DeepCore: A Comprehensive Library for Coreset Selection in Deep Learning

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Abstract. Coreset selection, which aims to select a subset of the most informative training samples, is a long-standing learning problem that can benefit many downstream tasks such as data-efficient learning, continual learning, neural architecture search, active learning, etc. However, many existing coreset selection methods are not designed for deep learning, which may have high complexity and poor generalization performance. In addition, the recently proposed methods are evaluated on models, datasets, and settings of different complexities. To advance the research of coreset selection in deep learning, we contribute a comprehensive code library³, namely DeepCore, and provide an empirical study on popular coreset selection methods on CIFAR10 and ImageNet datasets. Extensive experiments on CIFAR10 and ImageNet datasets verify that, although various methods have advantages in certain experiment settings, random selection is still a strong baseline.

Keywords: Coreset selection · Data-efficient learning · Deep learning

1 Introduction

Deep learning has shown unprecedented success in many research areas such as computer vision, etc. As it evolves, not only neural networks but also the training datasets are becoming increasingly larger, which requires massive memory and computation to achieve the state-of-the-art. One promising technique to reduce the computational cost is coreset selection [32,21,38,20] that aims to select a small subset of the most informative training samples \( S \) from a given large training dataset \( T \). The models trained on the coreset are supposed to have close generalization performance to those trained on the original training set.

³ The code is available in https://github.com/PatrickZH/DeepCore.

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Coreset selection has been widely studied since the era of traditional machine learning, whose research generally focuses on how to approximate the distribution of the whole dataset with a subset, for example, they assume that data are from a mixture of Gaussians in a given metric space [52,7,13,4,3]. However, for those classic coreset selection methods proposed for traditional machine learning tasks, their effectiveness in deep learning is doubtful, due to the high computational complexity and fixed data representations. Recently, the research of coreset selection for deep learning tasks emerges [49,38,21]. The newly developed coreset selection methods are evaluated in different settings in terms of models, datasets, tasks, and selection fractions, resulting in their performances hardly being compared fairly.

We focus our studies on image classification tasks. To address the above problems, in this paper, we provide an exhaustive empirical study on popular coreset selection methods in the same settings. We contribute a comprehensive code library, namely DeepCore, for advancing the research of coreset selection in deep learning. Specifically, we re-implement 12 popular coreset selection methods in a unified framework based on PyTorch [37]. These methods are compared in settings of various selection fractions from 0.1% to 90% on CIFAR10 [25] and ImageNet-1K [39] datasets. Besides the reported results in the paper, our library supports popular deep neural architectures, image classification datasets and coreset selection settings.

2 Review of Coreset Selection Methods

In this section, we first formulate the problem of coreset selection. Then, brief surveys of methods and applications of coreset selection are provided respectively.

2.1 Problem Statement

In a learning task, we are given a large training set \( \mathcal{T} = \{(x_i, y_i)\}_{i=1}^{|\mathcal{T}|} \), where \( x_i \in \mathcal{X} \) is the input, \( y_i \in \mathcal{Y} \) is the ground-truth label of \( x_i \), where \( \mathcal{X} \) and \( \mathcal{Y} \) denote the input and output spaces, respectively. Coreset selection aims to find the most informative subset \( S \subset \mathcal{T} \) with the constraint \( |S| < |\mathcal{T}| \), so that the model \( \theta^S \) trained on \( S \) has close generalization performance to the model \( \theta^\mathcal{T} \) trained on the whole training set \( \mathcal{T} \).

2.2 Survey: Methodologies

**Geometry Based Methods** It is assumed that data points close to each other in the feature space tend to have similar properties. Therefore, geometry based methods [7,41,46,1] try to remove those data points providing redundant information then the left data points form a coreset \( S \) where \( |S| \ll |\mathcal{T}| \).

**HERDING.** The HERDING method selects data points based on the distance between the coreset center and original dataset center in the feature space. The
algorithm incrementally and greedily adds one sample each time into the coreset that can minimize distance between two centers [52,7].

