Maximum Entropy Models for Fast Adaptation

Samarth Sinha 1, Anirudh Goyal 2, Animesh Garg 1,3

Abstract

Deep Neural Networks have shown great promise on a variety of downstream tasks; but their ability to adapt to new data and tasks remains a challenging problem. The ability of a model to perform few-shot adaptation to a novel task is important for the scalability and deployment of machine learning models. Recent work has shown that the learned features in a neural network follow a normal distribution [41], which thereby results in a strong prior on the downstream task. This implicit overfitting to data from training tasks limits the ability to generalize and adapt to unseen tasks at test time. This also highlights the importance of learning task-agnostic representations from data. In this paper, we propose a regularization scheme using a max-entropy prior on the learned features of a neural network; such that the extracted features make minimal assumptions about the training data. We evaluate our method on adaptation to unseen tasks by performing experiments in 4 distinct settings. We find that our method compares favorably against multiple strong baselines across all of these experiments.

1 Introduction

Deep Neural Networks have enabled great success in various machine learning domains such as computer vision [17, 23, 44], natural language processing [69, 11, 4], decision making [59, 60, 15], biomedical application [53, 24] etc. The success of neural networks on a variety of domains can be largely attributed to the ability of the networks to extract abstract features from data. Given a large amount of data, representations generalize effectively to a held-out ‘test’ set [57, 82]. Finetuning deep neural networks trained on large datasets, specially ImageNet [57], has lead to state-of-the-art performance in various tasks such as few-shot learning [9], semantic segmentation [48], object detection [12], deep metric learning [47]. Although such methods have shown promise, the ability of a network to adapt to novel data and tasks remains an open area of study. The ability of a model to adapt to novel tasks and data has recently been an area of focus in meta-learning [64, 14, 9], meta-reinforcement learning (meta-RL) [33, 83], zero-shot domain adaptation [68, 34], and metric learning [55, 20]. Methods rely on the training data distribution to learn the shared structure of the task and data, such that it is able to exploit learned structure at evaluation on a novel task. However, we want the model to capture the underlying task structure without overfitting to the training task itself. Recent work has shown that learning the reuse of the task is crucial for fast-adaption [50]. In this paper, we propose a simple and general solution for learning better task and data-agnostic representations to maximize fast-adaption by maximizing the entropy of the learned embedding to reduce the amount of prior belief that the network learns over the training data.

Recent work has successfully assumed that the learned features of a deep network follow a continuous multivariate Gaussian distribution [25, 65, 28, 75, 7]. Furthermore, recent theoretical work in deep and wide-neural networks have also proven that under certain conditions, the learned features of a neural network are normally distributed [41, 42, 46, 76]. Such conditions are approximately satisfied in modern neural network architectures [80, 77], weight initialization schemes [37, 22],

1 University of Toronto, Vector Institute, 2 Mila, University of Montreal, 3 Nvidia.
Corresponding author: samarth.sinha@mail.utoronto.ca

Preprint. Under review.
and gradient based optimization techniques [56]. This suggests that the features the models are learning impose a strong prior on the given downstream task. Having a strong prior on the training task makes it difficult to effectively draw from that experience to adapt and generalize to new tasks, unless there is a significant overlap between the tasks, which limits fast-adaptation. This notion of over-fitting to the training task may harm the models ability to learn to adapt quickly to a new task.

Ideally, it is desirable to make minimal assumptions over the training tasks, while also effectively solving them. Such an unassuming prior over the task should help the model in adapting to a new task, as the model is able to learn the implicit task structure without overfitting on the “source task”. Unlike a multivariate Gaussian, a complete ‘max-entropy’ prior puts equal likelihood in the feature space, and makes fewer assumptions about the data. In this paper, we propose to perform ‘max-entropy regularization’ on the learned features of a neural network by placing a uniform prior on the features space. Given that the learned feature space of a neural network automatically collapses to a gaussian during training, by placing a max-entropy, or simply a uniform prior on the feature space we regularize the network to reduce over-fitting and learn features that are task-agnostic. We perform this regularization using a GAN-like alternating optimization scheme [18].

Our contributions can be summarized as:

- We propose ‘max-entropy regularization’ in the learned feature space of deep neural networks to increase the ability of a network to fast adapt to novel tasks and data.
- We regularize the models using a GAN-like alternating optimization which learns a posterior using an adversarial objective.

We evaluate zero-shot data generalization using deep metric learning, zero-shot domain adaptation and out-of-distribution generalization and demonstrate the effectiveness and generality of max-entropy regularization over many strong, distinct baselines in each domain. We further evaluate on benchmark fast-task adaptation tasks using three different meta-learners, such as ProtoNets [64], Matching Networks [70] and MAML [14], and demonstrate a significant performance boost on benchmark datasets.

2 Background

2.1 Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) were proposed as a generative model which utilizes an alternative minimization scheme to solve a minimax two-player game between a Generator, \(G\), and a Discriminator, \(D\) [18]. The Generator is trained to map a sample from a prior \(z \sim p(z)\) and outputs the Generator distribution, \(G(z)\) and the Discriminator is trained to be an arbiter between the target data distribution \(p(x)\) and the Generator distribution \(G(z)\). The Generator is trained to trick the Discriminator into predicting that the \(G(z)\) actually comes from the target distribution. Although many different GAN objectives have been proposed, the “Non-Saturating Cost” objective of the Discriminator can be represented as

\[
\mathcal{L}_D = \max_D \mathbb{E}_{z \sim p(z)}[1 - \log D(G(z))] + \mathbb{E}_{x \sim p(x)}[\log D(x)]
\]  

(2.1)

and the Generator objective as:

\[
\mathcal{L}_G = \min_G \mathbb{E}_{z \sim p(z)}[1 - \log D(G(z))]
\]

(2.2)

where \(p(z)\) is the prior distribution for the Generator, and \(p(x)\) is a defined target distribution such as natural images.

