Uniform Sampling over Episode Difficulty

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Abstract

Episodic training is a core ingredient of few-shot learning to train models on tasks with limited labelled data. Despite its success, episodic training remains largely understudied, prompting us to ask the question: what is the best way to sample episodes? In this paper, we first propose a method to approximate episode sampling distributions based on their difficulty. Building on this method, we perform an extensive analysis and find that sampling uniformly over episode difficulty outperforms other sampling schemes, including curriculum and easy-/hard-mining. As the proposed sampling method is algorithm agnostic, we can leverage these insights to improve few-shot learning accuracies across many episodic training algorithms. We demonstrate the efficacy of our method across popular few-shot learning datasets, algorithms, network architectures, and protocols.

1 Introduction

Large amounts of high-quality data has been the key for the success of deep learning algorithms. Furthermore, factors such as data augmentation and sampling affect model performance significantly. Continuously collecting and curating data is a resource (cost, time, storage, etc) intensive process. Hence, recently, the machine learning community has been exploring methods for performing transfer-learning from large datasets to unseen tasks with limited data.

A popular genre of these approaches is called meta-learning few-shot approaches, where in addition to the limited data from the task of interest, a large dataset of a disjoint tasks is available for (pre-)training. These approaches are prevalent in the area of computer vision [26] and reinforcement learning [5]. A key component of these methods is the notion of episodic training, which refers to sampling tasks from the larger dataset for training. By learning to solve these tasks correctly, the model can generalize to new tasks.

However, sampling for episodic training remains surprisingly understudied despite numerous methods and applications that build on it. To the best of our knowledge, only a handful of works [59, 47, 28] explicitly considered the consequences of sampling episodes. In comparison, the stochastic [39] and mini-batch [3] sampling alternatives have been thoroughly analyzed from the perspectives of optimization [14, 4], information theory [23, 7], and stochastic processes [58, 56] among many others. Building a similar understanding of sampling for episodic training will help theoreticians and practitioners develop improved sampling schemes, and is thus of crucial importance to both.

In this paper, we explore many sampling methods to understand its impact on few-shot methods. Our work revolves around the following fundamental question: *what is the best way to sample episodes?* Our focus will be restricted to image classification in the few-shot learning setting – where "best" is taken to mean "higher transfer accuracy of unseen episodes" – and leave analyses and applications to other learning for future work.

Contrary to prior work, our experiments indicate that sampling uniformly with respect to *episode difficulty* yields higher classification accuracy — a scheme originally proposed to regularize metric

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learning [52]. To better understand those results, we take a closer look at the properties of episodes and what makes them difficult. Building on this understanding, we propose a method to approximate different sampling schemes, and demonstrate its efficacy on several standard few-shot learning algorithms and datasets.

Concretely, we make the following contributions:

- We provide a detailed empirical analysis of episodes and their difficulty. When sampled randomly, we show that episode difficulty follows a normal distribution and that the difficulty of an episode is largely independent of several modeling choices including the training algorithm, the network architecture, and the training iteration.
- Leveraging our analysis, we propose *simple and universally applicable* modifications to the episodic sampling pipeline to approximate *any* sampling scheme. We then use this scheme to thoroughly compare episode sampling schemes – including easy/hard-mining, curriculum learning, and uniform sampling – and report that sampling uniformly over episode difficulty yields the best results.
- Finally, we show that *sampling matters for few-shot classification* as it improves transfer accuracy for a diverse set of popular [46, 16, 12, 34] and state-of-the-art [54] algorithms on standard benchmarks.

2 Preliminaries

Episodic sampling and training. We define episodic sampling as subsampling few-shot tasks (or episodes) from a larger *base* one [6]. Assuming the base dataset admits a generative distribution, we sample an episode in two steps[1]. First, we sample the episode classes $\mathcal{C}_\tau$ from class distribution $p(\mathcal{C}_\tau)$; second, we sample the episode's data from data distribution $p(x, y \mid \mathcal{C}_\tau)$ conditioned on $\mathcal{C}_\tau$. This gives rise to the following log-likelihood for a model l_θ parameterized by θ:

$$\mathcal{L}(\theta) = \mathop{\mathrm{E}}_{\tau \sim q(\cdot)} [\log l_\theta(\tau)] \tag{1}$$

where $q(\tau)$ is the episode distribution induced by first sampling classes, then data. In practice, this expectation is approximated by sampling a batch of episodes $\mathcal{B}$ each with their set τ_Q of *query* samples. To enable transfer to unseen classes, it is also common to include a small set τ_S of *support* samples to provide statistics about τ. This results in the following Monte-Carlo estimator:

$$\mathcal{L}(\theta) \approx \frac{1}{|\mathcal{B}|} \sum_{\tau \in \mathcal{B}} \frac{1}{|\tau_Q|} \sum_{(x,y) \in \tau_Q} \log l_\theta(y \mid x, \tau_S), \tag{2}$$

where the data in τ_Q and τ_S are both distributed according to $p(x, y \mid \mathcal{C}_\tau)$. In few-shot image classification, the n-way k-shot setting corresponds to sampling $n = |\mathcal{C}_\tau|$ classes, each with $k = |\tau_S|$ support data points. The implicit assumption in the vast majority of few-shot methods is that both classes and data are sampled with *uniform* probability – *but are there better alternatives?* We carefully examines those underlying assumptions in the forthcoming sections.

