IPNET: Influential Prototypical Networks for Few Shot Learning

Ranjana Roy Chowdhury and Deepti R. Bathula
Department of Computer Science and Engineering, Indian Institute of Technology Ropar, India

Abstract. Prototypical network (PN) is a simple yet effective few shot learning strategy. It is a metric-based meta-learning technique where classification is performed by computing Euclidean distances to prototypical representations of each class. Conventional PN attributes equal importance to all samples and generates prototypes by simply averaging the support sample embeddings belonging to each class. In this work, we propose a novel version of PN that attributes weights to support samples corresponding to their influence on the support sample distribution. Influence weights of samples are calculated based on maximum mean discrepancy (MMD) between the mean embeddings of sample distributions including and excluding the sample. Further, the influence factor of a sample is measured using MMD based on the shift in the distribution in the absence of that sample.

Keywords: Prototypical Networks (PN) · Few Shot Learning (FSL) · Influence Factor (IF) · Maximum Mean Discrepancy (MMD)

1 Data preprocessing and augmentation

Firstly we have pretrained our model on Diabetic Retinopathy dataset that was published by California HealthCare Publication as a challenge in Kaggle as Diabetic Retinopathy Detection in 2015. The dataset has 5 classes with rating as the presence of diabetic retinopathy in each image on a scale of 0 to 4, according to the following scale:

- 0 - No DR
- 1 - Mild
- 2 - Moderate
- 3 - Severe
- 4 - Proliferative DR

We aim to apply few shot learning to train our model and so we have applied task oriented learning strategies to arrange our dataset. We have applied augmentation to them with normal parameters (scaling, rotation etc). After this we have fine tuned our model on the given dataset in DRAC Challenge and have tested over all images.

* Indian Institute of Technology Ropar
2 Method description

2.1 Preliminaries

Here we have considered the task based episodic training process of FSL \[1\] for our problem formulation. For each training episode, random samples are chosen from \(N\) classes to create a support set \(S = (s_i, y_i)_{i=1}^K\) and query set \(Q = (q_i, y_i)_{i=1}^K\). Here, \(s_i\) and \(q_i\) represent the sampled images and \(y_i\) their corresponding labels belonging to \(N\) categories. As the support set contains \(K\) training samples, this represents the \(N\)-way, \(K\)-shot classification task.

The support set forms the crux of prototype formation in PN \[4\]. The classic PN is a metric based FSL approach that learns a metric space by mapping each input by an embedding function that is parameterized by \(\theta\). In each episode, it computes a prototypical representation of each class by taking the mean of all support sample embedding of that class as:

\[
p_c = \frac{1}{|S_c|} \sum_{x_i \in S_c} f_\theta(x_i) \tag{1}
\]

where \(S_c\) is the set of samples from class \(c\). Subsequently, the class label of a new sample from the query set \(Q\) is predicted by calculating the Euclidean distance of the sample \(x_i\) to each class prototypical vector and applying softmax on the distances as:

\[
p_\theta(y_i = c | x_i, p_c) = \frac{\exp(-d(f_\theta(x_i), p_c))}{\sum_{c'} \exp(-d(f_\theta(x_i), p_{c'}))} \tag{2}
\]

where \(d(\cdot)\) is the Euclidean distance function between query sample and prototypical vector. The \(\theta\) parameter is updated likewise in order to improve the likelihood computed on \(Q\) and is given as:

\[
\sum_{(x, y_i) \in Q} \log p(y_i = c | x) \tag{3}
\]

where \(y_i\) is the ground truth of \(x_i\). Although simple and quite effective, this naive approach considers each support sample to be equally important for prototype formation.

2.2 Proposed Approach

Inspired by the efforts on influential sample selection \[2\] using MMD \[3\], we propose a novel and principled approach to creating prototypes. The idea is to assign weights to the samples according to their influence on the sample distribution of that class. And the influence of a particular sample can be measured by how much the distribution changes in the absence of that sample. We use MMD for this purpose.