2.2 Fast Adaptation

The notion of fast adaptation to a novel task has recently been popularized by different meta-learning strategies [14, 64]. These methods assume distinct meta-training and meta-testing task distributions, where the goal of a meta-learner is to learn to adapt fast to a novel test task given few only a
few samples and training ‘budget’. More specifically a few-shot meta-learner is evaluated to perform \( n \)-way classification given \( k \)= ‘shots’ or datapoints from a previously unseen class using up to \( m \)–training iterations or gradients steps. We note that there are two distinct types of meta-learners, ones that require \( m \)–training iterations for finetuning \([14, 51]\), and ones that do not \([64, 43]\). In the meta-learning phase, the meta-learner is trained to solve entire tasks as datapoints, to quickly adapt to novel test time tasks. Many different strategies are used to maximize the effectiveness of the meta-learning phase such as episodic training: where the model is trained by simulating ‘test-like’ conditions \([64, 70]\), or finetuning: where the model performs up to \( m \)-gradient steps on the new task \([14]\). Recent work has also shown that meta learning is limited to compact data distributions where features in the training set can be reused \([50]\).

Along with adapting to novel tasks, it is also important for a model to generalize to novel data. In metric learning \([78]\), a model is evaluated on the ability to perform zero-shot retrieval on novel data. The learner is trained on a training data distribution \( D_{ts} \) and evaluated on a testing data distribution \( D_{ts} \) where there are no shared classes between \( D_{tr} \) and \( D_{ts} \); however, the data generating function is assumed to be similar, such as natural images of birds \([74]\). In deep metric learning, the learner is parameterized using a deep neural networks \([55]\). Similar to deep metric learning, in zero-shot domain adaptation a learner is also trained on a distinct \( D_{tr} \) and evaluated on \( D_{ts} \). But unlike metric learning, in zero-shot domain adaptation the labels between the data distributions are shared but each distribution comes from distinct data generative functions, such as natural images of digits \([19]\) and handwritten images of digits \([39]\).

## 3 Max-Entropy Regularization

In this section we will introduce the max-entropy objective and the alternating GAN-like optimization scheme we utilize to perform the regularization in a computationally tractable manner.

### 3.1 Max-Entropy Objective

In Information Theory, the entropy of a continuous probability distribution, \( p(x) \) is defined as 

\[
H(x) = -\int p(x) \log p(x) \, dx.
\]

The entropy of \( p(x) \) is maximized when it is uniformly distributed. In this paper, we aim to perform max-entropy regularization on the embeddings of a neural network. For a network, \( q \), with embeddings \( z \), parameterized by \( \theta \), we can represent the objective as:

\[
L = \min_{\theta} \mathbb{E}_{(x,y) \sim D_{tr}} [L_T(q(x), y)] - H(z)
\]  

(3.1)

where \( L_T \) is any task-specific loss such as cross-entropy loss, \( (x, y) \) are samples from the training distribution \( D_{tr} \) and \( H(z) \) represents the entropy of the feature space. To effectively maximize the entropy of the features \( H(z) \), we set the prior on the learned feature space or embeddings of the network \( q(z|\theta) \) to be a unit hyper-cube, \( \mathcal{U}(-1, 1) \). By adding the prior, we are effectively increasing the entropy of the embeddings \( z \) of the network, since it is no longer able to collapse to a multivariate Gaussian. This would imply that we want to impose a regularization of the form:

\[
L = \min_{\theta} \mathbb{E}_{(x,y) \sim D_{tr}} [L_T(q(x), y)] + D_{x \sim D_{tr}} (q(z|x)||r(z))
\]  

(3.2)

where \( D \) is a divergence metric such as the KL-divergence and \( r(z) \) is the Uniform hypercube prior.

In practice, adding such a regularization does not have a simple solution since a bounded uniform distribution does not have a closed-form KL divergence metric to minimize. To address the practical limitation of solving Eqn. 3.1, we draw upon the GAN literature where GAN-style alternate optimization has been successfully used to match a generated distribution to a defined target distribution, such as a Uniform hypercube prior in our case.

### 3.2 Max-Entropy Optimization

We choose the Uniform distribution as our chosen prior \( r(z) \), due to its property of being the max-entropy distribution. Choosing a Uniform hypercube \( \mathcal{U}(-1, 1) \) is a design choice that we make.
Latent variables models such as the Adversarial Autoencoder [45] have used a GAN-style adversarial loss, instead of a KL divergence, in the latent space of their autoencoder to learn a rich posterior. Such latent variable models typically consider an isotropic Gaussian prior, but in practice, any well-defined distribution can be used as a prior, such as a Uniform hypercube \( U(-1, 1) \).

We can mould the GAN objective in Eqn. 2.2 for max-entropy optimization. To this end, we train a Discriminator, \( D \), to be an arbiter between which samples are from the learned distribution \( q(z|x) \), parameterized by \( \theta \), and from the prior \( \gamma \).

For max-entropy regularization, the Generator objective from Eqn. 2.2 can be adjusted to
\[
\mathcal{L}_{adv} = \min_{\theta} \mathbb{E}_{x \sim D_{tr}} \left[ \log(1 - D(q(z|x))) \right] \tag{3.3}
\]
and similarly, the Discriminator objective can simply be stated as:
\[
\mathcal{L}_D = \max_{D} \mathbb{E}_{x \sim D_{tr}} \left[ \log(1 - D(q(z|x))) \right] + \mathbb{E}_{\tilde{z} \sim r(z)} \log D(\tilde{z}) \tag{3.4}
\]

Intuitively, the model \( q \) is trying to fool the discriminator into thinking that samples from the learned features, \( q(z|x) \), come from the chosen target distribution, \( \gamma \), which is chosen to be the max-entropy uniform hypercube, \( U(-1, 1) \). Similar to a GAN Discriminator, \( D \) is trying to find the ground-truth assignment of a sample from the prior, \( \tilde{z} \sim \gamma \), and the learned features, \( q(z|x) \). While the notion of adding such an adversarial loss has been previously used in multiple papers [45, 67, 62], the key insight of this work is twofold: i) the effect of max-entropy regularization on fast-adaptation and ii) an efficient technique to optimize our proposed regularization.