Few-shot algorithms. We briefly present a few representative episodic learning algorithms. A more comprehensive treatment of few-shot algorithms is presented in Wang et al. [50] and Hospedales et al. [20]. A core question in few-shot learning lies in evaluating (and maximizing) the model likelihood l_θ. These algorithms can be divided in two major families: gradient-based methods, which adapt the model's parameters to the episode; and metric-based methods, which compute similarities between support and query samples in a learned embedding space.

Gradient-based few-shot methods are best illustrated through Model-Agnostic Meta-Learning [12] (MAML). The intuition behind MAML it is to learn a set of initial parameters which can quickly specialize to the task at hand. To that end, MAML computes l_θ by adapting the model parameters θ via one (or more) steps of gradient ascent and then computes the likelihood using the adapted parameters θ'. Concretely, we first compute the likelihood $p_\theta(y \mid x)$ using the support set τ_S, adapt the model parameters, and then evaluate the likelihood:

$$l_\theta(y \mid x, \tau_S) = p_{\theta'}(y \mid x) \quad \text{s.t.} \quad \theta' = \theta + \alpha \nabla_\theta \sum_{(x,y) \in \tau_S} \log p_\theta(y \mid x),$$

[1] We use the notation for a probability distribution and its probability density function interchangeably.

where $\alpha > 0$ is known as the adaptation learning rate. A major drawback of training with MAML lies in back-propagating through the adaptation phase, which requires higher-order gradients. To alleviate this computational burden, the Almost No Inner Loop [34] (ANIL) proposes to only adapt the last classification layer of the model architecture while tying the rest of the layers across episodes. They empirically demonstrate little classification accuracy drop while accelerating training times four-fold.

Akin to ANIL, metric-based methods also share most of their parameters across tasks; however, their aim is to learn a metric space where classes naturally cluster. To that end, metric-based algorithms learn a feature extractor ϕ_θ parameterized by θ and classify according to a non-parametric rule. A representative of this family is Prototypical Network [46] (ProtoNet), which classifies query points according to their distance to *class prototypes* — the average embedding for a class in the support set:

$$l_\theta(y \mid x, \tau_S) = \frac{\exp\left(-d(\phi_\theta(x), \phi_\theta^y)\right)}{\sum_{y' \in \mathcal{C}_\tau} \exp\left(-d(\phi_\theta(x), \phi_\theta^{y'})\right)} \quad \text{s.t.} \quad \phi_\theta^c = \frac{1}{k} \sum_{\substack{x, y \in \tau_S \\ y = c}} \phi_\theta(x),$$

where $d(\cdot, \cdot)$ is a distance function such as the Euclidean distance or the negative cosine similarity, and ϕ_θ^c is the class prototype for class c. Other classification rules include support vector clustering [27], neighborhood component analysis [25], and the earth-mover distance [57].

Episode difficulty. Given an episode τ and likelihood function l_θ, we define *episode difficulty* to be the negative log-likelihood incurred on that episode:

$$\Omega_{l_\theta}(\tau) = -\log l_\theta(\tau),$$

which is a surrogate for how hard it is to classify the samples in τ_Q correctly, given l_θ and τ_S. By definition, this choice of episode difficulty is tied to the choice of the likelihood function l_θ.

Dhillon et al. [9] use a similar surrogate as means to systematically report few-shot performances. We use this definition because it is equivalent to the loss associated with the likelihood function l_θ on episode τ, which is readily available at train-time.

3 Methodology

In this section, we describe the core assumptions and methodology used in our study of sampling methods for episodic training. Our proposed method builds on importance sampling [17] (IS) which we found compelling for the following three reasons: firstly, IS is *well understood* and solidly grounded from a theoretical standpoint; secondly, IS is *universally applicable* thus compatible with all episodic training algorithms; finally, IS is *simple to implement* with little requirement for hyper-parameter tuning.

Why should we care about episodic sampling? A back-of-the-envelope calculation[2] suggests that there are on the order of 10^{162} different training episodes for the smallest-scale experiments in Section 5. Since iterating through each of them is infeasible, we ought to express some preference over which episodes to sample. In the following, we describe a method that allows us to specify this preference.

