Adaptive Poincaré Point to Set Distance for Few-Shot Classification

Rongkai Ma\textsuperscript{1}, Pengfei Fang\textsuperscript{2,3\textdagger}, Tom Drummond\textsuperscript{4}, Mehrtash Harandi\textsuperscript{1,3}

\textsuperscript{1}Monash University, \textsuperscript{2}The Australian National University, \textsuperscript{3}DATA61-CSIRO, Australia, \textsuperscript{4}The University of Melbourne

\{rongkai.ma, mehrtash.harandi\}@monash.edu, pengfei.fang@anu.edu.au, tom.drummond@unimelb.edu.au

Abstract

Learning and generalizing from limited examples, i.e., few-shot learning, is of core importance to many real-world vision applications. A principal way of achieving few-shot learning is to realize an embedding where samples from different classes are distinctive. Recent studies suggest that embedding via hyperbolic geometry enjoys low distortion for hierarchical and structured data, making it suitable for few-shot learning. In this paper, we propose to learn a context-aware hyperbolic metric to characterize the distance between a point and a set associated with a learned set to set distance. To this end, we formulate the metric as a weighted sum on the tangent bundle of the hyperbolic space and develop a mechanism to obtain the weights adaptively and based on the constellation of the points. This not only makes the metric local but also dependent on the task in hand, meaning that the metric will adapt depending on the samples that it compares. We empirically show that such metric yields robustness in the presence of outliers and achieves a tangible improvement over baseline models. This includes the state-of-the-art results on five popular few-shot classification benchmarks, namely mini-ImageNet, tiered-ImageNet, Caltech-UCSD Birds-200-2011 (CUB), CIFAR-FS, and FC100.

1 Introduction

In the modern context of machine learning, deep neural networks (DNNs) have enjoyed enormous success by leveraging the rich availability of labeled data for supervised training. Despite this, deep supervised learning is primarily limited in terms of scaling towards unseen samples due to the high cost of acquiring large amounts of labeled data. This is in clear contrast to how humans learn, where in many cases, only a handful of training examples are sufficient for generalizing towards unseen samples. Few-Shot Learning (FSL) addresses this critical problem through the development of algorithms that can learn using limited data (Finn, Abbeel, and Levine 2017; Nichol, Achiam, and Schulman 2018; Snell, Swersky, and Zemel 2017; Sung et al. 2018; Vinyals et al. 2016; Ye et al. 2020; Hong et al. 2021; Wang et al. 2020).

Performing FSL well is essential towards creating robust frameworks that can learn with the efficiency of humans. In many cases, FSL methods deem to learn an embedding space to distinguish samples from different classes. Therein, the embedding space is a multidimensional Euclidean space and is realized via a deep neural network.

Employing hyperbolic geometry to encode data has been shown rewarding, as the volume of space expands exponentially (Ganea, Bécsineul, and Hofmann 2018; Khrulkov et al. 2020). Recent works have shown that a hierarchical structure exists within visual datasets and that the use of hyperbolic embeddings can yield significant improvements over Euclidean embeddings (Khrulkov et al. 2020; Fang, Harandi, and Petersson 2021).

Most existing FSL solutions learn a metric through comparing the distance between a query sample and the class prototypes, often modeled as the mean embeddings of each class. However, this does not take the adverse effects of outliers and noises into consideration (Sun et al. 2019). This severely limits the representation power of embedding-based methods since the outliers may drag the prototype away from the true center of the cluster (see Fig. 1(a)). For a more robust approach, we require an adaptive metric, which can faithfully capture the distribution per class, while being robust to outliers and other nuances in data (Fig. 1(b)).

With this in mind, we propose learning a context-
aware hyperbolic metric that characterizes the point to set (di)similarities. This is achieved through employing a Poincaré ball to model hyperbolic spaces and casting the (di)similarity as a weighted-sum between a query and a class that is learned adaptively. In doing so, each sample (from the support and query sets) is modeled by a set itself (i.e., a feature map). Therefore, we propose to make use of pairwise distances between elements of two sets, along with a refinement mechanism to disregard uninformative parts of the feature maps. This leads to a flexible and robust framework for the FSL tasks. We summarize our contributions as follows:

• We propose a novel adaptive Poincaré point to set (APP2S) distance metric for the FSL task.
• We further design a mechanism to produce a weight, dependent on the constellation of the point, for our APP2S metric.
• We conduct extensive experiments across five FSL benchmarks to evaluate the effectiveness of the proposed method.
• We further study the robustness of our method, which shows our method is robust against the outliers compared to competing baselines.

2 Preliminaries
In what follows, we use \( \mathbb{R}^n \) and \( \mathbb{R}^{m \times n} \) to denote the \( n \)-dimensional Euclidean space and space of \( m \times n \) real matrices, respectively. The \( n \)-dimensional hyperbolic space is denoted by \( \mathbb{H}^n \). The \( \text{arctanh} : (-1, 1) \to \mathbb{R}, \text{arctanh}(x) = \frac{1}{2} \ln(\frac{1+x}{1-x}), |x| < 1 \) refers to the inverse hyperbolic tangent function. The vectors and matrices (or 3-D tensors) are denoted by bold lower-case letters and bold upper-case letters throughout the paper.

2.1 Riemannian Geometry
In this section, we will give a brief recap of Riemannian geometry. A manifold, denoted by \( \mathcal{M} \), is a curved surface, which locally resembles the Euclidean space. The tangent space at \( x \in \mathcal{M} \) is denoted by \( T_x \mathcal{M} \). It contains all possible vectors passing through point \( x \) tangentially. On the manifold, the shortest path connecting two points is a geodesic, and its length is used to measure the distances on the manifold.