Our final objective for \( \theta \) can be written as
\[
\mathcal{L} = \min_{\theta} \mathbb{E}_{(x, y) \sim D_{tr}} \left[ \mathcal{L}_T(q(x), y) \right] + \gamma \mathbb{E}_{x \sim D_{tr}} \left[ \log(1 - D(q(z|x))) \right] \tag{3.5}
\]
where \( \gamma \) is a hyperparameter to control the amount of regularization added and \( \mathcal{L}_T \) is the downstream task loss. \( \gamma \) is chosen to balance out the ability of the model to generalize to new tasks, and the ability of the model to perform the downstream task. A value of \( \gamma \) being too high would result in the learned distribution closely resembling a uniform one, therefore making too few assumptions on the data and being unable to adapt to new tasks, as it is unable to utilize training experience. Similarly, a value of \( \gamma \) being too low would result in weak regularization, which in turn results in the learned feature distribution approximately collapsing to a multivariate Gaussian as in the case of regular supervised training. Even though we use deterministic mapping for \( q(z|x) \) instead of a stochastic function, we use the same argument as [45] that the data, \( D_{tr} \) itself adds is a sufficient source of stochasticity during training. We further discuss the value of \( \gamma \) used in the experiments in Sec. 4.1.

4 Experiments

In this paper, we seek to investigate how max-entropy regularization can affect the ability of a model to perform zero-shot generalization and fast-adapt to novel data and tasks. We note that in this section, we will refer to tasks where there we do not have samples from the testing distribution as generalization, and where we do have samples as adaptation (meta-learning). To this end, we seek to answer the following questions

- **Novel-data adaptation**: How do we perform zero-shot generalization at evaluation time for deep metric learning, zero-shot domain adaptation and OOD generalization with and without max-entropy regularization?
- **Novel-task adaptation**: How does the proposed method adapt to novel tasks during meta-learning for few-shot learning with and without max-entropy regularization?
Table 1: Deep Metric Learning (Zero-Shot Generalization). Comparison of several deep metric learning objectives with a ResNet-50 backbone [23]. The models are evaluated with and without max-entropy regularization and we report the mean Recall 1 and the Normalized Mutual Information (NMI) metric for all experiments. All baseline scores are taken from [55], and their official released code is used to run all experiments without any fine-tuning for the underlying metric learning model hyperparameters.

| Metric                        | CUB-200-2011 [74] | Cars-196 [35] |
|-------------------------------|-------------------|---------------|
| Softmax [81]                  | 61.66 ± 0.30 66.77 ± 0.36 | 78.91 ± 0.27 66.35 ± 0.30 |
| Softmax + Entropy             | 65.02 ± 0.13 68.76 ± 0.16 | 80.58 ± 0.21 68.30 ± 0.21 |
| Contrastive [20]              | 61.50 ± 0.17 66.45 ± 0.27 | 75.78 ± 0.39 64.04 ± 0.13 |
| Contrastive + Entropy         | 63.28 ± 0.18 67.45 ± 0.29 | 76.90 ± 0.38 65.06 ± 0.15 |
| Margin (D, β = 1.2) [75]      | 63.09 ± 0.46 68.21 ± 0.33 | 79.86 ± 0.33 67.36 ± 0.34 |
| Margin (D, β = 1.2) + Entropy | 64.96 ± 0.33 69.47 ± 0.13 | 82.47 ± 0.09 68.92 ± 0.22 |
| Multisimilarity [72]          | 62.80 ± 0.70 68.55 ± 0.38 | 81.68 ± 0.19 69.43 ± 0.38 |
| Multisimilarity + Entropy     | 65.87 ± 0.45 70.49 ± 0.16 | 82.20 ± 0.15 70.51 ± 0.25 |

Unless otherwise specified, we use a γ value of 0.1 and a Discriminator parameterized using a three-layer MLP with 100 hidden units in each layer. The Discriminator is trained using the Adam optimizer [32] with a learning rate of 10⁻⁵. For stability, we perform a single gradient step on the Discriminator for every 10 gradient steps on the underlying network. For deep metric learning (DML), since the base model (ResNet-50 [23]) starts off with ImageNet pre-trained weights, we use γ = 0.4, to address the introduced ImageNet bias. We perform no hyperparameter tuning on the base algorithms, and use the same hyperparameters that the original papers proposed; we simply add the entropy loss, along with the task loss as in Eqn. 3.5. Further details on all algorithms and implementations are available in the Appendix A.

4.1 Experimental Setup

Zero-shot Generalization: We look at how max-entropy regularization affects zero-shot retrieval in deep metric learning and zero-shot classification for domain adaptation. For deep metric learning, we use four benchmark deep metric learning losses (Contrastive Loss [20], Margin Loss [75], Softmax Loss [81] and MultiSimilarity Loss [72]) studied in [55], and evaluate them over two standard datasets: CUB-200 [74], and Cars-196 [35]. For zero-shot domain adaptation, we conduct digit recognition experiments, transferring models between MNIST [39], SVHN [19] and USPS [61]. In this setting we train the model on a source dataset, and test it directly on the testing dataset. Since each of the datasets contain digits, the networks are assessed to classify digits on the target dataset, without any training. For the domain adaptation task, we consider a vanilla ResNet18 baseline [23], as well as Adversarial Discriminative Domain Adaptation [68], which was proposed for domain adaptation, with and without max-entropy regularization and see if max-entropy regularization improves upon the baselines.

OOD Generalization: We look at how max-entropy regularization affects a model’s ability to generalize to OOD samples. We train the model on CIFAR-10 [36], and evaluate on a test set where the images have been randomly translated [-4, 4] pixels, rotated [-30, 30] degrees and scaled by [0.75 – 1.25]. When performing semantic-preserving augmentations, we obtain samples with a different distribution than the training samples thereby evaluating the performance of the model to extrapolate using its training experience. We evaluate the performance of ResNet-18 [23], WideResNet-50 [80] and ResNext-50 [77] with and without max-entropy regularization.