3.1 Importance sampling for episodic training

Let us assume that the sampling scheme described in Section 2 induces a distribution $q(\tau)$ over episodes. We call it the *proposal distribution*, and assume knowledge of its density function. We wish to estimate the expectation in Eq. (1) when sampling episodes according to a *target distribution* $p(\tau)$ of our choice, rather than $q(\tau)$. To that end, we can use an importance sampling estimator which simply re-weights the observed values for a given episode τ by $w(\tau) = \frac{p(\tau)}{q(\tau)}$, the ratio of the target and proposal distributions:

$$\mathop{\mathrm{E}}_{\tau \sim p(\cdot)} \left[\log l_\theta(\tau)\right] = \mathop{\mathrm{E}}_{\tau \sim q(\cdot)} \left[w(\tau) \log l_\theta(\tau)\right].$$

The importance sampling identity holds whenever $q(\tau)$ has non-zero density over the support of $p(\tau)$, and effectively allows us to sample from *any* target distribution $p(\tau)$.

[2] For a base dataset with K classes and N input-output pairs per class, there are a total of $\binom{K}{k}\binom{N}{n}^k$ possible episodes that can be created when sampling n pairs each from k classes.

A practical issue of the IS estimator arises when some values of $w(\tau)$ become much larger than others; in that case, the likelihoods $l_\theta(\tau)$ associated with mini-batches containing heavier weights dominate the others, leading to disparities. To account for this effect, we can replace the mini-batch average in the Monte-Carlo estimate of Eq. (2) by the *effective sample size* $\text{ESS}(\mathcal{B})$ [24, 29]:

$$\mathop{\text{E}}_{\tau\sim p(\cdot)}[\log l_\theta(\tau)] \approx \frac{1}{\text{ESS}(\mathcal{B})}\sum_{\tau\in\mathcal{B}} w(\tau)\log l_\theta(\tau) \quad \text{s.t.} \quad \text{ESS}(\mathcal{B}) = \frac{(\sum_{\tau\in\mathcal{B}} w(\tau))^2}{\sum_{\tau\in\mathcal{B}} w(\tau)^2}, \tag{3}$$

where $\mathcal{B}$ denotes a mini-batch of episodes sampled according to $q(\tau)$. Note that when $w(\tau)$ is constant, we recover the standard mini-batch average setting as $\text{ESS}(\mathcal{B}) = |\mathcal{B}|$. Empirically, we observed that normalizing with the effective sample size avoided instabilities. This method is summarized in Algorithm 1.

3.2 Modeling the proposal distribution

A priori, we do not have access to the proposal distribution $q(\tau)$ (nor its density) and thus need to estimate it empirically. Our main assumption is that sampling episodes from $q(\tau)$ induces a normal distribution over episode difficulty. With this assumption, we model the proposal distribution by this induced distribution, therefore replacing $q(\tau)$ with $\mathcal{N}(\Omega_{l_\theta}(\tau) \mid \mu, \sigma^2)$ where μ, σ^2 are the mean and variance parameters. As we will see in Section 5.2, this normality assumption is experimentally supported on various datasets, algorithms, and architectures.

Algorithm 1: Episodic training with IS

Input: target (p) and proposal (q) distributions, likelihood function l_θ, optimizer OPT.
Randomly initialize model parameters θ.
repeat
  Sample a mini-batch $\mathcal{B}$ of episodes from $q(\tau)$.
  for each episode τ in mini-batch $\mathcal{B}$ **do**
    Compute episode likelihood: $l_\theta(\tau)$.
    Compute importance weight: $w(\tau) = \frac{p(\tau)}{q(\tau)}$.
  end for
  Aggregate: $\mathcal{L}(\theta) \leftarrow \sum_{\tau\in\mathcal{B}} w(\tau)\log l_\theta(\tau)$.
  Compute effective sample size $\text{ESS}(\mathcal{B})$.
  Update model parameters: $\theta \leftarrow \text{OPT}(\frac{\mathcal{L}(\theta)}{\text{ESS}(\mathcal{B})})$.
until parameters θ have converged.

We consider two settings for the estimation of μ and σ^2: offline and online. The *offline* setting consists of sampling $1,000$ training episodes before training, and computing μ, σ^2 using a model pre-trained on the same base dataset. Though this setting seems unrealistic, *i.e.* having access to a pre-trained model, several meta-learning few shot methods start with a pre-trained model which they further build upon. Hence, for such methods there is no overhead. For the *online* setting, we estimate the parameters on-the-fly using the model currently being trained. This is justified by the analysis in Section 5.2 which shows that episode difficulty transfers across model parameters during training. We update our estimates of μ, σ^2 with an exponential moving average:

$$\mu \leftarrow \lambda\mu + (1-\lambda)\Omega_{l_\theta}(\tau) \quad \text{and} \quad \sigma^2 \leftarrow \lambda\sigma^2 + (1-\lambda)(\Omega_{l_\theta}(\tau) - \mu)^2,$$

where $\lambda \in [0, 1]$ controls the adjustment rate of the estimates, and the initial values of μ, σ^2 are computed in a warm-up phase lasting 100 iterations. Keeping $\lambda = 0.9$ worked well for all our experiments (Section 5). We opted for this simple implementation as more sophisticated approaches like West [51] yielded little to no benefit.