2.2 Hyperbolic Space
Hyperbolic spaces are Riemannian manifolds with constant negative curvature and can be studied using the Poincaré ball model (Ganea, Bécigneul, and Hofmann [2018], Khrulkov et al. [2020]). The Poincaré ball \( (\mathbb{D}^n_c, g^c) \) is a smooth \( n \)-dimensional manifold identified by satisfying \( \mathbb{D}^n_c = \{ x \in \mathbb{R}^n : c ||x|| < 1, c \geq 0 \} \), where \( c \) is the absolute value of the curvature for a Poincaré ball, while the real curvature value is \(-c\). The Riemannian metric \( g^c \) at \( x \) is defined as
\[ g^c = \lambda^c_x g^E, \]
where \( g^E \) is the Euclidean metric tensor and \( \lambda^c_x \) is the conformal factor, defined as:
\[ \lambda^c_x := \frac{2}{1 - c ||x||^2}. \] (1)

Since the hyperbolic space is a non-Euclidean space, the rudimentary operations, such as vector addition, cannot be applied (as they are not faithful to the geometry). The Möbius gyrovector space provides many standard operations for hyperbolic spaces. Essential to our developments in this work is the Möbius addition of two points \( x, y \in \mathbb{D}^n_c \), which is calculated as:
\[ x \oplus_c y = \frac{(1 + 2c(x, y) + c^2 ||x||^2 + c^2 ||y||^2)y + (1 - c ||x||^2)y}{1 + 2c(x, y) + c^2 ||x||^2 ||y||^2}. \] (2)
The geodesic distance between two points \( x, y \in \mathbb{D}^n_c \) can be obtained as:
\[ d_c(x, y) = \frac{2}{\sqrt{c}} \text{arctanh}(\sqrt{c} - ||x \oplus_c y||). \] (3)

Another essential operation used in our model is the hyperbolic averaging in Klein model (i.e., \( x_{p2s} \)) ball model to Klein model (i.e., \( x_K \)) using the transformation:
\[ x_K = \frac{2x_{p2s}}{1 + c ||x_{p2s}||^2}. \] (4)

Then, the hyperbolic averaging in Klein model is obtained as:
\[ \text{HypAve}(x_1, \ldots, x_N) = \frac{\sum_{i=1}^N \gamma_i x_i}{\sum_{i=1}^N \gamma_i}, \] (5)
where \( \gamma_i = \frac{1}{\sqrt{1 - c ||x_i||^2}} \) are the Lorentz factors. Finally, we transform the coordinates back to Poincaré model using:
\[ x_K = \frac{2x_{p2s}}{1 + \sqrt{1 - c ||x_{p2s}||^2}}. \] (6)

In our work, we make use of the tangent bundle of the \( \mathbb{D}^n_c \). The logarithm map defines a function from \( \mathbb{D}^n_c \to T_x \mathbb{D}^n_c \), which projects a point in the Poincaré ball onto the tangent space at \( x \), as:
\[ \pi_x(y) = \frac{2}{\sqrt{c\lambda^c_x}} \text{arctanh}(\sqrt{c} - x \oplus_c y) \frac{-x \oplus_c y}{||-x \oplus_c y||}. \] (7)

2.3 Point to Set Distance
Let \( S = \{ s_1, \ldots, s_k \} \) be a set. The distance from a point \( p \) to the set \( S \) can be defined in various forms. The min and max distance from a point \( p \) to the set \( S \) are two simple metrics, which can be defined as:
\[ d^i_{p2s}(p; S) = \inf \{d(p, s_i) | s_i \in S \}, \] (8)
\[ d^h_{p2s}(p; S) = \sup \{d(p, s_i) | s_i \in S \}, \] (9)
where \( \inf \) and \( \sup \) are the infimum and supremum functions, respectively. Given their geometrical interpretation, \( d^i_{p2s} \) and \( d^h_{p2s} \) define the lower and upper pairwise bounds, and fail to encode structured information about the set. Therefore, we opt for a weighted-sum formalism to measure the distance between a point and a set in §3.3

1In the supplementary material, we provide further details regarding the Poincaré ball model and its properties.
3 Method

This section will give an overview of the proposed method, followed by a detailed description of each component in our model.

3.1 Problem Formulation

We follow the standard protocol to formulate few-shot learning (FSL) with episodic training. An episode represents an $N$-way $K$-shot classification problem (i.e., the training set, named support set, includes $N$ classes where each class has $K$ examples). As the name implies, $K$ (i.e., the number of examples per class) is small (e.g., $K = 1$ or 5). The goal of learning is to realize a function $F : X \rightarrow \mathbb{R}^n$ to embed the support set to a latent and possibly lower-dimensional space, such that query samples can be represented easily using a nearest neighbor classifier. To be specific, an episode or task $E_i$ consists of a query set $X_q = \{(X_i^q, y_i^q)|i = 1, \ldots, N\}$, where $X_i^q$ denotes a query example sampled from class $y_i^q$, and a support set $X_s = \{(X_{ij}^q, y_{ij}^q)|i = 1, \ldots, N, j = 1, \ldots, K\}$, where $X_{ij}^q$ denotes the $j$-th sample in the class $y_{ij}^q$. The embedding methods for FSL, our solution being one, often formulate training as:

$$F^* := \arg \min_{F} \sum_{X_s^q \in X_q} \delta(F(X_{ij}^q), F(X_i^q)) \quad \text{s.t.} \quad y_{ij}^q = y_i^q,$$

where $\delta$ measures a form of distance between the query and the support samples.