Meta Learning: We look at how max-entropy regularization affects meta-training for few-shot learning tasks. For experiments, we use 3 distinct meta-learning baselines: Matching Networks [70], ProtoTypical Networks [64] and MAML [14] with and without max-entropy regularization. We evaluate the models over 4 benchmark datasets Double MNIST [39], Omniglot [38], CIFAR-FS [36] and MiniImagenet [1] using benchmark few-shot learning tasks using TorchMeta [10].
Deep Metric Learning  To further investigate the role of max-entropy regularization in learning data-agnostic features, we thoroughly investigate the ability of a model to perform zero-shot generalization in deep metric learning (DML) and zero-shot domain adaptation. In both setups, the model is evaluated on a different distribution than the training distribution, which highlights the importance of learning models that can utilize their prior experience for fast-adaptation. The results for DML are summarized in Table 1 and on domain adaptation in Table 2. In both cases, we further see substantial gains in performance across a diverse set of baselines. More surprisingly, less competitive, less competitive methods such as [81], are able to significantly outperform all baselines without max-entropy regularization on the CUB-200 dataset [74]. Even the stronger baselines, such as MultiSimilarity [72], see substantial performance gains on both datasets and across all standard evaluation metrics.

Zero-shot Domain Adaptation  Domain adaptation results are summarized in Table 2. For domain adaptation, we test the model over two different architectures: LeNet [40] and ResNet-18 [23], as well as use distinct models (Adversarial Discriminative Domain Adaptation (ADDA) [68]). When training on the only the source data, we see that networks with max-entropy regularization significantly outperform the baseline models, by as much as 18%, on the target dataset. The gain in performance for ResNets and LeNets trained only on the source data demonstrates that such models disproportionately overfit to the training (or source) data, using max-entropy regularization, we can learn better data-agnostic feature embeddings. The performance gain is also evident in ADDA as using max-entropy regularization, boosts its performance significantly, even though ADDA is significantly different than the “Source Only” baseline model. The performance of ADDA with max-entropy regularization bridges the gap between zero-shot domain adaptation with entropy regularization and using supervised learning on the target data (“Target Only”). The improvement on two distinct model architectures and a domain adaptation algorithm further showcase the generality of the proposed regularization technique in learning fast adaptive models.

OOD Generalization  Finally, we evaluate trained models on their ability to generalize to OOD data. We perform severe augmentations on an image using: random translations $[-4, 4]$ pixels, random rotations $[-30, 30]$ degrees and scaling by a factor between $[0.75, 1.25]$. These transformations are physical transformations to the image, and completely preserve the semantics of the image. We evaluate three state-of-the-art architectures [23, 77, 80], on generalizing to OOD CIFAR-10 [36], where we again see the disproportionate usefulness of max-entropy regularization. Similar to

| Source $\rightarrow$ Target | Backbone | MNIST $\rightarrow$ USPS | USPS $\rightarrow$ MNIST | SVHN $\rightarrow$ MNIST |
|----------------------------|----------|---------------------------|-------------------------|--------------------------|
| Source Only                | ResNet-18| 49.0 ± 0.20               | 42.8 ± 0.07             | 69.7 ± 0.06              |
| Source Only + Entropy      | ResNet-18| 67.2 ± 0.11               | 56.2 ± 0.10             | 71.3 ± 0.13              |
| Source Only                | LeNet    | 75.2 ± 0.016              | 57.1 ± 0.017             | 60.1 ± 0.11             |
| Source Only + Entropy      | LeNet    | 79.6 ± 0.04               | 62.6 ± 0.01             | 65.8 ± 0.03             |
| ADDA [68]                  | LeNet    | 89.4 ± 0.002              | 90.1 ± 0.008           | 76.0 ± 0.018           |
| ADDA + Entropy             | LeNet    | 93.5 ± 0.09               | 94.8 ± 0.03             | 81.6 ± 0.03             |
| Target Only                | ResNet-18| 98.1 ± 0.2               | 99.8 ± 0.1               | 99.8 ± 0.1               |

Table 2: Zero-Shot Domain Adaptation. Comparison of several zero-shot domain adaptation strategies on the digit recognition task. The models are evaluated with and without max-entropy regularization and we report the mean accuracy and standard deviation over 5 random seeds. The results for Adversarial Domain Discriminative Adaptation (ADDA) and the “Source Only” + LeNet backbone are taken directly from [68]. “Target Only” refers to a model directly being trained and evaluated on the target distribution. We perform no hyperparameter tuning, and the exact hyperparameters are used as in [68].

| Backbone | MNIST $\rightarrow$ USPS | USPS $\rightarrow$ MNIST | SVHN $\rightarrow$ MNIST |
|----------|---------------------------|-------------------------|--------------------------|
| ResNet-18| 35.6 ± 1.2                | **41.3 ± 1.3**          | 39.6 ± 1.2               |
| wideResNet-50 | + Entropy | 43.9 ± 0.9               | 40.1 ± 0.8               |
| ResNeXt-50 | + Entropy | 43.8 ± 1.1               |                          |

Table 3: Out-of-Distribution Generalization. Comparison of several network architectures on their performance on OOD Generalization. We report mean accuracy and standard deviation over 5 random seeds. To generate OOD samples, we perform random translations, rotations, and scaling over each test image.
4.2 Meta Learning

We summarize our results on meta-learning in Tables 4 and 5, where we show results with and without max-entropy regularization on small and large scale meta-learning datasets for all 3 baselines. We note that Table 4 shows error rate instead of accuracy, since meta-learning on datasets like Double MNIST and Omniglot are able to achieve near perfect accuracy, which makes error rate a more useful metric to compare algorithms. We see that adding max-entropy regularization improves the performance of the baseline algorithms in most tasks and datasets. With the exception of the CIFAR-FS (5-shot, 5-way) setup, we see that adding max-entropy regularization is able to improve the performance of the meta-learner. The gains are most apparent on MiniImageNet since that is the “hardest” dataset of the ones considered, and therefore meta-learners have the most “room-to-grow”, in terms of performance. Both 5-way, 1-shot and 5-way, 5-shot on all three baseline meta-learners are significantly improved. We note that the biggest performance gain is found when using 1-shot By adding max-entropy regularization during training, we are able to decrease the amount of training-task bias such that the network is able to perform better fast-adaptation to the test distribution of tasks.