3.3 Modeling the target distribution

Similar to the proposal distribution, we model the target distribution by its induced distribution over episode difficulty. Our experiments compare four different approaches, all of which share parameters μ, σ^2 with the normal model of the proposal distribution. For numerical stability, we truncate the support of all distributions to $[\mu - 2.58\sigma, \mu + 2.58\sigma]$, which gives approximately 99% coverage for the normal distribution centered around μ.

The first approach (HARD) takes inspiration from hard negative mining [44], where we wish to sample only more challenging episodes. The second approach (EASY) takes a similar view but instead only samples easier episodes. We can model both distributions as follows:

$$\mathcal{U}(\Omega_{l_\theta}(\tau) \mid \mu, \mu + 2.58\sigma) \tag{HARD}$$

and

$$\mathcal{U}(\Omega_{l_\theta}(\tau) \mid \mu - 2.58\sigma, \mu) \tag{EASY}$$

where $\mathcal{U}$ denotes the uniform distribution. The third (CURRICULUM) is motivated by curriculum learning [1], which slowly increases the likelihood of sampling more difficult episodes:

$$\mathcal{N}(\Omega_{l_\theta}(\tau) \mid \mu_t, \sigma^2) \qquad \text{(CURRICULUM)}$$

where μ_t is linearly interpolated from $\mu - 2.58\sigma$ to $\mu + 2.58\sigma$ as training progresses. Finally, our fourth approach, UNIFORM, resembles distance weighted sampling [52] and consists of sampling uniformly over episode difficulty:

$$\mathcal{U}(\Omega_{l_\theta}(\tau) \mid \mu - 2.58\sigma, \mu + 2.58\sigma). \qquad \text{(UNIFORM)}$$

Intuitively, UNIFORM can be understood as a uniform prior over unseen test episodes, with the intention of performing well across the entire difficulty spectrum. This acts as a regularizer, forcing the model to be equally discriminative for both easy and hard episodes.

4 Related Works

This paper studies task sampling in the context of few-shot [30, 11] and meta-learning [42, 48].

Few-shot learning. This settings has received a lot of attention over recent years [49, 36, 40, 15]. Broadly speaking, state-of-the-art methods can be categorized in two major families: metric-based and gradient-based.

Metric-based methods learn a shared feature extractor which is used to compute distance between samples in embedding space [46, 2, 37, 25]. The choice of metric mostly differentiates one method from another; for example, popular choices include Euclidean distance [46], cosine similarity [16], support vector machines [27], set-to-set functions [54], or the earth-mover distance [57].

Gradient-based algorithms such as MAML [12], propose an objective to learn a network initialization that can quickly adapt to new tasks. Due to its minimal assumptions, MAML has been extended to probabilistic formulations [18, 55] to incorporate learned optimizers — implicit [13] or explicit [33] — and simplified to avoid expensive second-order computations [31, 35]. In that line of work, ANIL [34] claims to match MAML's performance when adapting only the last classification layer – thus greatly reducing computational burden and bringing gradient and metric-based methods closer together.

Sampling strategies. Sampling strategies have been studied for different training regimes. Wu et al. [52] demonstrated that "sampling matters" in the context of metric learning. They propose to sample a triplet with probability proportional to the distance of its positive and negative samples, and observe stabilized training and improved accuracy. This observation was echoed by Katharopoulos and Fleuret [23] when sampling mini-batches: carefully choosing the constituting samples in the mini-batch improves convergence rate and asymptotic performance. Like ours, their method builds on importance sampling [45, 10, 22] but whereas they compute importance weights using the magnitude of the model's gradients, we use the episode's difficulty. Similar insights were also observed in reinforcement learning, where Schaul et al. [41] suggests a scheme to sample transitions according to the temporal difference error.

Closer to our work, Sun et al. [47] present a hard-mining scheme where the most challenging classes across episodes are pooled together and used to create new episodes. Observing that the difficulty of a class is intrinsically linked to the other classes in the episode, Liu et al. [28] propose a mechanism to track difficulty across every class pair. They use this mechanism to build a curriculum [1, 53] of increasingly difficult episodes.