3.2 Model Overview

We begin by providing a sketch of our method (see the conceptual diagram in Fig. 2(a) and Fig. 2(b)). The feature extractor network, denoted by $F$, maps the input to a hyperbolic space in our work. We model every class in the support set by its signature. The signature is both class and episodic-aware, meaning that the signature will vary if the samples of a class or samples in the episode vary. This will enable us to calculate an adaptive distance from the query point to every support-class while being vigilant to the arrangement and constellation of the support samples. We stress that our design is different from many prior works where class-specific prototypes are learned for FSL. For example, in [Khrulkov et al. 2020; Snell, Swersky, and Zemel 2017; Sung et al. 2018], the prototypes are class-specific but not necessarily episodic-aware.

To obtain the signatures for each class in the support set, we project the support samples onto the tangent space of the query point and feed the resulting vectors to a signature generator $f_s$. The signature generator realizes a permutation-invariant function and refines and summarizes its inputs to one signature per class. We then leverage a relational network $f_r$ to contrast samples of a class against their associated signature and produce a relational score. To obtain the adaptive P2S distance, we first compute a set to set (S2S) distance between the query feature map and each support feature map using the distance module $f_c$. Moreover, a weighted-sum is calculated using the relational score acting as the weight on the corresponding S2S distance, which serves as the P2S distance.

Given P2S distances, our network is optimized by minimizing the adaptive P2S distance between the query and its corresponding set while ensuring that the P2S distance to other classes (i.e., wrong classes) is maximized.

3.3 Adaptive Poincaré Point to Set Distance

In FSL, we are given a small support set of $K$ images, $X_i^s = \{X_{ij}^q, y_{ij}^q\}$ per class $y_i^q$ to learn a classification model. We use a deep neural network to first encode the input to a multi-channel feature map, as $S_i = F(X_i^q)$, with $S_i = \{S_{i1}, \ldots, S_{iK}| S_{ij} \in \mathbb{R}^{H \times W \times C}\}$, where $H$, $W$, and $C$ indicate the height, width, and channel size of the instance feature map. Each feature map consists of a set of patch descriptors (local features), which can be further represented as $S_i = \{s_{ij}^1, \ldots, s_{ij}^H\}$.

In our work, we train the network to embed the representation in the Poincaré ball; thus, we need to impose a constraint on patch descriptors at each spatial location $s_{ij}$ as follows:

$$s_{ij}^r = \begin{cases} s_{ij}^r & \text{if } \| s_{ij}^r \| \leq \mu \\ \frac{\mu s_{ij}^r}{\| s_{ij}^r \|} & \text{if } \| s_{ij}^r \| > \mu, \end{cases}$$

(11)

where $\mu$ is the norm upper bound of the vectors in the Poincaré ball. In our model, we choose $\mu = (1 - \epsilon)/c$, where $c$ is the curvature of the Poincaré ball and $\epsilon$ is a small value that makes the system numerically stable. The same operation applies to the query sample, thereby obtaining an instance feature map for the query sample $Q = \{q^1, \ldots, q^W\}$ with $q^r \in \mathbb{R}^C$. Then the P2S distance between the query sample $Q$ and the support set per class $S_i$ can be calculated using Eq. (8) or Eq. (9). However, those two metrics only determine the lower or upper bound of P2S distance, thereby ignoring the structure and distribution of the set to a great degree. To make better use of the distribution of samples in a set, we propose the adaptive P2S distance metric as:

$$d_{P2S}^{adp}(Q, S_i) := \frac{\sum_{j=1}^{K} w_{ij}d(Q, S_{ij})}{\sum_{j=1}^{K} w_{ij}},$$

(12)

where $w_{ij}$ is the adaptive factor for $d(Q, S_{ij})$. We refer to the distance in Eq. (12) as Adaptive Poincaré Point to Set (APP2S) distance, hereafter.

In Eq. (12), we need to calculate the distance between two feature maps (i.e., $d(Q, S_{ij})$). In doing so, we formulate a feature map as a set (i.e., $\{q^r, \ldots, q^W\}$ and $\{s_{ij}^r, s_{ij}^H\}$), such that a set to set (S2S) distance can be obtained. One-sided Hausdorff and two-sided Hausdorff distances [Huttenlocher, Klanderman, and Rucklidge 1993] are two widely used metrics to measure the distance between sets. However, these two metrics are sensitive to...
The overall pipeline of our method. Given an episode, we use a backbone network to extract and map the inputs to a hyperbolic space. Then we project the support samples onto the tangent plane of the query point and employ a refinement function to obtain the class and episode-aware signature of every class in the support set. This is followed by a mapping to a hyperbolic space. We then project the support samples onto the tangent plane and employ a refinement function as learning the context of the support set by seeing all the samples, thereby highlighting the discriminative samples and restraining the non-informative samples such as outliers for all the samples. Then the signature for each class is obtained by summarizing as: $\tilde{S}_i = \sum_{j=1}^{K} \tilde{S}_{ij} / K$.

**Remark 1** Our proposed set-signature generator $f_c$ is similar to the set-to-set function in FEAT (Ye et al. 2020), in the sense that both functions perform self-attention over the input features. However, the fundamental difference is that our module exploits the relation between the spatial feature descriptors of all samples in a support set (e.g., $\tilde{s}_{ij}$) instead of prototypes as proposed in FEAT (Ye et al. 2020), which possibly gives the model more flexibility to encode meaningful features.