Table 4: Meta-Learning. Comparison of several meta-learning algorithms on two benchmark few-shot learning datasets. The models are evaluated with and without max-entropy regularization and we report the mean error rate and standard deviation over 5 seeds. No hyperparameter tuning is performed on the meta-learner and we use the exact hyperparameters as proposed in the original paper.

| Error Rates | Omniglot [38] | Double MNIST [39] |
|-------------|---------------|-------------------|
|             | (5, 1) (5,5)  | (20, 1) (20, 5)   |
| Matching Networks [70] | 2.1±0.2 1.0±0.2 5.9±0.3 2.5±0.3 | 4.2±0.2 2.7±0.2 |
| Matching Networks + Entropy | 1.7±0.1 0.9±0.1 5.0±0.2 2.0±0.2 | 3.2±0.1 2.3±0.3 |
| MAML [14] | 4.8±0.4 1.5±0.4 16.2±0.7 3.9±0.4 | 7.9±0.7 1.9±0.3 |
| MAML + Entropy | 4.1±0.5 1.3±0.2 12.4±0.7 2.9±0.4 | 7.3±0.2 1.5±0.3 |
| Prototypical Network [64] | 1.6±0.2 0.4±0.1 5.9±0.3 1.2±0.2 | 1.3±0.2 0.2±0.2 |
| Prototypical Network + Entropy | 1.2±0.3 0.4±0.1 4.6±0.2 1.1±0.2 | 1.0±0.2 0.2±0.2 |

Table 5: Meta-Learning. Comparison of recent meta-learning algorithms on CIFAR-FS and MiniImageNet. The models are evaluated with and without max-entropy regularization and we report the mean accuracy and standard deviation over 5 seeds. No hyperparameter tuning is performed on the meta-learner and we use the exact hyperparameters as proposed in the original paper.

| Accuracy | CIFAR-FS [36] | MiniImageNet [1] |
|----------|---------------|------------------|
|          | (5, 1) (5,5)  | (5, 1) (5,5)     |
| Matching Networks [70] | 46.7±1.1 62.9±1.0 | 43.2±0.3 50.3±0.9 |
| Matching Networks + Entropy | 49.3±0.4 63.1±0.7 | 47.1±0.8 53.1±0.7 |
| MAML [14] | 52.1±0.8 67.1±0.9 | 47.2±0.7 62.1±1.0 |
| MAML + Entropy | 52.9±0.4 67.1±0.9 | 48.9±0.8 64.1±1.0 |
| Prototypical Network [64] | 52.4±0.7 67.1±0.5 | 45.4±0.6 61.3±0.7 |
| Prototypical Network + Entropy | 52.6±0.8 66.8±0.5 | 46.8±0.5 64.4±0.9 |

domain adaptation, we see that the network trained on a defined downstream task is able to significantly improve its ability to generalize to a new data distribution when entropy regularization is added. We note that the reason for relatively high variance is results is due to the stochastic nature of the data augmentation techniques. The data augmentation during evaluation randomly performs a physical transformation on the image, which means that the different models will likely see unique augmentations of the same image during evaluation, which can explain the high standard deviation in results.
Table 6: We perform an ablation study on the choice of prior, \( r(z) \), and its effect on the performance. We report mean accuracy and standard deviation over 5 runs on the task of MNIST \( \rightarrow \) USPS and USPS \( \rightarrow \) MNIST zero-shot domain adaptation using a ResNet-18 backbone. The only difference between the experiments is the choice of \( r(z) \) fed to the Discriminator. Identical hyperparameters, including the value of \( \gamma \), are used for each experiment. Note: The “Baseline” and \( \mathcal{U}(-1, 1) \) are the unregularized and proposed solutions, respectfully.

| Task         | Baseline | \( \mathcal{N}(0, 0.1 \times I) \) | \( \mathcal{N}(0, I) \) | \( \mathcal{N}(0, 5 \times I) \) | \( \mathcal{N}(0, 10 \times I) \) | \( \mathcal{U}(-1, 1) \) |
|--------------|----------|----------------------------------|-------------------------|---------------------------------|---------------------------------|-------------------------|
| MNIST \( \rightarrow \) USPS | 49.0 ± 0.20 | 43.98 ± 0.23 | 43.45 ± 0.16 | 56.45 ± 0.36 | 59.80 ± 0.12 | 67.2 ± 0.11 |
| USPS \( \rightarrow \) MNIST | 42.8 ± 0.07 | 27.23 ± 0.28 | 26.02 ± 0.87 | 37.96 ± 0.32 | 43.76 ± 0.48 | 56.2 ± 0.10 |

4.3 Ablation Study

For a Gaussian distribution, \( \mathcal{N}(\mu, \sigma^2) \), the entropy can be written in closed form as \( \frac{1}{2} \log(2\pi e\sigma^2) \). The entropy of a Gaussian increases with \( \sigma^2 \); therefore we evaluate the importance of the entropy of the prior in Table 6 where we provide an ablation study studying the effect of the prior \( r(z) \) on the performance of the model. We evaluate the model’s ability to perform zero-shot domain adaptation from MNIST \( \rightarrow \) USPS, and the backward task of USPS \( \rightarrow \) MNIST using a ResNet-18 [23]. We show that as the entropy of \( r(z) \) is increased, the ability of the network to perform domain adaptation also increases. When \( \sigma^2 \) is small, thereby having a low-entropy, the model is unable to adapt to the novel data; similarly, as \( \sigma^2 \) of \( r(z) \) is increased, the network significantly improves its ability to perform the adaptation task. The ablation study shows how the performance of the ablated experiments also increases the performance over the baseline on MNIST \( \rightarrow \) USPS transfer, but does not match the performance of the proposed regularization. The difference between the proposed solution and ablated baselines is more evident on the backward task of USPS \( \rightarrow \) MNIST, since there are less labels present in the USPS dataset, thereby making overfitting a greater issue when the network is trained on USPS.