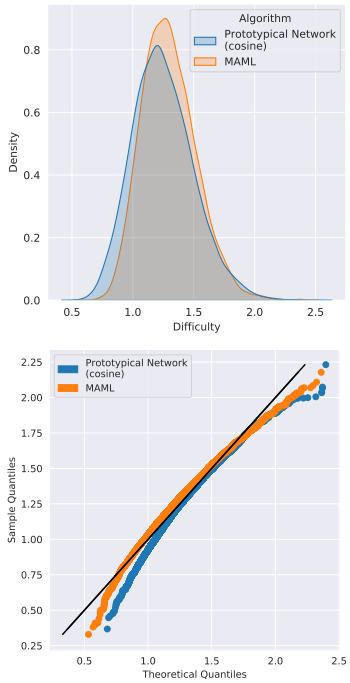

Figure 1: **Episode difficulty is approximately normally distributed.** Density (top) and Q-Q (bottom) plots of the episode difficulty computed by conv$(64)_4$'s on Mini-ImageNet (1-shot 5-way), trained with ProtoNet (cosine) and MAML. The density plot follows a bell curve and the Q-Q plot is close to identity, both suggesting that episode difficulty distribution can be normally approximated.

In contrast to these two approaches, our proposed method makes use of importance sampling to mimic the target distribution rather than sampling from it directly. This helps achieve fast and efficient sampling without any pre-processing requirements.

5 Experiments

We first validate the assumptions underlying our proposed IS estimator and shed light on the properties of episode difficulty. Then, we answer our question, namely: *what is the best way to sample episodes?* Finally, we ask if better sampling improves few-shot classification.

5.1 Experimental setup

We review the standardized few-shot benchmarks used. A detailed description (incl. hyper-parameters, compute) can be found in the Appendix.

Datasets. We use two standardized image classification datasets, Mini-ImageNet [49] and Tiered-ImageNet [38], both subsets of ImageNet [8]. Mini-ImageNet consists of 64 classes for training, 16 for validation, and 20 for testing; we use the class splits introduced by Ravi and Larochelle [36]. Tiered-ImageNet contains 608 classes split into 351, 97, and 160 for training, validation, and testing, respectively.

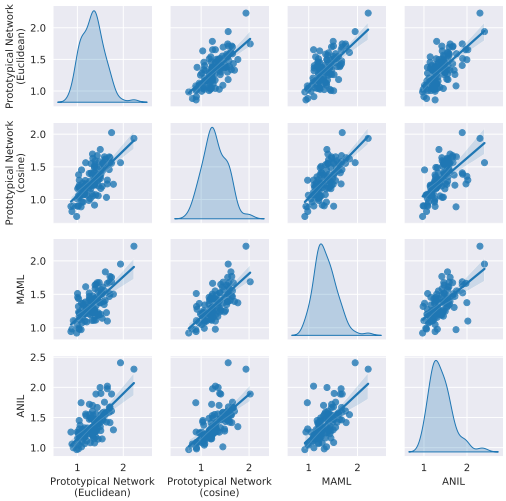

Figure 2: **Episode difficulty transfers across training algorithms.** Scatter plots (with regression lines) of the episode difficulty computed on 1k Mini-ImageNet test episodes (1-shot 5-way) by conv$(64)_4$'s trained using different algorithms. The positive correlation suggests that an episode that is difficult for one training algorithm will be difficult for another.

Network architectures. We train two different models, a 4-layer convolution network conv$(64)_4$ Vinyals et al. [49] with 64 channels per layer. We also use ResNet-12, a 12-layer deep residual network [19], originally introduced in Oreshkin et al. [32]. Both architectures use batch normalization [21] after every convolutional layer and ReLU as the non-linearity.

Training algorithms. For the metric-based family, we use ProtoNet with Euclidean [46] and scaled negative cosine similarity measures [16]. Additionally, we use MAML [12] and ANIL [34] as representative gradient-based algorithms.

Hyper-parameters. We tune hyper-parameters for each algorithm and dataset to work well across different few-shot settings and network architectures. Additionally, we keep the hyper-paramters the same across all different sampling methods for a fair comparison. We train for 20k iterations with a mini-batch of size 16 and 32 for Mini-ImageNet and Tiered-ImageNet respectively, and validate every 1k iterations on 1k episodes. The best performing model is finally evaluated on 1k test episodes.

5.2 Understanding episode difficulty

All the models in this section are trained using baseline sampling, *i.e.*, episodic training without importance sampling as described in Section 2.

Episode difficulty is approximately normally distributed. We begin our analysis by verifying that the distribution over episode difficulty induced by $q(\tau)$ is approximately normal. In Fig. 1, we show a density plot for the difficulty of 10k test episodes sampled with $q(\tau)$. The difficulties are computed using conv$(64)_4$ trained with ProtoNet and MAML on Mini-ImageNet for 1-shot 5-way classification. Episode difficulty follows a bell curve, which is naturally modeled with a normal distribution. Fig. 1 also includes Q-Q plots, typically used to assess normality: the closer

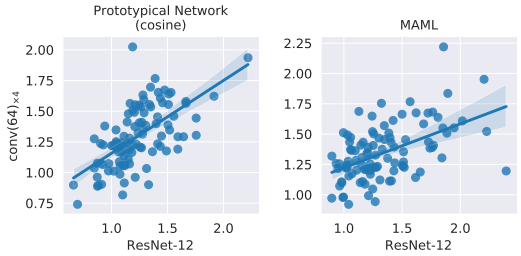

Figure 3: **Episode difficulty transfers across network architectures.** Scatter-plots (with regression lines) of the episode difficulty computed by conv$(64)_4$ and ResNet-12's trained using different algorithms. This is computed for 1k 1-shot 5-way test episodes from Mini-ImageNet. We observe a strong positive correlation between the computed values for both network architectures.