Given sample features in a class $\tilde{s}_i = \{\tilde{s}_{i1}, \ldots, \tilde{s}_{iK}\}$ and the corresponding class signature $\tilde{S}_i$, we use a relation generator (i.e., $f_\phi$ in Fig. 2(a)) to compare the relationship between an individual feature map and the class signature. In doing so, we first concatenate the individual feature maps and their class signature along the channel dimension to obtain a hybrid representation, as:

$$G_{ij} = \text{CONCAT}(\tilde{S}_{ij}, \tilde{S}_i).$$

Given the hybrid representation $G_{ij}$, the relation generator produces a relation score as:

$$w_{ij} = f_\phi(G_{ij}).$$
Algorithm 1: Train network using adaptive Poincaré point to set distance

Input: An episodic $E$, with their associated support set $X^s = \{x_i^s, y_i^s\}_{i=1, \ldots, N}$ and a query sample $X^q$

Output: The optimal parameters for $\mathcal{F}, f_\omega, f_\zeta, \text{and } f_\phi$

1: Map $X^s$ and $X^q$ into Poincaré ball
2: Obtain the tangent support set $S$ using Eq. (7)
3: $\tilde{S} = f_\omega(S)$ \(\triangleright\) the refined support set
4: for $i \in \{1, \ldots, N\}$ do
5: \hspace{1em} $S_i = \sum_{j=1}^K \tilde{S}_{ij} / K$ \(\triangleright\) the set signature
6: \hspace{1em} $G_{ij} = \text{CONCAT}(\tilde{S}_{ij}, \tilde{S}_i)$ \(\triangleright\) the hybrid representation
7: \hspace{1em} $\omega_{ij} = f_\phi(G_{ij})$ \(\triangleright\) the weight
8: \hspace{1em} Compute point to set distance and set to set distance using Eq. (12) and Eq. (13)
9: end for
10: Optimize the model using Eq. (10)
5 Experiments

5.1 Datasets
In this section, we will empirically evaluate our approach across five standard benchmarks, i.e., mini-ImageNet (Ravi and Larochelle 2016), tiered-ImageNet (Ren et al. 2018), Caltech-UCSD Birds-200-2011 (CUB) (Wah et al. 2011), CIFAR-FS (Bertinetto et al. 2018) and Fewshot-CIFAR100 (FC100) (Oreshkin, López, and Lacoste 2018). Full details of the datasets and implementation are described in the supplementary material. In the following, we will briefly describe our results on each dataset.

5.2 Main Result
We evaluate our methods for 100 epochs, and in each epoch, we sample 100 tasks (episodes) randomly from the test set, for both 5-way 1-shot and 5-way 5-shot settings. Following the standard protocol (Simon et al. 2020), we report the mean accuracy with 95% confidence interval.

mini-ImageNet. As shown in Table 1, we evaluate our model using ResNet-12 and ResNet-18 as the backbones on mini-ImageNet. Between them, ResNet-12 produces the best results. In addition, our model also outperforms recent state-of-the-art models in most of the cases. Interestingly, our model further outperforms hyperbolic ProtoNet by 7.77% and 7.11% for 5-way 1-shot and 5-way 5-shot with ResNet-18, respectively. With ResNet-12, we outperform the hyperbolic ProtoNet by 5.60% and 7.29% for 5-way 1-shot and 5-way 5-shot, respectively.

tiered-ImageNet. We further evaluate our model on tiered-ImageNet with ResNet backbones. The results in Table 1 indicate that with ResNet-12, our model outperforms the hyperbolic ProtoNet by 4.62% and 7.12% for 5-way 1-shot and 5-way 5-shot, respectively, and achieves state-of-the-art results for inductive few-shot learning.

CIFAR-FS and FC100. As the results in Table 2 suggested, our model also achieves comparable performance with the relevant state-of-the-art methods on this dataset, with ResNet-12 backbone, which vividly shows the superiority of our method.

CUB. We use ResNet-18 as our backbone to evaluate our method on the CUB dataset. Table 3 shows that our model improves the performance over baseline by 3.94% and 4.88% for 5-way 1-shot and 5-way 5-shot settings, respectively. Besides, our model achieves 77.64% and 90.43% for 5-way 1-shot and 5-way 5-shot settings on this dataset, which outperforms state-of-the-art models (i.e., DeepEMD (Zhang et al. 2020) and P-transfer (Shen et al. 2021)) and achieve competitive performance on this dataset.

5.3 Robustness to Outliers
To further validate the robustness of our method, we conduct experiments in the presence of outliers in the form of mislabelled images. In the first study, we add a various number of outliers (e.g., 1, 2, 3, 4), whose classes are disjoint to the support-class, to each class of the support set. We performed this study with ResNet-12 backbone on the 5-way 5-shot setting on tiered-ImageNet. Fig. 4(a) shows that the performances of hyperbolic ProtoNet degrade remarkably. On the contrary, both our APP2S and Euclidean AP2S are robust to outliers, which shows the superiority of our adaptive metric. Comparing to Euclidean AP2S, APP2S is even more robust (see the slope of Fig. 4(a)) and performs consistently even in the presence of 20 outliers. This suggests that integrating our proposed adaptive metric and hyperbolic geometry can further bring robustness to our framework.

In the second study (shown in Fig. 4(b)), we conduct the same experiments on mini-ImageNet. The results show a similar trend as the previous one, which further proves the effectiveness of our proposed method.