5 Related Work

Adversarial Representation Learning Latent variable models, such as Adversarial Autoencoder, have used GAN-style training in the latent space [45, 67]. Such models utilize the GAN-style training to learn a rich posterior. Recent efforts have made such training effective in different contexts such as active learning [63, 31], domain adaptation [68, 26], among other topics [62, 13, 2, 3].

Metric Learning and Generalization The goal of a metric learning algorithm is to learn a metric space such that at evaluation, the metric learner is able to perform zero-shot generalization on novel data. Different methods for distance metric learning primarily differ in their proposed objectives [75, 72, 81, 20, 8]; but different solutions such as better triplet mining [21, 73, 54], and self-supervision [47, 5] have also shown great promise. Recently, [55] have performed an extensive survey on the various DML objectives. The goal of performing OOD generalizations from data has also been of great interest [26, 68, 34]. Recent work has also shown theoretical benefits of a learning a Uniform hypersphere for zero-shot generalization [71]. Such representations allow models to learn features that are invariant to semantic-preserving transformations in data.

Meta Learning The goal of a meta learner is to be learn an effective initialization to be able to quickly adapt to novels tasks. Many different types of algorithms have recently been proposed such as memory-augmented methods [52, 49, 58], metric-space based approaches [70, 64, 66], different optimization techniques [43, 14, 51, 79], and more recently finetuning using ImageNet [57] pre-training [9, 16] Different unsupervised have also been used to learn such initializations [27, 6, 30]. Meta-learning has also been explored for fast-adaptation of novel tasks in reinforcement learning [33, 83, 29].

Discussion

In this paper, we propose a regularization technique for the challenging task of fast-adaptation in neural networks. We present a simple and general solution, max-entropy regularization, that works in many different contexts and improves strong, distinct baselines in meta-learning, deep metric
learning, zero-shot domain adaptation and OOD generalization. We further perform an ablation study which highlights the role of the entropy of the prior in generalization and adaptation. Future work can include how to design better priors for such fast-adaptation as well as better optimization algorithms for zero-shot and few-shot learning.

Acknowledgements

We would like to thank Karsten Roth for help with experiments, and Homanga Bharadhwaj for insightful discussions and feedback on the draft. We also thank Kyle Hsu, Eleni Triantafillou and Hugo Larochelle for insightful discussions. Finally, we also acknowledge Vector Institute for providing resources for this research.

References

[1] Tinyimagenet dataset. https://tinyimagenet.herokuapp.com/.

[2] C. Beckham, S. Honari, V. Verma, A. M. Lamb, F. Ghadiri, R. D. Hjelm, Y. Bengio, and C. Pal. On adversarial mixup resynthesis. In Advances in Neural Information Processing Systems, pages 4348–4359, 2019.

[3] D. Berthelot, C. Raffel, A. Roy, and I. Goodfellow. Understanding and improving interpolation in autoencoders via an adversarial regularizer. arXiv preprint arXiv:1807.07543, 2018.

[4] T. B. Brown, B. Mann, N. Ryder, M. Subbiah, J. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, S. Agarwal, A. Herbert-Voss, G. Krueger, T. Henighan, R. Child, A. Ramesh, D. M. Ziegler, J. Wu, C. Winter, C. Hesse, M. Chen, E. Sigler, M. Litwin, S. Gray, B. Chess, J. Clark, C. Berner, S. McCandlish, A. Radford, I. Sutskever, and D. Amodei. Language models are few-shot learners, 2020.

[5] X. Cao, B.-C. Chen, and S.-N. Lim. Unsupervised deep metric learning via auxiliary rotation loss. arXiv preprint arXiv:1911.07072, 2019.

[6] M. Caron, P. Bojanowski, A. Joulin, and M. Douze. Deep clustering for unsupervised learning of visual features. In Proceedings of the European Conference on Computer Vision (ECCV), pages 132–149, 2018.

[7] W. Chen, X. Chen, J. Zhang, and K. Huang. Beyond triplet loss: a deep quadruplet network for person re-identification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 403–412, 2017.

[8] W. Chen, X. Chen, J. Zhang, and K. Huang. Beyond triplet loss: a deep quadruplet network for person re-identification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 403–412, 2017.

[9] Y. Chen, X. Wang, Z. Liu, H. Xu, and T. Darrell. A new meta-baseline for few-shot learning. arXiv preprint arXiv:2003.04390, 2020.

[10] T. Deleu, T. Würfl, M. Samiei, J. P. Cohen, and Y. Bengio. Torchmeta: A meta-learning library for pytorch. arXiv preprint arXiv:1909.06576, 2019.

[11] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805, 2018.

[12] X. Du, T.-Y. Lin, P. Jin, G. Ghiassi, M. Tan, Y. Cui, Q. V. Le, and X. Song. Spinenet: Learning scale-permuted backbone for recognition and localization. arXiv preprint arXiv:1912.05027, 2019.

[13] S. Ebrahimi, F. Meier, R. Calandra, T. Darrell, and M. Rohrbach. Adversarial continual learning. arXiv preprint arXiv:2003.09553, 2020.

[14] C. Finn, P. Abbeel, and S. Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In Proceedings of the 34th International Conference on Machine Learning-Volume 70, pages 1126–1135. JMLR. org, 2017.
[15] S. Fujimoto, H. Van Hoof, and D. Meger. Addressing function approximation error in actor-critic methods. *arXiv preprint arXiv:1802.09477*, 2018.

[16] S. Gidaris and N. Komodakis. Dynamic few-shot visual learning without forgetting. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 4367–4375, 2018.

[17] R. Girshick. Fast r-cnn. In *Proceedings of the IEEE international conference on computer vision*, pages 1440–1448, 2015.

[18] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. Generative adversarial nets. In *Advances in neural information processing systems*, pages 2672–2680, 2014.