**K-CENTER GREEDY**. This method tries to solve the *minimax facility location* problem [12], i.e. selecting $k$ samples as $S$ from the full dataset $T$ such that the largest distance between a data point in $T \setminus S$ and its closest data point in $S$ is minimized:

$$\min_{S \subseteq T} \max_{x_i \in T \setminus S} \min_{x_j \in S} D(x_i, x_j),$$

where $D(\cdot, \cdot)$ is the distance function. The problem is NP-hard, and a greedy approximation known as K-CENTER GREEDY has been proposed in [41]. K-CENTER GREEDY has been successfully extended to a wide range of applications, for instance, active learning [41,1] and efficient GAN training [46].

**Uncertainty Based Methods** Samples with lower confidence may have a greater impact on model optimization than those with higher confidence, and should therefore be included in the coreset. The following are commonly used metrics of sample uncertainty given a certain classifier and training epoch, namely LEAST CONFIDENCE, ENTROPY and MARGIN [9], where $C$ is the number of classes. We select samples in descending order of the scores:

$$s_{\text{least confidence}}(x) = 1 - \max_{i=1,...,C} P(\hat{y} = i | x)$$

$$s_{\text{entropy}}(x) = -\sum_{i=1}^{C} P(\hat{y} = i | x) \log P(\hat{y} = i | x)$$

$$s_{\text{margin}}(x) = 1 - \min_{y \neq \hat{y}} (P(\hat{y} | x) - P(y | x)).$$

**Error/Loss Based Methods** In a dataset, training samples are more important if they contribute more to the error or loss when training neural networks. Importance can be measured by the loss or gradient of each sample or its influence on other samples’ prediction during model training. Those samples with the largest importance are selected as the coreset.

**FORGETTING EVENTS**. Toneva et al. [49] count how many times the *forgetting* happens during the training, i.e. the misclassification of a sample in the current epoch after having been correctly classified in the previous epoch, formally $acc_i^t > acc_i^{t+1}$, where $acc_i^t$ indicates the correctness (True or False) of the prediction of sample $i$ at epoch $t$. The number of forgetting reveals intrinsic properties of the training data, allowing for the removal of unforgettable examples with minimal performance drop.

**GRAND and EL2N Scores**. The GRAND score [38] of sample $(x, y)$ at epoch $t$ is defined as

$$\chi_t(x, y) \triangleq \mathbb{E}_{\theta, t} ||\nabla_{\theta, t} \ell(x, y; \theta_t)||_2.$$

It measures the average contribution from each sample to the decline of the training loss at early epoch $t$ across several different independent runs. The score calculated at early training stages, e.g. after a few epochs, works well, thus
this method requires less computational cost. An approximation of the GRAND score is also provided, named EL2N score, which measures the norm of error vector:

$$\chi^*_t(x, y) \triangleq \mathbb{E}_{\theta_t} ||p(\theta_t, x) - y||_2.$$  

(4)

**Importance Sampling.** In importance sampling (or adaptive sampling), we define $s(x, y)$ is the upper-bounded (worst-case) contribution to the total loss function from the data point $(x, y)$, aka sensitivity score. It can be formulated as:

$$s(x, y) = \max_{\theta \in \theta} \frac{\ell(x, y; \theta)}{\sum_{(x', y') \in T} s(x', y')}.$$  

(5)

where $\ell(x, y)$ is a non-negative cost function with parameter $\theta \in \theta$. For each data point in $T$, the probability of being selected is set as $p(x, y) = \frac{s(x, y)}{\sum_{(x, y) \in T} s(x, y)}$. The coreset $S$ is constructed based on the probabilities [3,34]. Similar ideas are proposed in *Black box learners* [10] and JTT [30], where wrongly classified samples will be upweighted or their sampling probability will be increased.

**Decision Boundary Based Methods** Since data points distributed near the decision boundary are hard to separate, those data points closest to the decision boundary can also be used as the coreset.

**Adversarial DeepFool.** While exact distance to the decision boundary is inaccessible, Ducoffe and Precioso [11] seek the approximation of these distances in the input space $\mathcal{X}$. By giving perturbations to samples until the predictive labels of samples are changed, those data points require the smallest adversarial perturbation are closest to the decision boundary.

**Contrastive Active Learning.** To find data points near the decision boundary, Contrastive Active Learning (CAL) [31] selects samples whose predictive likelihood diverges the most from their neighbors to construct the coreset.