Figure 4: Robustness analysis. Horizontal axis: The number of outliers. Vertical axis: Accuracy. (a): The performance vs. the number of outliers on tiered-ImageNet. (b): The performance vs. the number of outliers on mini-ImageNet.

5.4 Ablation Study
We further conduct the ablation study to verify the effectiveness of each component in our method on the tiered-ImageNet dataset using the ResNet-12 backbone.

Experiments Set-Up. For setting (ii) in Table 4, we disable the relation module $f_\phi$ and signature generator $f_\omega$. The P2S distance can be obtained by Eq. (12) and Eq. (13) with equal weights (i.e., 1). Moreover, we enable the relation generator $f_\phi$ but not the signature generator in setting (iii). We use the class prototype instead of the signature for this experiment. We enable both $f_\phi$ and $f_\omega$ and use the Euclidean distances for setting (iv). In the end, we enable the Poincaré ball but disable the $f_\phi$ for setting (v). In terms of implementation of (v), the backbone is designed to output a feature vector instead of a feature map, such that the P2S distance can be directly computed by Eq. (5) and Eq. (12).

Effectiveness of Point to Set Distance. In this experiment, we first evaluate the effectiveness of the P2S distance by comparing to its point to point (P2P) distance counterpart (i.e., hyperbolic ProtoNet). From Table 4 we could observe that the P2S distance can learn a more discriminative embedding space than P2P distance (i.e., (i) vs. (ii)), and the adaptive P2S can further bring performance gain to our application (i.e., (ii) vs. (iii)). This observation shows the potential of our P2S distance setting in the FSL task.

Effectiveness of Signature Generator. We further evaluate another essential component in our work, i.e., the signature generator, which refines the entire support set and produces a signature per class. As shown in Table 4(i.e., (iii) and (v)),

\begin{center}
\begin{tabular}{|c|c|c|}
\hline
Dataset & mini-ImageNet & tiered-ImageNet \\
\hline
Model & Hyperbolic ProtoNet & APP2S \\
\hline
\end{tabular}
\end{center}
we could observe that our method benefits from the signature generator, which shows that the signature of each class could help to generate an informative weight for individual feature map within the same class.

**Effectiveness of Hyperbolic Geometry.** We also implement our model in the Euclidean space to verify the effectiveness of our method. The row (iv) and (vi) in Table 3 vividly show that the representation in the Poincaré ball has a richer embedding than that in Euclidean spaces.

| Model | Backbone | mini-ImageNet | tiered-ImageNet |
|-------|----------|---------------|-----------------|
| ProtoNet (Snell, Swersky, and Zemel 2017) | ResNet-12 | 70.40 ± 0.70 | 81.20 ± 0.50 |
| MatchingNet (Vinyals et al. 2016) | ResNet-12 | 72.20 ± 0.70 | 83.50 ± 0.50 |
| MetaOptNet (Lee et al. 2019) | ResNet-12 | 71.80 ± 0.70 | 83.50 ± 0.50 |
| DeepEMD | ResNet-12 | 70.70 ± 0.70 | 83.50 ± 0.50 |
| P-transfer (Shen et al. 2021) | ResNet-12 | 73.80 ± 0.70 | 83.50 ± 0.50 |
| Hyperbolic ProtoNet (Khrulkov et al. 2020) | ResNet-12 | 73.70 ± 0.70 | 83.50 ± 0.50 |

Table 1: Few-shot classification accuracy and 95% confidence interval on mini-ImageNet and tiered-ImageNet with ResNet backbones. "★" notes the result obtained by the self-implemented network.

| Model | Backbone | CIFAR-FS | FC100 |
|-------|----------|---------|-------|
| TEAM (Quo et al. 2019) | ResNet-12 | 70.40 | 81.30 |
| ProtoNet (Snell, Swersky, and Zemel 2017) | ResNet-12 | 72.20 ± 0.70 | 83.50 ± 0.50 |
| TADAM (Oreshkin, Lopez, and Lacoste 2018) | ResNet-12 | - | - |
| DeepEMD | ResNet-12 | - | - |
| Hyperbolic ProtoNet (Khrulkov et al. 2020) | ResNet-12 | *70.70 ± 0.22 | *80.98 ± 0.16 |
| Ours (APP2S) | ResNet-12 | *73.70 ± 0.22 | *85.55 ± 0.13 |

Table 2: Few-shot classification accuracy and 95% confidence interval on CIFAR-FS and FC100 with ResNet-12 backbones. "★" notes the result obtained by the self-implemented network.

Table 3: Few-shot classification accuracy and 95% confidence interval on CUB. "★" notes the result obtained by the self-implemented network. "●" denotes the method using ResNet-12 as the backbone, otherwise ResNet-18.

**Effectiveness of Set to Set Distance.** The comparison between (v) and (vi) shows that our set to set distance generator associated with the feature map outputs richer information than using a feature vector to directly compute the APP2S.

**6 Conclusion**

In this paper, we propose a novel adaptive Poincaré point to set (APP2S) distance metric for the few-shot learning, which can adapt depending on the samples at hands. Empirically, we showed that this approach is expressive with both hyperbolic geometry and Euclidean counterpart. Our model improves the performances over baseline models and achieves competing results on five standard FSL benchmarks.
7 Supplementary Material

In this supplementary material, we provide an additional description of operations in Poincaré Ball and details of the each public few-shot learning benchmark we used. Furthermore, we conduct additional experiments, including ablation studies on the effect of the curvature $c$, global feature vector implementation and parameter and time complexity analysis to analyze our model. Finally, we provide the details of the implementation of our model and extra visualizations and discussion of APP2S.

