2021. URL https://ojs.aaai.org/index.php/AAAI/article/view/17021.

Jinlu Liu, Liang Song, and Yongqiang Qin. Prototype rectification for few-shot learning. In Computer Vision - ECCV 2020 - 16th European Conference, Glasgow, UK, August 23-28, 2020, Proceedings, Part I, 2020.

Yanbin Liu, Juho Lee, Mineop Park, Saehoon Kim, Eunho Yang, Sungju Hwang, and Yi Yang. Learning to propagate labels: Transductive propagation network for few-shot learning. In International Conference on Learning Representations, 2019.

Mingsheng Long, ZHANGJIE CAO, Jianmin Wang, and Michael I Jordan. Conditional adversarial domain adaptation. In Advances in Neural Information Processing Systems, volume 31. Curran Associates, Inc., 2018.

Jiawei Ma, Hanchen Xie, Guangxing Han, Shih-Fu Chang, Aram Galstyan, and Wael Abd-Almageed. Partner-assisted learning for few-shot image classification. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 10573–10582, 2021.
Puneet Mangla, Nupur Kumari, Abhishek Sinha, Mayank Singh, Balaji Krishnamurthy, and Vineeth N Balasubramanian. Charting the right manifold: Manifold mixup for few-shot learning. In Proceedings of the IEEE/CVF winter conference on applications of computer vision, pp. 2218–2227, 2020.

Leland McInnes, John Healy, and James Melville. Umap: Uniform manifold approximation and projection for dimension reduction. arXiv preprint arXiv:1802.03426, 2018.

Nikhil Mishra, Mostafa Rohaninejad, Xi Chen, and Pieter Abbeel. A simple neural attentive meta-learner. In International Conference on Learning Representations, 2018.

Cuong C. Nguyen, Thanh-Toan Do, and Gustavo Carneiro. Uncertainty in model-agnostic meta-learning using variational inference. CoRR, 2019.

Alex Nichol, Joshua Achiam, and John Schulman. On first-order meta-learning algorithms. CoRR, abs/1803.02999, 2018a.

Alex Nichol, Joshua Achiam, and John Schulman. On first-order meta-learning algorithms, 2018b.

Jaehoon Oh, Hyungjun Yoo, ChangHwan Kim, and Se-Young Yun. Boil: Towards representation change for few-shot learning. In International Conference on Learning Representations, 2021. URL https://openreview.net/forum?id=umIdUL6rMH.

Boris Oreshkin, Pau Rodríguez López, and Alexandre Lacoste. Tadam: Task dependent adaptive metric for improved few-shot learning. In Advances in Neural Information Processing Systems, volume 31, 2018.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. In Advances in Neural Information Processing Systems 32. 2019.

Massimiliano Patacchiola, Jack Turner, Elliot J. Crowley, Michael F. P. O’Boyle, and Amos J. Storkey. Bayesian meta-learning for the few-shot setting via deep kernels. In NeurIPS, 2020. URL https://proceedings.neurips.cc/paper/2020/hash/b9cfe8b6042cf759dc400ccb27a6737-Abstract.html.

Aravind Rajeswaran, Chelsea Finn, Sham M Kakade, and Sergey Levine. Meta-learning with implicit gradients. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d’Alch´e-Buc, E. Fox, and R. Garnett (eds.), Advances in Neural Information Processing Systems, volume 32. Curran Associates, Inc., 2019. URL https://proceedings.neurips.cc/paper/2019/file/072b030ba126b2f4b2374f342be9ed44-Paper.pdf.

Sachin Ravi and Alex Beatson. Amortized bayesian meta-learning. In International Conference on Learning Representations, 2019. URL https://openreview.net/forum?id=rkgpy3C5tX.

Sachin Ravi and H. Larochelle. Optimization as a model for few-shot learning. In ICLR, 2017a.

Sachin Ravi and Hugo Larochelle. Optimization as a model for few-shot learning. In International Conference on Learning Representations, 2017b. URL https://openreview.net/forum?id=rJYoKc11.

Mengye Ren, Sachin Ravi, Eleni Triantafillou, Jake Snell, Kevin Swersky, Josh B. Tenenbaum, Hugo Larochelle, and Richard S. Zemel. Meta-learning for semi-supervised few-shot classification. In International Conference on Learning Representations, 2018. URL https://openreview.net/forum?id=HJcSzz-CZ.

James Requeima, Jonathan Gordon, John Bronskill, Sebastian Nowozin, and Richard E Turner. Fast and flexible multi-task classification using conditional neural adaptive processes. In Advances in Neural Information Processing Systems, volume 32, 2019.