**Gradient Matching Based Methods** Deep models are usually trained using (stochastic) gradient descent algorithm. Therefore, we expect that the gradients produced by the full training dataset $\sum_{(x, y) \in T} \nabla_\theta \ell(x, y; \theta)$ can be replaced by the (weighted) gradients produced by a subset $\sum_{(x, y) \in S} w_x \nabla_\theta \ell(x, y; \theta)$ with minimal difference:

$$\min_{w, S} D\left(\frac{1}{|T|} \sum_{(x, y) \in T} \nabla_\theta \ell(x, y; \theta), \frac{1}{|W|_1} \sum_{(x, y) \in S} w_x \nabla_\theta \ell(x, y; \theta)\right)$$  

(6)

where $w$ is the subset weight vector, $|W|_1$ is the sum of the absolute values and $D(\cdot, \cdot)$ measures the distance between two gradients.

**Craig.** Mirzasoleiman et al. [32] try to find an optimal coreset that approximates the full dataset gradients under a maximum error $\varepsilon$ by converting gradient matching problem to the maximization of a monotone submodular function $F$ and then use greedy approach to optimize $F$. 

The coreset $S$ is constructed based on the probabilities [3,34]. Similar ideas are proposed in *Black box learners* [10] and JTT [30], where wrongly classified samples will be upweighted or their sampling probability will be increased.
GradMatch. Compared to CRAIG, the GradMatch [20] method is able to achieve the same error $\varepsilon$ of the gradient matching but with a smaller subset. GradMatch introduces a squared $l_2$ regularization term over the weight vector $w$ with coefficient $\lambda$ to discourage assigning large weights to individual samples. To solve the optimization problem, it presents a greedy algorithm — Orthogonal Matching Pursuit, which can guarantee $1 - e^{\frac{-\lambda}{\lambda + k\nabla_{\max}^2}}$ error with the constraint $|S| \leq k$, $k$ is a preset constant.

Bilevel Optimization Based Methods Coreset selection can be posed as a bilevel optimization problem. Existing studies usually consider the selection of subset (optimization of samples $S$ or selection weights $w$) as the outer objective and the optimization of model parameters $\theta$ on $S$ as the inner objective. Representative methods include cardinality-constrained bilevel optimization [5] for continual learning, RETRIEVE for semi-supervised learning (SSL) [22], and GLISTER [21] for supervised learning and active learning.

RETRIEVE. The RETRIEVE method [22] discusses the scenario of SSL under bilevel optimization, where we have both a labeled set $T$ and an unlabeled set $P$. The bilevel optimization problem in RETRIEVE is formulated as

$$w^* = \arg \min_w \sum_{(x, y) \in T} \ell_s(x, y; \arg \min_\theta \sum_{(x, y) \in T} \ell_s(x, y; \theta) + \lambda \sum_{x \in P} w_x \ell_u(x; \theta)),$$

where $\ell_s$ is the labeled-data loss, e.g. cross-entropy and $\ell_u$ is the unlabeled-data loss for SSL, e.g. consistency-regularization loss. $\lambda$ is the regularization coefficient.

GLISTER. To guarantee the robustness, GLISTER [21] introduces a validation set $V$ on the outer optimization and the log-likelihood $\ell \ell$ in the bilevel optimization:

$$S^* = \arg \max_{S \subset T} \sum_{(x, y) \in V \setminus \ell \ell(x, y; \arg \max_\theta \sum_{(x, y) \in S} \ell \ell(x, y; \theta)).$$

Submodularity Based Methods Submodular functions [17] are set functions $f : 2^V \to \mathbb{R}$, which return a real value for any $\mathcal{U} \subset V$. $f$ is a submodular function, if for $\mathcal{A} \subset \mathcal{B} \subset V$ and $\forall x \in V \setminus \mathcal{B}$:

$$f(\mathcal{A} \cup \{x\}) - f(\mathcal{A}) \geq f(\mathcal{B} \cup \{x\}) - f(\mathcal{B}).$$

Submodular functions naturally measure the diversity and information, thus can be a powerful tool for coreset selection by maximizing them. Many functions obey the above definition, e.g. Graph Cut (GC), Facility Location (FL), Log Determinant [16], etc. For maximizing submodular functions under cardinality constraint, greedy algorithms have been proved to have a bounded approximation factor of $1 - \frac{1}{e}$ [35].