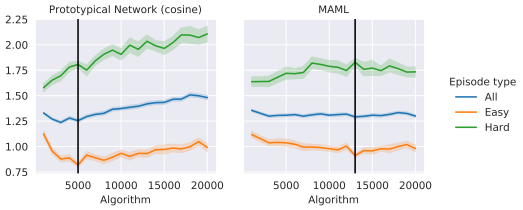

Figure 4: **Episode difficulty is transferred across model parameters during training.** We select the 50 easier and harder episodes and track their difficulty throughout training. The average difficulty of the episodes decreases over time, until convergence (vertical line), after which the model overfits. Additionally, easier episodes remain easy while harder episodes remain hard, indicating that episode difficulty transfers from one set of parameters to the next.

the curve is to the identity line, the closer the distribution is to a normal. Finally, we compute the Shapiro-Wilk test for normality [43], which tests for the null hypothesis that the data is drawn from a normal distribution. Since the p-value for this test is sensitive to the sample size[3], we subsample 50 values 100 times and average rejection rates over these subsets. With $\alpha = 0.05$, the null hypothesis is rejected 14% and 17% of the time for Mini-ImageNet and Tiered-ImageNet respectively, thus suggesting that episode difficulty can be reliably approximated with a normal distribution.

Independence from modeling choices. The notion of episode difficulty is tightly coupled to the model likelihood l_θ, and hence to the modeling variables such as network architecture, learning algorithm, and model parameters. We check if episode difficulty transfers across different choices for these variables. We are concerned with the *relative ranking* of the episode difficulty and not the actual values.To this end, we will use the Spearman rank-order correlation coefficient, a non-parametric measure of the monotonicity of the relationship between two sets of values. It varies within $[-1; 1]$, with 0 implying no correlation and $+1$ and -1 implying exact positive and negative relationships.

Firstly, we check the dependence on the training algorithm. Across all 4 algorithms, the Spearman rank-order correlation coefficients for the episode difficulty of 1k Mini-ImageNet test episodes (1-shot 5-way) on conv$(64)_4$'s is > 0.65. This positive correlation is illustrated in Fig. 2 and suggests that an episode that is difficult for one training algorithm is very likely to be difficult for another.

Next we analyze the dependence on the network architecture. We use conv$(64)_4$ and ResNet-12's trained on Mini-ImageNet (1-shot 5-way) with all training algorithms, and compute the Spearman correlation for episode difficulties for 1k test episodes across the two architectures, for a given algorithm. The correlation coefficients are

Table 1: **Few-shot accuracies on benchmark datasets for 5-way few-shot episodes in the offline setting.** Best results for a fixed scenario are shown in bold, † indicates matching or improving over baseline sampling.

	Mini-ImageNet	
	1-shot (%)	5-shot (%)
ProtoNet (Euclidean)	49.67±0.64	67.45±0.51
+ EASY	51.08±0.63†	67.30±0.52†
+ HARD	52.50±0.62†	**71.03±0.51**†
+ CURRICULUM	50.00±0.61†	70.49±0.51†
+ UNIFORM	**53.94±0.63**†	**70.79±0.49**†
ProtoNet (cosine)	52.85±0.64	62.11±0.52
+ EASY	53.35±0.63†	63.55±0.53†
+ HARD	52.65±0.63†	70.15±0.51†
+ CURRICULUM	53.21±0.65†	65.89±0.52†
+ UNIFORM	**54.27±0.65**†	**70.85±0.51**†
MAML	49.92±0.65	63.93±0.59
+ EASY	51.62±0.67†	64.33±0.61†
+ HARD	49.57±0.69†	**66.93±0.55**†
+ CURRICULUM	**52.21±0.67**†	66.25±0.60†
+ UNIFORM	**52.65±0.65**†	**66.76±0.57**†
ANIL	**49.65±0.65**	59.51±0.56
+ EASY	49.40±0.64†	56.73±0.60
+ HARD	47.91±0.62	62.05±0.59†
+ CURRICULUM	**50.22±0.66**†	61.76±0.57†
+ UNIFORM	**49.56±0.62**†	**64.72±0.60**†

[3]For a large sample size, the p-values are not reliable as they may detect trivial departures from normality.

0.57 for ProtoNet (Euclidean), 0.72 for ProtoNet (cosine), 0.58 for MAML, and 0.49 for ANIL. Fig. 3 illustrates this correlation, suggesting that episode difficulty is transferred across network architectures with high probability.