MMD is a kernel based approach that measures the distributional discrepancy between two datasets as distance between the mean embeddings of their features.
Given two datasets with distributions \( A \) and \( B \) respectively, the MMD between them is given as:

\[
\text{MMD}_\phi(A, B) = ||\mu_\phi(A) - \mu_\phi(B)||
\]

where \( \phi \) represents the mapping function to the latent space. Consequently, the conformity of a particular data sample \( (s) \) to its corresponding dataset distribution \( (V) \) can be measured using MMD as:

\[
\text{MMD}(s) = \text{MMD}_\phi(V, V') = ||\mu_\phi(V) - \mu_\phi(V')||
\]

where \( V \) represents the whole dataset and \( V' \) is the same dataset but excluding the sample \( s \). As \( \text{MMD}_\phi(A, B) = 0 \) if \( A = B \), samples with lower MMD scores indicate high compliance with the distribution and data points with high MMD score signify deviation from the sample distribution. As the samples with high conformity to the distribution should be given more importance in creating the prototypical vectors, we define the influential (IF) weight of sample as \( \text{IF}(s) = 1 - \text{MMD}(s) \) after normalizing the MMD scores of all samples in the support set.

As a result, the prototypical representation of each class in our proposed IPNet is formed using:

\[
p_c = \frac{\sum_{i=1}^{\mid S_c \mid} \text{IF}(f_\theta(x_i)) f_\theta(x_i)}{\sum_{i=1}^{\mid S_c \mid} \text{IF}(f_\theta(x_i))}
\]

3 Post Processing

3.1 Implementation Details

To ensure fair comparison, of standard Conv-6 backbone with batch normalization. It is a 6 layer CNN where each block consisting of a \( 3 \times 3 \) convolutional layer with 64 channels and a \( 2 \times 2 \) max-pooling layer followed by Stochastic Gradient Descent (SGD) for optimization and ReLU as the activation function. We use a batch size of 5 and set the learning rate and momentum to 0.01 and 0.9 respectively.

3.2 Experiments

We have performed the experiments in the following manner:

- Firstly we train the model on the Diabetic Retinopathy Dataset as described above with 10000 epochs and in a few shot learning manner. Here we choose n-way k-shot learning where for training \( n=3 \) (classes) and \( k=50 \) (images) were taken for each task.
- In Testing Phase, we firstly fine tune our model with the same task learning having \( n=3 \) and \( k=20 \) with 5 query images for each task on the given dataset in DRAC 2022.
4 Results

As we have implemented our method in a few shot learning manner so the learning will happen in each task. Once training is done, the fine tuning happens and then we generate class probabilities for each class. We have generated class probabilities for the test images multiple times and so we have kept a counter on each image about how many times it was encountered in testing. Finally we sum up the probabilities for each class respectively and divide them by the counter for that image. Thus at the end we have class probabilities for each class of an image and at the end we predict for each image the class which corresponds to the highest probability.

5 Link to public code repository

https://github.com/ranjana78/MICCAI-Submission-2022

References

1. Author, Kushagra Mahajan and Monika Sharma and Lovekesh Vig, S.: Meta-DermDiagnosis: Few-Shot Skin Disease Identification using Meta-Learning. In: Editor, F., Editor, S. (eds.) 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR Workshops 2020.
2. Author, Been Kim and Oluwasanmi Koyejo and Rajiv Khanna, S.: Examples are not enough, learn to criticize! Criticism for Interpretability. In: Editor, F., Editor, S. (eds.)Advances in Neural Information Processing Systems 29: Annual Conference on Neural Information Processing Systems 2016, December 5-10, 2016, Barcelona, Spain.
3. Author, Rushil Anirudh and Jayaraman J. Thiagarajan and Rahul Sridhar and Timo Bremer, S.: Influential Sample Selection: A Graph Signal Processing Approach. In: Editor, F., Editor, S. (eds.)CoRR
4. Author, Jake Snell and Kevin Swersky and Richard S. Zemel, S.: Prototypical Networks for Few-shot Learning. In: Editor, F., Editor, S. (eds.)Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017.