Fass. Wei et al. [51] discuss the connection between likelihood functions and submodularity, proving that under a cardinality constraint, maximizing likelihood function is equivalent to maximization of submodular functions for Naïve
Bayes or Nearest Neighbor classifier, naturally providing a powerful tool for coreset selection. By introducing submodularity into Naive Bayes and Nearest Neighbor, they propose a novel framework for active learning namely **FILTERED ACTIVE SUBMODULAR SELECTION (FASS)**.

**Prism.** Kaushal et al. [19] develop **Prism**, a submodular method for **targeted subset selection**, which is a learning scenario similar to active learning. In targeted subset selection, a subset \( S \) will be selected to be labeled from a large unlabeled set \( P \), with additional requirement that \( S \) has to be aligned with the targeted set \( T \) of specific user intent.

**Similar.** Kothawade et al. [24] introduce **Similar**, a unified framework of submodular methods that successfully extends submodularity to broader settings which may involve rare classes, redundancy, out-of-distribution data, etc.

**Proxy Based Methods**

Many coreset selection methods require to train models on the whole dataset for calculating features or some metrics for one or many times. To reduce this training cost, **Selecion via Proxy** methods [9,40] are proposed, which train a lighter or shallower version of the target models as proxy models. Specifically, they create proxy models by reducing hidden layers, narrowing dimensions, or cutting down training epochs. Then, coresets are selected more efficiently on these proxy models.

2.3 Survey: Applications

**Data-efficient Learning.** The basic application of coreset selection is to enable efficient machine learning [49,32,38,20]. Training models on coresets can reduce the training cost while preserving testing performance. Especially, in Neural Architecture Search (NAS) [44], thousands to millions deep models have to be trained and then evaluated on the same dataset. Coreset can be used as a proxy dataset to efficiently train and evaluate candidates [9,40], which significantly reduces computational cost.

**Continual Learning.** Coreset selection is also a key technique to construct memory for continual learning or incremental learning [2,5,55], in order to relieve the catastrophic forgetting problem. In the popular continual learning setting, a memory buffer is maintained to store informative training samples from previous tasks for rehearsal in future tasks. It is proven that continual learning performance heavily relies on the quality of memory, i.e. coreset [23].

**Active Learning.** Active learning [42,43] aims to achieve better performance with the minimal query cost by selecting informative samples from the unlabeled pool \( P \) to label. Thus, it can be posed as a coreset selection problem [51,41,11,24,31].

Besides the above, coreset selection is studied and successfully applied in many other machine learning problems, such as robust learning against noise [33,22,24], clustering [4,3,47], semi-supervised learning [6,22], unsupervised learning [18], efficient GAN training [46], regression tasks [34,8] etc.
3 DeepCore Library

In the literature, coreset selection methods have been proposed and tested in different experiment settings in terms of dataset, model architecture, coreset size, augmentation, training strategy, etc. This may lead to unfair comparisons between different methods and unconvincing conclusions. For instance, some methods may have only been evaluated on MNIST with shallow models, while others are tested on the challenging ImageNet dataset with deep neural networks. Even though tested on the same dataset, different works are likely to use different training strategies and data augmentations which significantly affect the performance. Furthermore, it causes future researchers inconvenience in identifying and improving the state-of-the-art.

Therefore, we develop DeepCore, an extensive and extendable code library, for coreset selection in deep learning, reproducing dozens of popular and advanced coreset selection methods and enabling a fair comparison of different methods in the same experimental settings. DeepCore is highly modular, allowing to add new architectures, datasets, methods and learning scenarios easily. We build DeepCore on PyTorch [37].