Lastly, we study the dependence on model parameters during training. We select the 50 *easiest* and 50 *hardest* episodes, *i.e.*, episodes with the lowest and highest difficulty respectively, from 1k test episodes. We track the episode difficulty for all episodes over the training phase and visualize the trend in Fig. 4 for conv$(64)_4$'s trained using ProtoNet (cosine) and MAML on Mini-ImageNet (1-shot 5-way). Throughout training, easy episodes remain easy and hard episodes remain hard, hence suggesting that episode difficulty transfers across different model parameters during training. These observations justify the *online* modeling of the proposal distribution with running averages in Section 3.1.

5.3 Comparing episode sampling methods

Now, we compare different methods for episode sampling. To ensure fair comparisons, we use the offline formulation of Section 3.3 so that all sampling methods share the same pre-trained network when computing proposal likelihoods. We compute results over 2 datasets, 2 network architectures, 4 algorithms and 2 few-shot protocols, resulting in 24 total scenarios. The full suite of results is available in the Appendix, while Table 1 reports a representative sample across training algorithms and Table 2 across datasets.

We observe that, although not strictly dominant, UNIFORM tends to outperform other methods as it is within statistical confidence of the best method in $19/24$ scenarios. On the $5/24$ scenarios where UNIFORM underperforms, it closely trails behind the best methods: the average degradation is -0.58%, and at most -1.44%. Conversely, it boosts accuracy over baseline sampling by as much as 8.74% and on average by 3.17%. We attribute this overall good performance to implicit regularization of uniform sampling; namely, putting a uniform prior on the set of test episodes and encouraging the model to perform well on the whole gamut of episode difficulty. Second best is baseline sampling as it is statistically competitive on $10/24$ scenarios, while EASY, HARD, and CURRICULUM only appear among the better methods in $4/24, 4/24, 9/24$ scenarios, respectively.

Table 2: **Few-shot accuracies on benchmark datasets for 5-way few-shot episodes in the offline setting.** Mean accuracy and 95% confidence interval computed over 1k test episodes. Best results for a fixed scenario are shown in bold, † indicates matching or improving over baseline sampling.

	Mini-ImageNet				Tiered-ImageNet	
	conv$(64)_4$		ResNet-12		ResNet-12	
	1-shot (%)	5-shot (%)	1-shot (%)	5-shot (%)	1-shot (%)	5-shot (%)
ProtoNet (cosine)	**50.03±0.61**	61.56±0.53	52.85±0.64	62.11±0.52	**60.01±0.73**	72.75±0.59
+ EASY	**49.60±0.61**†	65.17±0.53†	53.35±0.63†	63.55±0.53†	**60.03±0.75**†	74.65±0.57†
+ HARD	49.01±0.60	**66.45±0.50**†	52.65±0.63†	70.15±0.51†	55.44±0.72	75.97±0.55†
+ CURRICULUM	49.38±0.61	64.12±0.53†	53.21±0.65†	65.89±0.52†	**60.37±0.76**†	75.32±0.58†
+ UNIFORM	**50.07±0.59**†	**66.33±0.52**†	**54.27±0.65**†	**70.85±0.51**†	**60.27±0.75**†	**78.36±0.54**†

5.4 Online approximation of the proposal distribution

Although the offline formulation is better suited for analysis experiments, it is expensive as it requires a pretraining phase for the proposal network and 2 forward passes during episodic training (one for the episode loss, another for the proposal density). In this section, we show that the online formulation faithfully approximates offline sampling and can retain most of the performance improvements from UNIFORM.

We take the same 24 scenarios as in the previous subsection, and compare baseline sampling against offline and online UNIFORM. Table 3 reports the full suite of results, where we see that baseline is statistically competitive on $8/24$ scenarios; on the other hand, offline and online UNIFORM perform similarly in aggregate, as they are within the best results in $16/24$ and $15/24$ scenarios respectively. We also compute the mean accuracy difference between the offline and online formulation, which is

$0.07\% \pm 0.35$ accuracy points and further confirms that both methods produce quantitatively similar outcomes.

Table 3: **Few-shot accuracies on benchmark datasets for 5-way few-shot episodes in the offline and online settings.** Mean accuracy and 95% confidence interval are for 1k test episodes. Best results for a fixed scenario are shown in bold, † indicates matching or improving over baseline sampling.