7.1 Hyperbolic Operations

**Exponential Map.** The exponential map defines a function from $T_x \mathbb{D}^n \rightarrow \mathbb{D}^n$, which maps Euclidean vectors to the hyperbolic space. Formally, it is defined as:

$$\Omega_c^x (v) = x \odot_c (\tanh(\sqrt{c}||v||) \cdot \frac{v}{\sqrt{c}||v||}).$$

(16)

The exponential map and logarithmic map (introduced in the main paper) have simpler forms when $x = 0$:

$$\Omega^0 (v) = \tanh(\sqrt{c}||v||) \cdot \frac{v}{\sqrt{c}||v||}.$$  

(17)

**Parallel Transport.** Parallel transport provides a way to move tangent vectors along geodesics $P_{x \rightarrow y} : T_x \mathcal{M} \rightarrow T_y \mathcal{M}$ and defines a canonical way to connect tangent spaces. For further details of hyperbolic space and geometry, please refer to the thesis (Ganea 2019).

7.2 Set to Set Distance

Set to set distance has been widely adopted in computer vision tasks (Fang et al. 2021; Conci and Kubrusly 2018; Hutterlocher, Klanderman, and Rucklidge 1993). In this section, we discuss the well-known Hausdorff distance. There are two variants of Hausdorff distance, including one-sided Hausdorff distance and bidirectional Hausdorff distance. The one-sided Hausdorff distance between set $A = \{a_1, a_2, \ldots, a_n\}$ and set $B = \{b_1, b_2, \ldots, b_n\}$ can be defined as:

$$d^c_{\text{Haus}}(A, B) = \max_{a \in A} \min_{b \in B} d(c, a, b),$$

(19)

and the bidirectional Hausdorff distance can be defined as:

$$d^b_{\text{Haus}}(A, B) = \max(d^c_{\text{Haus}}(A, B), d^c_{\text{Haus}}(B, A)).$$

(20)

7.3 Datasets

**mini-ImageNet.** The mini-ImageNet is a subset of ImageNet (Deng et al. 2009). The size of images in mini-ImageNet is fixed to $84 \times 84$. It has 100 classes, with each having 600 samples. We adopt the standard setting form (Ravi and Larochelle 2016) to split the dataset into 64, 16, and 20 classes for training, validation, and testing.

**tiered-ImageNet.** Like mini-ImageNet, tiered-ImageNet (Ren et al. 2018) is also sampled from ImageNet, while it has more classes than the mini-ImageNet. This dataset is split into 351 classes from 20 categories, 97 classes from 6 categories, and 160 classes from 8 different categories for training, validation, and testing.

**CUB.** The CUB dataset (Wah et al. 2011) consists of 11,788 images from 200 different species of birds. Following the standard split (Liu et al. 2020), the CUB dataset is divided into 100 species for training, 50 species for validation, and another 50 species for testing.

**CIFAR-FS and FC100.** Both CIFAR-FS (Bertinetto et al. 2018) and FC100 (Oreshkin, López, and Lacoste 2018) are modified from the CIFAR-100 dataset containing 100 classes, with 600 samples per class. The CIFAR-FS is split into 64, 16, and 20 classes for training, validation, and testing, respectively. While the FC100 dataset is split into 60, 20, and 20 classes for training, validation, and testing, respectively.

7.4 Additional Experiments

**Conv-4 Backbone.** We also employ the simple 4-convolutional network (Conv-4) to evaluate our method on mini-ImageNet comparing with some early works. The Table 5 summarizes our results.

| Model                     | 5-way 1-shot | 5-way 5-shot |
|---------------------------|-------------|-------------|
| MatchingNet (Vinyals et al. 2016) | 45.60 ± 0.84 | 55.31 ± 0.73 |
| MAML (Finn, Abbeel, and Levine 2017) | 46.70 ± 1.84 | 63.11 ± 0.92 |
| RelationNet (Sung et al. 2018) | 50.44 ± 0.82 | 65.32 ± 0.70 |
| R2-D2 (Bertinetto et al. 2018) | 48.70 ± 0.60 | 65.50 ± 0.60 |
| Reptile (Nichol, Recht, and Schulman 2018) | 49.97 ± 0.32 | 65.99 ± 0.58 |
| ProtoNet (Vineet, Srikant, and Zemel 2019) | 49.42 ± 0.78 | 68.20 ± 0.66 |
| Neg-Cosine (Liu et al. 2020) | 52.84 ± 0.76 | 70.41 ± 0.66 |
| Hyperbolic ProtoNet (Krutakov et al. 2020) | 54.43 ± 0.28 | 72.67 ± 0.15 |
| Ours (APP2S) | 55.74 ± 0.20 | 72.86 ± 0.22 |

Table 5: Few-shot classification accuracy and 95% confidence interval on mini-ImageNet with Conv-4 Backbone.

**Comparison with DN4 and FEAT.** The comparison of our APP2S, DN4, and FEAT on mini-ImageNet and tiered-ImageNet with Conv-4 and ResNet-12 backbones is summarized in Table 6.

| Model                     | Backbone | mini-ImageNet 1-shot | mini-ImageNet 5-shot | tiered-ImageNet 1-shot | tiered-ImageNet 5-shot |
|---------------------------|----------|----------------------|----------------------|-----------------------|------------------------|
| DN4 (Li et al. 2019b)     | Conv-4   | 51.24                | 71.02                | -                      | -                      |
| FEAT (Ye et al. 2020)     | Conv-4   | 55.15                | 71.13                | -                      | -                      |
| Ours                      | Conv-4   | 55.73                | 72.86                | -                      | -                      |
| FEAT                      | ResNet-12| 66.78                | 82.05                | 70.80                  | 84.79                  |
| Ours                      | ResNet-12| 66.25                | 83.42                | 72.00                  | 86.23                  |

Table 6: The comparison of our model, DN4 and FEAT on the mini-ImageNet and tiered-ImageNet with Conv-4 and ResNet-12 backbones.