**Coreset Methods.** We list the methods that have been re-implemented in DeepCore according to the categories in 2.2, they are 1) geometry based methods **Contextual Diversity (CD)** [1], **Herding** [52] and **k-Center Greedy** [41]; 2) uncertainty based methods **Least Confidence**, **Entropy** and **Margin** [9]; 3) error/loss based methods **Forgetting** [49] and **GRaND** [38]; 4) decision boundary based methods **CAL** [31] and **DEEPFOOL** [11]; 5) gradient matching based methods **CRAIG** [32] and **GRADMATCH** [20]; 6) bilevel optimization methods **GLiSTER** [21]; and 7) submodularity based methods with **GRAPH CUT (GC)** and **FACILITY LOCATION (FL)** functions [16]. We also have **RANDOM** selection as the baseline.

**Datasets.** We provide the experiment results on CIFAR10 [25] and ImageNet-1K [39] in this paper. Besides, our DeepCore has provided the interface for other popular computer vision datasets, namely MNIST [29], QMNIST [54], FashionMNIST [53], SVHN [36], CIFAR100 [25] and TinyImageNet [27].

**Network Architectures.** We provide the code of popular architectures, namely MLP, LeNet [28], AlexNet [26], VGG [45], Inception-v3 [48], ResNet [14], WideResNet [56] and MobileNet-v3 [15].

4 Experiment Results

In this section, we use our DeepCore to evaluate different coreset selection methods in multiple learning settings on CIFAR10 and ImageNet-1K datasets. ResNet-18 is used as the default architecture in all experiments.

4.1 CIFAR10 Results

For CIFAR10 experiments, we use SGD as the optimizer with batch size 128, initial learning rate 0.1, Cosine decay scheduler, momentum 0.9, weight decay
Forgetting methods outperform size increases, especially when selecting more than 30% training data. Except for a fair comparison, we use the ResNet-18 models trained on the whole dataset for 10 epochs to extract above-mentioned metrics. When gradient vector $\nabla_{\theta} \ell(x,y;\theta)$ is required, we use the gradients of the parameters in the final fully-connected layer as suggested in many previous studies [32,20,21]. This allows gradient vectors to be easily obtained without back-propagation throughout the whole network. While DeepCore supports both balanced and imbalanced sample selection, experiments in this paper all adopt balanced selection, namely, the same number of samples are selected for every class.

Table 1. Coreset selection performances on CIFAR10. We train randomly initialized ResNet-18 on the coresets of CIFAR10 produced by different methods and then test on the real testing set. 5 \times 10^{-4} and 200 training epochs. We select subsets with fractions of 0.1%, 0.5%, 1%, 5%, 10%, 20%, 30%, 40%, 50%, 60%, 90% of the whole training set respectively. The training on the whole dataset can be considered as the upper-bound. For data augmentation, we apply random crop with 4-pixel padding and random flipping on the 32x32 training images.

For some methods, the gradient, prediction probability, or feature vector of each sample is required to implement sample selection. For a fair comparison, we use the ResNet-18 models trained on the whole dataset for 10 epochs to extract above-mentioned metrics. When gradient vector $\nabla_{\theta} \ell(x,y;\theta)$ is required, we use the gradients of the parameters in the final fully-connected layer as suggested in many previous studies [32,20,21]. This allows gradient vectors to be easily obtained without back-propagation throughout the whole network. While DeepCore supports both balanced and imbalanced sample selection, experiments in this paper all adopt balanced selection, namely, the same number of samples are selected for every class.

Tab. 1 shows the detailed results of different methods on CIFAR10, and Fig. 1 depicts the performance curves. The mean and standard deviation is calculated with 5 random seeds. Good experimental results come from the submodular function based methods, in both small and large learning setting. Especially in small fractions of 0.1%-1%, the advantage of submodular function based methods is obvious. Graph Cut (GC) is more prominent among them, and achieves the best results when selecting 0.1% to 10% of the training data. In particular, Graph Cut outperforms the other methods by more than 5% in the testing accuracy when 50 samples are selected per class, i.e. 1% of the whole training set. CAL also shows superiority in small fractions between 0.1%-5%, with performance comparable to Facility Location (FL). However, its superiority disappears when the coreset size increases, especially when selecting more than 30% training data. Except the above methods, all other methods fail to outperform the random sampling baseline in small settings between 0.1% and 1%. Forgetting method outperforms...
others in 30%-fraction setting. Between 40% and 60%, GRANd and uncertainty score based methods stand out. In all fraction settings, GRADMATCH and HERDING barely beat the random sampling. For GRADMATCH, the experiment setting in the original paper is adaptive sampling, where subsets iteratively updated along with network training. Here, for a fair comparison, coresets are selected and then fixed for all training epochs. HERDING is originally designed for fixed representations from a mixture of Gaussians, thus its performance heavily depends on the embedding function. Note that the above findings are based on one hyper-parameter setting, the findings may change if hyper-parameters change. For example, HERDING may have better performances if the model for feature extraction is fully trained. We study the influence of some hyper-parameters later.