	Mini-ImageNet				Tiered-ImageNet	
	conv$(64)_4$		ResNet-12		ResNet-12	
	1-shot (%)	5-shot (%)	1-shot (%)	5-shot (%)	1-shot (%)	5-shot (%)
ProtoNet (Euclidean)	**49.06±0.60**	65.28±0.52	49.67±0.64	67.45±0.51	**59.10±0.73**	76.95±0.56
+ UNIFORM (Offline)	48.19±0.62	66.73±0.52†	**53.94±0.63**†	**70.79±0.49**†	58.63±0.76†	**78.62±0.55**†
+ UNIFORM (Online)	48.39±0.62	**67.86±0.50**†	52.97±0.64†	**70.63±0.50**†	**59.67±0.70**†	**78.73±0.55**†
ProtoNet (cosine)	**50.03±0.61**	61.56±0.53	52.85±0.64	62.11±0.52	60.01±0.73	72.75±0.59
+ UNIFORM (Offline)	**50.07±0.59**†	**66.33±0.52**†	**54.27±0.65**†	**70.85±0.51**†	60.27±0.75†	**78.36±0.54**†
+ UNIFORM (Online)	**50.06±0.61**†	**65.99±0.52**†	**53.90±0.63**†	68.78±0.51†	**61.37±0.72**†	77.81±0.56†
MAML	**46.88±0.60**	55.16±0.55	49.92±0.65	63.93±0.59	55.37±0.74	**72.93±0.60**
+ UNIFORM (Offline)	**46.67±0.63**†	**62.09±0.55**†	**52.65±0.65**†	**66.76±0.57**†	54.58±0.77	72.00±0.66
+ UNIFORM (Online)	**46.70±0.61**†	**61.62±0.54**†	51.17±0.68†	65.63±0.57†	**57.15±0.74**†	71.67±0.67
ANIL	**46.59±0.60**	**63.47±0.55**	**49.65±0.65**	59.51±0.56	**54.77±0.76**	69.28±0.67
+ UNIFORM (Offline)	**46.93±0.62**†	62.75±0.60	**49.56±0.62**†	**64.72±0.60**†	54.15±0.79†	**70.44±0.69**†
+ UNIFORM (Online)	**46.82±0.63**†	62.63±0.59	**49.82±0.68**†	**64.51±0.62**†	**55.18±0.74**†	69.55±0.71†

5.5 Better sampling improves few-shot classification

The results in the previous subsection suggest that online UNIFORM yields a *simple and universally applicable* method to improve episode sampling. To validate that state-of-the-art methods can also benefit from better sampling, we take the recently proposed FEAT [54] algorithm and augment it with our IS-based implementation of online UNIFORM. Concretely, we use their open-source implementation[4] to train both baseline and UNIFORM sampling. We use the prescribed hyper-parameters without any modifications. Results for ResNet-12 on Mini-ImageNet and Tiered-ImageNet are reported in Section 5.5, where online UNIFORM outperforms baseline sampling on $3/4$ scenerios and is matched on the remaining one. Thus, better episodic sampling can improve few-shot classification even for the very best methods.

	Mini-ImageNet	
	1-shot (%)	5-shot (%)
FEAT	66.02±0.20	81.17±0.14
+ UNIFORM (online)	**66.27±0.20**	**81.54±0.14**
	Tiered-ImageNet	
	1-shot (%)	5-shot (%)
FEAT	**70.50±0.23**	84.26±0.16
+ UNIFORM (online)	**70.61±0.23**	**84.42±0.16**

Table 4: **Combining FEAT with UNIFORM.** Mean accuracy and 95% confidence interval over 10k test episodes with a ResNet-12. FEAT improves with better sampling in 3/4 scenarios.

6 Conclusion

This manuscript presents a careful study of sampling in the context of few-shot learning, with an eye on episodes and their difficulty. We conduct a thorough empirical study on episode difficulty and its properties which facilitates us to introduce importance sampling in the context of episodic training. This simple and efficient method can approximate *any* episodic sampling scheme while remaining agnostic to the choice of learning algorithm. We use this method to empirically analyse different episodic sampling schemes and propose to sample uniformly over episode difficulty. This scheme performs the best across several datasets, training algorithms, network architectures and few-shot protocols. Additionally, an online version of the algorithm results in a similar performance boost without much computational overhead.

[4] Available at: `https://github.com/Sha-Lab/FEAT`

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The checklist follows the references. Please read the checklist guidelines carefully for information on how to answer these questions. For each question, change the default **[TODO]** to [Yes] , [No] , or [N/A] . You are strongly encouraged to include a **justification to your answer**, either by referencing the appropriate section of your paper or providing a brief inline description. For example:

- Did you include the license to the code and datasets? [Yes] See Section **??**.
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Please do not modify the questions and only use the provided macros for your answers. Note that the Checklist section does not count towards the page limit. In your paper, please delete this instructions block and only keep the Checklist section heading above along with the questions/answers below.

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes] Covered in Section 3 and Section 5
   (b) Did you describe the limitations of your work? [Yes] Yes, we extensively discuss our assumptions in Section 5.2.
   (c) Did you discuss any potential negative societal impacts of your work? [No] Our work is an empirical analysis of existing algorithms.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes] And as far as we understand our work is a good example of the "indirectness" difficulty mentioned there.
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   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]