**The Curvature of Poincaré ball.** The curvature of the Poincaré ball is an important parameter, which determines the radius of the Poincaré ball. We conduct experiments with different values of $c$ on tiered-ImageNet. The results are summarized in Table 7. As the results suggested, our model is not very sensitive to $c$. However, with a larger $c$ value, the performance is slightly better.
Table 7: The influence from the curvature of Poincaré ball on the performance, given tiered-ImageNet and ResNet-12 backbone on 5-way 5-shot setting.

| Model   | 0.7   | 0.5   | 0.1   | 0.05  | 0.01  | 0.001 |
|---------|-------|-------|-------|-------|-------|-------|
| APP2S   | 86.23 | 85.92 | 85.21 | 85.18 | 84.43 | 84.19 |

1-shot case. To fully leverage the capability of APP2S for 1-shot setting, we require more than one sample in the set. Therefore, we followed the practice in (Simon et al. 2020) to augment the support images by flipping. To have a fair comparison, we also applied augmentation to our baseline model (i.e., hyperbolic ProtoNet (Khrulkov et al. 2020)) on both mini-ImageNet and tiered-ImageNet, given ResNet-12 backbone. Table 8 shows that the image augmentation does not boost the performance of the baseline model significantly.

Table 8: The accuracy without and with augmentation for 1-shot setting. “*” notes the results obtained by self-implemented network.

| Model                  | mini-ImageNet w/o Aug. | mini-ImageNet w/ Aug. | tiered-ImageNet w/o Aug. | tiered-ImageNet w/ Aug. |
|------------------------|------------------------|-----------------------|-------------------------|-------------------------|
| hyperbolic ProtoNet    | 60.65                  | 59.97                 | 67.38                   | 67.84                   |
| APP2S                  | -                      | 66.25                 | -                       | 72.00                   |

any-shot setting. We follow the any-way & any-shot setting introduced in (Lee et al. 2019a) to further validate the efficacy of our algorithm. We use a variant of our final model (APP2S without f_c) to perform this experiments due to less computation requirement on this experiment setting. The results are shown in Table 9.

Table 9: The results of our model under any-way & any-shot setting compared to ProtoNet and L2G PrptoNet.

| Model                  | mini-ImageNet Conv-4 | ResNet-12 | tiered-ImageNet Conv-4 | ResNet-12 |
|------------------------|----------------------|-----------|------------------------|-----------|
| ProtoNet               | 51.02 ± 0.30         | 51.00 ± 0.29 | 64.02 ± 0.15          | 70.01 ± 0.17 |
| L2G ProtoNet           |                      |           |                        |           |
| Lee et al. [2019a]     | 64.23 ± 0.15         | 75.32 ± 0.17 | 80.62 ± 0.16          | 90.01 ± 0.17 |
| Ours                   |                      |           |                        |           |

Using Global Feature Vectors. We performed extra experiments using global feature vectors in our method. The table below shows that our method, even with global feature vectors, outperforms the Hyperbolic ProtoNet significantly, and the local features can further boost our methods. Note that we use ResNet-18 backbone for CUB dataset and ResNet-12 for the rest.

Table 10: The results of our model using the global feature vectors compared to Hyperbolic ProtoNet.

| Dataset   | Hyperbolic ProtoNet | Ours w/o global feature | Ours w/ local feature |
|-----------|---------------------|-------------------------|-----------------------|
| mini-ImageNet | 76.33 ± 0.21      | 80.13 ± 0.14            | 86.23 ± 0.15         |
| tiered-ImageNet | 79.11 ± 0.22      | 84.12 ± 0.15            | 90.24 ± 0.15         |
| CUB       | 81.52 ± 0.13       | 90.24 ± 0.15            | 90.24 ± 0.15         |
| CIFAR10   | 80.99 ± 0.16       | 84.08 ± 0.16            | 85.69 ± 0.16         |

Parameter and time complexity analysis. Comparing to Hyperbolic ProtoNet, we have 3 extra modules, including f_o, f_phi, and f_c to realize the adaptive distances. We summarize the parameter numbers (PNs) and FLOPs for each module and the backbone network. We can find that the PNs and FLOPs of our module are acceptable as compared with the backbone network. We also compare the time complexity to the SOTA method, i.e., DeepEMD, given that both methods are using local feature maps. The FPS value of our method is 83, as compared to 0.6 of DeepEMD under the 5-shot setting, clearly showing that our method runs faster than DeepEMD. Note that both models are tested on a single Nvidia Quadro-GV100 graphic card.