### 4.2 ImageNet Results

For ImageNet, we train ResNet-18 models on coresets with batch size 256 for 200 epochs. The training images are randomly cropped and then resized to $224 \times 224$. The left-right flipping with the probability of 0.5 is also implemented. Other experimental settings and hyper-parameters are consistent with CIFAR10 experiments. Due to the long running time of DEEPFOOL on ImageNet, its results are not provided. For k-CENTER GREEDY and CONTEXTUAL DIVERSITY, here we do not provide the results when only 1 sample is selected from each class (i.e. fraction of 0.1%), because their first sample is drawn randomly from each class as initialization. Hence, they are identical to RANDOM baseline for fraction 0.1% on ImageNet. We run all experiments for 3 times with random seeds.
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...are selected as the coreset. However, none of methods will outperform Random experiments on four representative methods, (Forgetting being selected on one architecture and then tested on other architectures. We do good performance are model-agnostic, i.e., whether coresets perform well when we conduct cross-architecture experiments to examine whether methods with different hyper-parameters. The same to that on CIFAR10, these findings on ImageNet may vary when the coreset size is large, i.e., 30% data. Random is still a strong and stable baseline. The same to that on CIFAR10, these findings on ImageNet may vary for different hyper-parameters.

### 4.3 Cross-architecture Generalization

We conduct cross-architecture experiments to examine whether methods with good performance are model-agnostic, i.e., whether coresets perform well when being selected on one architecture and then tested on other architectures. We do experiments on four representative methods, (FORGETTING, GLISTER, GRAND and GRAPH CUT) with four representative architectures (VGG-16 [45], Inception-v3 [48], ResNet-18 [14] and WideResNet-16-8 [56]) under two selection fractions (1% and 10%). All other unspecified settings are the same to those in Sec. 4.1. In Tab. 3, the rows represent models used to obtain coresets, and the columns indicate models on which coresets are evaluated. We can see submodular selection with Graph Cut provides stably good testing results, regardless of which model architecture is used to perform the selection. However, GRAND shows preference of the model on which gradient norms are computed. Coresets obtained on Inception-v3 generally have the best performance, while those obtained on ResNet-18 are the worst. The possible reason is that the ranking of gradient norm is sensitive to the architecture. The architecture used to implement selection also has obvious influence on GLISTER and FORGETTING methods.