Pau Rodríguez, Issam Laradji, Alexandre Drouin, and Alexandre Lacoste. Embedding propagation: Smoother manifold for few-shot classification. In European Conference on Computer Vision, pp. 121–138. Springer, 2020.
Andrei A. Rusu, Dushyant Rao, Jakub Sygnowski, Oriol Vinyals, Razvan Pascanu, Simon Osindero, and Raia Hadsell. Meta-learning with latent embedding optimization. In *International Conference on Learning Representations*, 2019. URL https://openreview.net/forum?id=BjgklhAcK7

Victor Garcia Satorras and Joan Bruna Estrach. Few-shot learning with graph neural networks. In *International Conference on Learning Representations*, 2018. URL https://openreview.net/forum?id=BJj6qGbRW

Xi SHEN, Yang Xiao, Shell Xu Hu, Othman Sbai, and Mathieu Aubry. Re-ranking for image retrieval and transductive few-shot classification. In A. Beygelzimer, Y. Dauphin, P. Liang, and J. Wortman Vaughan (eds.), *Advances in Neural Information Processing Systems*, 2021. URL https://openreview.net/forum?id=sneJD9juaN1

Jake Snell and Richard Zemel. Bayesian few-shot classification with one-vs-each pòlya-gamma augmented gaussian processes. In *International Conference on Learning Representations*, 2021. URL https://openreview.net/forum?id=lgNx56yZh8a

Jake Snell, Kevin Swersky, and Richard Zemel. Prototypical networks for few-shot learning. In *Advances in Neural Information Processing Systems*, volume 30, 2017.

Zhuo Sun, Jijie Wu, Xiaoxu Li, Wenming Yang, and Jing-Hao Xue. Amortized bayesian prototype meta-learning: A new probabilistic meta-learning approach to few-shot image classification. In *Proceedings of The 24th International Conference on Artificial Intelligence and Statistics*, Proceedings of Machine Learning Research, 2021.

Flood Sung, Yongxin Yang, Li Zhang, Tao Xiang, Philip H.S. Torr, and Timothy M. Hospedales. Learning to compare: Relation network for few-shot learning. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2018.

Hung-Yu Tseng, Hsin-Ying Lee, Jia-Bin Huang, and Ming-Hsuan Yang. Cross-domain few-shot classification via learned feature-wise transformation. *arXiv preprint arXiv:2001.08735*, 2020.

Vladimir Naumovich Vapnik. Estimation of dependences based on empirical data. *Estimation of Dependences Based on Empirical Data*, 2006.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems*, volume 30, 2017.

Oriol Vinyals, Charles Blundell, Timothy Lillicrap, koray kavukcuoglu, and Daan Wierstra. Matching networks for one shot learning. In *Advances in Neural Information Processing Systems*, volume 29, 2016.

Yan Wang, Wei-Lun Chao, Kilian Q. Weinberger, and Laurens van der Maaten. Simpleshot: Revisiting nearest-neighbor classification for few-shot learning, 2019.

P. Welinder, S. Branson, T. Mita, C. Wah, F. Schroff, S. Belongie, and P. Perona. Caltech-UCSD Birds 200. Technical Report CNS-TR-2010-001, California Institute of Technology, 2010.

Davis Wertheimer, Luming Tang, and Bharath Hariharan. Few-shot classification with feature map reconstruction networks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 8012–8021, June 2021.

Jiamin Wu, Tianzhu Zhang, Yongdong Zhang, and Feng Wu. Task-aware part mining network for few-shot learning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 8433–8442, 2021.

Weijian Xu, yifan xu, Huaijin Wang, and Zhuowen Tu. Attentional constellation nets for few-shot learning. In *International Conference on Learning Representations*, 2021. URL https://openreview.net/forum?id=vujTf_I8Kmc
Ling Yang, Liangliang Li, Zilun Zhang, Xinyu Zhou, Erjin Zhou, and Yu Liu. Dpgn: Distribution propagation graph network for few-shot learning. *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 13387–13396, 2020.

Han-Jia Ye, Hexiang Hu, De-Chuan Zhan, and Fei Sha. Few-shot learning via embedding adaptation with set-to-set functions. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 8808–8817, 2020.

Jaesik Yoon, Taesup Kim, Ousmane Dia, Sungwoong Kim, Yoshua Bengio, and Sungjin Ahn. Bayesian model-agnostic meta-learning. In *Advances in Neural Information Processing Systems*, volume 31, 2018.

Baoquan Zhang, Xutao Li, Yunming Ye, Zhichao Huang, and Lisai Zhang. Prototype completion with primitive knowledge for few-shot learning. In *CVPR*, pp. 3754–3762, 2021a.

Jian Zhang, Chenglong Zhao, Bingbing Ni, Minghao Xu, and Xiaokang Yang. Variational few-shot learning. In *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*, pp. 1685–1694, 2019. doi: 10.1109/ICCV.2019.00177.

Xueting Zhang, Debin Meng, Henry Gouk, and Timothy M Hospedales. Shallow bayesian meta learning for real-world few-shot recognition. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 651–660, 2021b.

Imtiaz Masud Ziko, Jose Dolz, Eric Granger, and Ismail Ben Ayed. Laplacian regularized few-shot learning. In *ICML*, pp. 11660–11670, 2020.