[19] I. J. Goodfellow, Y. Bulatov, J. Ibarz, S. Arnoud, and V. Shet. Multi-digit number recognition from street view imagery using deep convolutional neural networks. *arXiv preprint arXiv:1312.6082*, 2013.

[20] R. Hadsell, S. Chopra, and Y. LeCun. Dimensionality reduction by learning an invariant mapping. In *2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06)*, volume 2, pages 1735–1742. IEEE, 2006.

[21] B. Harwood, B. Kumar, G. Carneiro, I. Reid, T. Drummond, et al. Smart mining for deep metric learning. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 2821–2829, 2017.

[22] K. He, X. Zhang, S. Ren, and J. Sun. Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. In *Proceedings of the IEEE international conference on computer vision*, pages 1026–1034, 2015.

[23] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[24] M. H. Hesamian, W. Jia, X. He, and P. Kennedy. Deep learning techniques for medical image segmentation: Achievements and challenges. *Journal of digital imaging*, 32(4):582–596, 2019.

[25] M. Heusel, H. Ramsauer, T. Unterthiner, B. Nessler, and S. Hochreiter. Gans trained by a two time-scale update rule converge to a local nash equilibrium. In *Advances in neural information processing systems*, pages 6626–6637, 2017.

[26] J. Hoffman, E. Tzeng, T. Park, J.-Y. Zhu, P. Isola, K. Saenko, A. A. Efros, and T. Darrell. Cycada: Cycle-consistent adversarial domain adaptation. *arXiv preprint arXiv:1711.03213*, 2017.

[27] K. Hsu, S. Levine, and C. Finn. Unsupervised learning via meta-learning. *arXiv preprint arXiv:1810.02334*, 2018.

[28] J. Hu, J. Lu, and Y.-P. Tan. Discriminative deep metric learning for face verification in the wild. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1875–1882, 2014.

[29] A. Jabri, K. Hsu, A. Gupta, B. Eysenbach, S. Levine, and C. Finn. Unsupervised curricula for visual meta-reinforcement learning. In *Advances in Neural Information Processing Systems*, pages 10519–10530, 2019.

[30] S. Khodadadeh, L. Boloni, and M. Shah. Unsupervised meta-learning for few-shot image classification. In *Advances in Neural Information Processing Systems*, pages 10132–10142, 2019.

[31] K. Kim, D. Park, K. I. Kim, and S. Y. Chun. Task-aware variational adversarial active learning. *arXiv preprint arXiv:2002.04709*, 2020.

[32] D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.
[33] L. Kirsch, S. van Steenkiste, and J. Schmidhuber. Improving generalization in meta reinforcement learning using learned objectives. *arXiv preprint arXiv:1910.04098*, 2019.

[34] E. Kodirov, T. Xiang, Z. Fu, and S. Gong. Unsupervised domain adaptation for zero-shot learning. In *Proceedings of the IEEE international conference on computer vision*, pages 2452–2460, 2015.

[35] J. Krause, M. Stark, J. Deng, and L. Fei-Fei. 3d object representations for fine-grained categorization. In *Proceedings of the IEEE international conference on computer vision workshops*, pages 554–561, 2013.

[36] A. Krizhevsky, G. Hinton, et al. Learning multiple layers of features from tiny images. Technical report, Citeseer, 2009.

[37] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105, 2012.

[38] B. M. Lake, R. Salakhutdinov, and J. B. Tenenbaum. The omniglot challenge: a 3-year progress report. *Current Opinion in Behavioral Sciences*, 29:97–104, 2019.

[39] Y. LeCun. The mnist database of handwritten digits. *http://yann.lecun.com/exdb/mnist/*, 1998.

[40] Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, et al. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.

[41] J. Lee, Y. Bahri, R. Novak, S. S. Schoenholz, J. Pennington, and J. Sohl-Dickstein. Deep neural networks as gaussian processes. *arXiv preprint arXiv:1711.00165*, 2017.

[42] J. Lee, L. Xiao, S. Schoenholz, Y. Bahri, R. Novak, J. Sohl-Dickstein, and J. Pennington. Wide neural networks of any depth evolve as linear models under gradient descent. In *Advances in neural information processing systems*, pages 8570–8581, 2019.

[43] K. Lee, S. Maji, A. Ravichandran, and S. Soatto. Meta-learning with differentiable convex optimization. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 10657–10665, 2019.

[44] J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3431–3440, 2015.

[45] A. Makhzani, J. Shlens, N. Jaitly, I. Goodfellow, and B. Frey. Adversarial autoencoders. *arXiv preprint arXiv:1511.05644*, 2015.

[46] A. G. d. G. Matthews, M. Rowland, J. Hron, R. E. Turner, and Z. Ghahramani. Gaussian process behaviour in wide deep neural networks. *arXiv preprint arXiv:1804.11271*, 2018.

[47] T. Milbich, K. Roth, H. Bharadhwaj, S. Sinha, Y. Bengio, B. Ommer, and J. P. Cohen. Diva: Diverse visual feature aggregation for deep metric learning. *arXiv preprint arXiv:2004.13458*, 2020.

[48] R. Mohan and A. Valada. Efficientps: Efficient panoptic segmentation. *arXiv preprint arXiv:2004.02307*, 2020.

[49] T. Munkhdalai, X. Yuan, S. Mehri, and A. Trischler. Rapid adaptation with conditionally shifted neurons. *arXiv preprint arXiv:1712.09926*, 2017.

[50] A. Raghul, M. Raghul, S. Bengio, and O. Vinyals. Rapid learning or feature reuse? towards understanding the effectiveness of maml. *arXiv preprint arXiv:1909.09157*, 2019.

[51] A. Rajeswaran, C. Finn, S. M. Kakade, and S. Levine. Meta-learning with implicit gradients. In *Advances in Neural Information Processing Systems*, pages 113–124, 2019.

[52] S. Ravi and H. Larochelle. Optimization as a model for few-shot learning. 2016.
[53] O. Ronneberger, P. Fischer, and T. Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.