| Method   | 0.1%  | 0.5%  | 1%   | 5%   | 10%  | 30%  | 100% |
|----------|-------|-------|------|------|------|------|------|
| Random   | 0.76±0.01 | 3.78±0.14 | 8.85±0.46 | 40.09±0.21 | 52.10±0.22 | 64.11±0.05 | 69.52±0.45 |
| CD       | -     | 1.18±0.06 | 2.16±0.18 | 25.82±0.02 | 43.84±0.12 | 62.13±0.45 | 69.52±0.45 |
| Herding  | 0.34±0.01 | 1.70±0.13 | 4.17±0.26 | 17.41±0.34 | 28.06±0.05 | 48.58±0.49 | 69.52±0.45 |
| k-Center Greedy | - | 1.57±0.09 | 2.06±0.24 | 27.36±0.08 | 44.84±1.03 | 62.12±0.46 | 69.52±0.45 |
| Least Confidence | 0.29±0.04 | 1.03±0.25 | 2.05±0.38 | 27.05±3.25 | 44.47±1.42 | 61.80±0.33 | 69.52±0.45 |
| Entropy  | 0.31±0.02 | 1.01±0.17 | 2.26±0.30 | 28.21±2.83 | 44.68±1.54 | 61.82±0.31 | 69.52±0.45 |
| Margin   | 0.47±0.02 | 1.99±0.29 | 4.73±0.64 | 35.99±1.67 | 50.29±0.92 | 63.62±0.15 | 69.52±0.45 |
| Forgetting | 0.76±0.01 | 4.09±0.17 | 14.02±0.13 | 47.64±0.03 | 55.12±0.13 | 64.29±0.11 | 69.52±0.45 |
| GraNd    | 1.04±0.04 | 7.92±0.05 | 18.10±0.22 | 43.54±0.19 | 49.92±0.21 | 57.98±0.17 | 69.52±0.45 |
| Cal      | 1.29±0.09 | 7.50±0.26 | 15.94±1.30 | 38.32±0.78 | 46.49±0.29 | 58.31±0.32 | 69.52±0.45 |
| Craig    | 1.13±0.08 | 5.44±0.52 | 9.40±1.69 | 32.39±1.24 | 38.77±0.56 | 44.89±3.72 | 69.52±0.45 |
| GradMatch| 0.94±0.04 | 5.10±0.22 | 12.28±0.49 | 40.16±2.28 | 45.91±1.73 | 52.69±2.16 | 69.52±0.45 |
| Glister  | 0.98±0.06 | 5.91±0.42 | 14.87±0.14 | 44.95±0.28 | 52.04±1.18 | 60.26±0.28 | 69.52±0.45 |
| FL       | 1.23±0.03 | 5.78±0.08 | 12.72±0.21 | 40.85±1.25 | 51.05±0.59 | 63.14±0.03 | 69.52±0.45 |
| GC       | 1.21±0.09 | 7.66±0.43 | 16.45±0.53 | 42.23±0.60 | 50.53±0.42 | 63.22±0.26 | 69.52±0.45 |

Table 2. Coreset selection performances on ImageNet-1K. We train randomly initialized ResNet-18 on the coresets of ImageNet produced by different methods and then test on the real testing set.
training samples that can be more informative than real samples in the original

An alternative way to reduce training set size is dataset condensation (or distillation) \[50,58,57\]. Instead of selecting subsets, it learns to synthesize informative

Table 3. Cross-architecture generalization performance (%) of four representative methods (FORGETTING, GRaNd, GLISTER and GRAPH CUT). The coreset is selected based on one (row) architecture and then evaluated on another (column) architecture.

### 4.4 Sensitiveness to Pre-trained Models

As previously mentioned, some coreset selection methods rely on a pre-trained model to obtain metrics, e.g. feature, gradient and loss, for selecting samples. This experiment explores the influence of the pre-trained models, which are pre-trained for different epochs, on the final coreset performance. Similar to Sec. 4.3, four representative methods (FORGETTING, GLISTER, GRaNd and GRAPH CUT) and two selection fractions (1% and 10%) are tested in this experiment. Except for different pre-training epochs, all other settings and hyper-parameters are consistent with those in Sec. 4.1. We report our results in Tab. 4. For FORGETTING, good results can be achieved with models pre-trained for only 2 epochs, i.e. selecting samples based on whether the first forgetting event occurs on each sample. Spending more epochs in calculating forgetting events does not lead to improvements. The forgetting events can only be counted for more than 2 training epochs, thus no results are provided for FORGETTING in epoch 0 and 1. GRaNd also performs best with models pre-trained for 2 epochs. The results indicate that it is not necessary to pre-train a model for too many epochs to obtain the metrics.

### 5 Extended Related Work

An alternative way to reduce training set size is dataset condensation (or distillation) \[50,58,57\]. Instead of selecting subsets, it learns to synthesize informative training samples that can be more informative than real samples in the original
training set. Although remarkable progress has been achieved in this research area, it is still challenging to apply dataset condensation on large-scale and high-resolution datasets, e.g. ImageNet-1K, due to the expensive and difficult optimization.

### 6 Conclusion

In this work, we contribute a comprehensive code library – DeepCore for coreset selection in deep learning, where we re-implement dozens of state-of-the-art coreset selection methods on popular datasets and network architectures. Our code library enables a convenient and fair comparison of methods in various learning settings. Extensive experiments on CIFAR10 and ImageNet datasets verify that, although various methods have advantages in certain experiment settings, random selection is still a strong baseline.

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