Table 11: The Parameter and time complexity analysis.

| complexity metrics | f_o   | f_phi | f_c   | f_o |
|--------------------|-------|-------|-------|-----|
| PNs (×10^9)        | 1.64  | 0.74  | 0.02  | 12.42 |
| FLOPs (×10^9)      | 2.01  | 0.17  | 0.0008 | 6.98 |

7.5 Implementation Details

Network and Optimizer. We mainly use ResNet (He et al. 2016), including ResNet-12 and ResNet-18, as our backbones across all datasets. We also employ the simple 4-convolutional network (Conv-4) to evaluate our method comparing with some early works. The size of the input image is fixed to 84 × 84. We use Adam (Kingma and Ba 2014) and SGD (Ye et al. 2020) for Conv-4 and ResNet backbones, respectively. In the SGD optimizer, we adopt the L2 regularizer with 0.0005 weight decay coefficient. In the ResNet-12 backbones, we disable the average pooling and remove the last fully connected (FC) layer, such that the networks generate the feature map with size of 640 × 5 × 5. For ResNet-18, we set the average pooling layer to generate the feature map with the size of 512 × 5 × 5. Note that we set c (the curvature of the Poincaré ball) to 0.7 and 0.5 for 5-way-5-shot setting and for 5-way-1-shot setting, respectively, with ResNet backbones, across all datasets. While for Conv-4, we set c to 0.4 for both 5-way 5-shot and 5-way 1-shot settings across all datasets.

Training. Following the excellent practice in state-of-the-art methods (Ye et al. 2020; Zhang et al. 2020; Simon et al. 2020), network training has two stages, i.e., pre-training stage and meta-learning stage. In the pre-training process, the backbone network followed by a FC layer is trained on all training classes with the standard classification task. The network with the highest validation accuracy is selected as the pre-trained backbone for the next training stage. In the meta-learning stage, we also follow the standard training protocol, where the network is trained for 200 epochs, and each epoch samples 100 tasks randomly. In order to create the set for 5 way 1-shot setting, we follow the previous practice in (Simon et al. 2020), which augments the image per class by horizontal flipping.

Signature Generator. For the signature generator, we choose Transformer encoder as the set refinement function f_c, as it performs contextualization over the whole support set with permutation invariant property. Note that the Transformer is implemented with single-head self-attention be-
cause more heads do not boost the performance but require more computational power for our model by experiments. Moreover, We follow the implementation of (Carion et al., 2020) to provide spatial encoding along with flattened feature map into the transformer.

**Relation Generator.** We implemented the relation generator using a simple two-layer CNN followed by a flatten operation in the end. In the first layer, the linear transformation is followed by the batch normalization and activation. The second layer uses the sigmoid function to bound the output. Finally, a softmax layer is implemented to convert the output into a probability distribution. The structure of the relation generator can be summarized into Table 12.

| layer name   | output size | operation parameter                  |
|--------------|-------------|---------------------------------------|
| conv1        | 3 x 3       | 3 x 3, 64, stride 1                   |
| batch norm   | 3 x 3       |                                       |
| relu         | 3 x 3       | -                                     |
| dropout      | 3 x 3       | p = 0.5                               |
| conv2        | 1 x 1       | 3 x 3, 1, stride 1                    |
| batch norm   | 1 x 1       | 1                                     |
| sigmoid      | 1 x 1       | -                                     |

Table 12: The structure of the Relation Generator.

**Set to Set Distance Generator.** We simply implement a two layer MLP (i.e., 625 → 25 → 1) as the set to set distance generator. The structure is summarized into Table 13.

| layer name       | output size | operation parameter                  |
|------------------|-------------|---------------------------------------|
| linear           | 25          | 625 → 25                              |
| 1D batch norm    | 25          |                                       |
| relu             | 25          |                                       |
| dropout          | 25          | p = 0.5                               |
| linear2          | 1           | 25 → 1                                |
| 1D batch norm    | 1 x 1       | 1                                     |

Table 13: The structure of the Set to Set Distance Generator.

7.6 Extra Visualizations and Discussion

We also provide extra visualizations to show that the APP2S will adapt depending on the constellation of the points in a set. Fig. 5 shows that in both cases 5(b) and 5(c) APP2S assigns larger weights (dark blue area) to the points that are closer to the center of the cluster, while smaller weights (light blue) to the outliers.

Figure 5: (a): The P2S distances based on the minimum and maximum distances are sensitive to outliers and ignore the distribution of the points in the set to a great degree, (b) and (c): Our proposed point to set distance is bounded between the infimum and the supremum and, it is also non-linear due to the weighted-sum. It covers the distribution of the individual sample in the set and adapts based on the relationship between the sample distribution and overall set distribution.

Our P2S. The existing P2S distance metrics (i.e., the min and max distances discussed in Preliminary) only consider the lower bound and upper bound of P2S distance, thereby ignoring the distribution of the samples of the set to a great degree. Furthermore, such metrics are very sensitive to the outliers in the set (see Fig. 5(a)). Our proposed adaptive P2S distance is a more flexible metric and able to adapt based on the distribution of the samples in the set. See Fig. 5(b) and 5(c) for an example, the measurement from our proposed metric is more flexible than the existing ones. Note that the weight (i.e., w_{ij}) generated by our method is distance-dependent. This is due to the way we model the problem using the tangent space of the hyperbolic space. To see this, recall that the norm of projected sample vector in support-class, which is the input of the relation generator, is indeed the geodesic distance between the associated support vector and the query vector on the manifold (i.e., ∥ś̃_{ij}∥ = dₚ(q, ś̃_{ij})).

**RelationNet.** Our relation generator resembles the RelationNet. However, instead of computing the relation score between the prototype and the query, our relation generator computes the relation score between each support sample and its corresponding class-signature, further used as the adaptive factors for our point-to-set distance.

**DN4.** The distance in DN4 resembles the point to set distance in our work. However and in contrast to DN4, our point to set distance is adaptive, while that in DN4 is fixed weighted summation.

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