[54] K. Roth, T. Milbich, and B. Ommer. Pads: Policy-adapted sampling for visual similarity learning. *arXiv preprint arXiv:2003.11113*, 2020.

[55] K. Roth, T. Milbich, S. Sinha, P. Gupta, B. Ommer, and J. P. Cohen. Revisiting training strategies and generalization performance in deep metric learning. *arXiv preprint arXiv:2002.08473*, 2020.

[56] D. E. Rumelhart, G. E. Hinton, and R. J. Williams. Learning internal representations by error propagation. Technical report, California Univ San Diego La Jolla Inst for Cognitive Science, 1985.

[57] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, et al. Imagenet large scale visual recognition challenge. *International journal of computer vision*, 115(3):211–252, 2015.

[58] A. Santoro, S. Bartunov, M. Botvinick, D. Wierstra, and T. Lillicrap. Meta-learning with memory-augmented neural networks. In *International conference on machine learning*, pages 1842–1850, 2016.

[59] J. Schulman, S. Levine, P. Abbeel, M. Jordan, and P. Moritz. Trust region policy optimization. In *International conference on machine learning*, pages 1889–1897, 2015.

[60] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

[61] A. K. Seewald. Digits-a dataset for handwritten digit recognition. *Austrian Research Institut for Artificial Intelligence Technical Report, Vienna (Austria)*, 2005.

[62] S. Sinha, H. Bharadhwaj, A. Goyal, H. Larochelle, A. Garg, and F. Shkurti. Dibs: Diversity inducing information bottleneck in model ensembles. *arXiv preprint arXiv:2003.04514*, 2020.

[63] S. Sinha, S. Ebrahimi, and T. Darrell. Variational adversarial active learning. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 5972–5981, 2019.

[64] J. Snell, K. Swersky, and R. Zemel. Prototypical networks for few-shot learning. In *Advances in neural information processing systems*, pages 4077–4087, 2017.

[65] B. Sun and K. Saenko. Deep coral: Correlation alignment for deep domain adaptation. In *European conference on computer vision*, pages 443–450. Springer, 2016.

[66] F. Sung, Y. Yang, L. Zhang, T. Xiang, P. H. Torr, and T. M. Hospedales. Learning to compare: Relation network for few-shot learning. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 1199–1208, 2018.

[67] I. Tolstikhin, O. Bousquet, S. Gelly, and B. Schoelkopf. Wasserstein auto-encoders. *arXiv preprint arXiv:1711.01558*, 2017.

[68] E. Tzeng, J. Hoffman, K. Saenko, and T. Darrell. Adversarial discriminative domain adaptation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 7167–7176, 2017.

[69] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin. Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008, 2017.

[70] O. Vinyals, C. Blundell, T. Lillicrap, and D. Wierstra. Matching networks for one shot learning. In *Advances in neural information processing systems*, 2016.

[71] T. Wang and P. Isola. Understanding contrastive representation learning through alignment and uniformity on the hypersphere. *arXiv preprint arXiv:2003.10242*, 2020.
[72] X. Wang, X. Han, W. Huang, D. Dong, and M. R. Scott. Multi-similarity loss with general pair weighting for deep metric learning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 5022–5030, 2019.

[73] Y. Wang, J. Choi, V. Morariu, and L. S. Davis. Mining discriminative triplets of patches for fine-grained classification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 1163–1172, 2016.

[74] P. Welinder, S. Branson, T. Mita, C. Wah, F. Schroff, S. Belongie, and P. Perona. Caltech-ucsd birds 200. 2010.

[75] C.-Y. Wu, R. Manmatha, A. J. Smola, and P. Krahenbuhl. Sampling matters in deep embedding learning. In Proceedings of the IEEE International Conference on Computer Vision, pages 2840–2848, 2017.

[76] L. Xiao, Y. Bahri, J. Sohl-Dickstein, S. S. Schoenholz, and J. Pennington. Dynamical isometry and a mean field theory of cnns: How to train 10,000-layer vanilla convolutional neural networks. arXiv preprint arXiv:1806.05393, 2018.

[77] S. Xie, R. Girshick, P. Dollár, Z. Tu, and K. He. Aggregated residual transformations for deep neural networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1492–1500, 2017.

[78] L. Yang and R. Jin. Distance metric learning: A comprehensive survey. Michigan State University, 2(2):4, 2006.

[79] M. Yin, G. Tucker, M. Zhou, S. Levine, and C. Finn. Meta-learning without memorization. arXiv preprint arXiv:1912.03820, 2019.

[80] S. Zagoruyko and N. Komodakis. Wide residual networks. arXiv preprint arXiv:1605.07146, 2016.

[81] A. Zhai and H.-Y. Wu. Classification is a strong baseline for deep metric learning. arXiv preprint arXiv:1811.12649, 2018.

[82] B. Zhou, A. Lapedriza, A. Khosla, A. Oliva, and A. Torralba. Places: A 10 million image database for scene recognition. IEEE transactions on pattern analysis and machine intelligence, 40(6):1452–1464, 2017.

[83] L. Zintgraf, K. Shiarlis, M. Igl, S. Schulze, Y. Gal, K. Hofmann, and S. Whiteson. Varibad: A very good method for bayes-adaptive deep rl via meta-learning. arXiv preprint arXiv:1910.08348, 2019.
A Experimental Details

Max-entropy regularization was added to the output of the CNNs for all networks. For ResNet-variants [23, 77, 80], it was applied to the output of the CNNs, just before the single fully-connected layer. For meta-learning, the regularization is applied directly on the learned metric space for the metric-space based meta learners [14, 70], and applied to the output of the meta parameters for MAML [14].

The value of $\gamma$ is chosen to be 0.1 for all experiments, except for Deep Metric Learning. For Deep Metric Learning, a value of $\gamma = 0.4$ is chosen, since the effect of regularization needs to be stronger, since Deep Metric Learners start off with networks that are already pre-trained on ImageNet. Since the pre-trained networks already have a learning bias, a greater value of $\gamma$ is chosen for more regularization.