Rethinking Dataset Quantization: Efficient Coreset Selection via Semantically-Aware Data Augmentation

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Abstract

Coreset selection aims to reduce the computational burden of training large-scale deep learning models by identifying representative subsets from massive datasets. However, existing state-of-the-art methods face a fundamental accessibility dilemma: they either require extensive training on the target dataset to compute selection metrics, or depend heavily on large pre-trained models, undermining the core purpose of coreset selection in resource-constrained scenarios. Dataset Quantization (DQ) avoids full dataset training but relies on expensive pre-trained models, introducing computational overhead and domain-specific biases that limit generalization. In this work, we comprehensively redesign the DQ framework to establish a truly accessible, theoretically sound, and domain-agnostic paradigm for coreset selection. Through rigorous analysis, we identify that: (1) MAE functions primarily as biased data augmentation leveraging memorized ImageNet patterns; (2) MAE benefits ImageNet-related datasets but harms out-of-distribution performance; (3) the original pipeline suffers from feature inconsistency between selection and training phases. We propose DQ_v2, which: (1) eliminates pre-trained model dependencies via Semantically-Aware Data Augmentation (SDA) using randomly initialized CNNs; (2) restructures the pipeline by performing augmentation before selection, ensuring feature consistency. Extensive experiments demonstrate that DQ_v2 achieves superior performance across diverse domains (such as ImageNet-1k, CUB-200, Food-101, and medical imaging) while reducing computational costs by 75% in the augmentation phase, establishing a robust and practical solution for resource-constrained scenarios.

1 Introduction

Deep learning has become the gold standard for many computer vision and machine learning tasks (Dosovitskiy et al., 2021), which have seen rapid growth due to increasing model sizes and dataset volumes. However, training emerging deep models, e.g., vision transformers (ViTs) (Dosovitskiy et al., 2021), on large-scale datasets like ImageNet (Deng et al., 2009) and LAION (Schuhmann et al., 2021) requires substantial computational resources, including high-performance GPUs, large memory capacity, and high-speed storage (Bartoldson et al., 2023). These requirements pose a significant barrier to entry for many researchers and practitioners, especially those in resource-constrained environments. Thus, efficiently training large-scale deep learning models with limited resources has become a common concern in both academia and industry.

Recent research has shown that large-scale datasets contain many redundant and irrelevant samples (Xia et al., 2024; He et al., 2024), which can be compressed into smaller representative subsets without losing model performance. Coreset selection and dataset distillation, as crucial methods to address this issue, aim to choose or synthesize representative subsets from large-scale datasets to reduce computational complexity while maintaining model performance (Guo et al., 2022; Bartoldson et al., 2023). However, **existing coreset selection methods face a fundamental dilemma**: they either require full or partial training on the

This work made limited use of a large language model (LLM) to assist with writing.

target dataset to compute selection metrics, or they depend heavily on large pre-trained models, undermining the very purpose of coreset selection—reducing computational burden in resource-constrained scenarios.

The computational accessibility problem. Recent state-of-the-art coreset selection methods exhibit severe practical limitations. Methods like D^2 Pruning Maharana et al. (2023) and CCS Zheng et al. (2023) require training on the complete target dataset to compute forgetting scores or AUM (Area Under the Margin) scores, while MoSo Tan et al. (2023) demands training a surrogate network for 50 epochs to observe full training dynamics. This creates a paradoxical situation: coreset selection methods designed to reduce training costs actually require substantial upfront computational investments that many practitioners cannot afford.

Dataset Quantization (DQ) (Zhou et al., 2023; Zhao et al., 2024) represents progress by avoiding full dataset training but introduces a different dependency on large pre-trained models, particularly a Masked Autoencoder (MAE) (He et al., 2022). This dependence introduces two critical problems: (1) *Computational overhead* from the MAE model's substantial parameters; (2) *Domain-specific biases* where ImageNet pre-training benefits related tasks but can harm out-of-distribution performance, limiting generalizability.

These limitations motivate a fundamental question: *Can we develop a coreset selection method that is both computationally accessible and free from pre-training dependencies while maintaining or exceeding state-of-the-art performance across diverse domains?*

In this paper, we answer this question affirmatively by comprehensively redesigning the DQ framework. Through rigorous empirical and theoretical analysis, we reveal that: (1) MAE functions primarily as biased data augmentation, leveraging memorized ImageNet patterns rather than general image understanding; (2) MAE benefits ImageNet-related datasets but harms out-of-distribution performance; (3) the original DQ pipeline suffers from feature inconsistency between selection and training phases.

Based on these findings, we propose DQ_v2, a comprehensively redesigned framework that establishes a new practical paradigm for coreset selection: truly accessible, theoretically sound, and domain-agnostic. Our key contributions are:

- **Systematic problem identification**: We rigorously analyze fundamental limitations in DQ including MAE's distribution-specific overfitting, feature inconsistency in the pipeline, and broader accessibility problems in coreset selection methods.
- **Novel augmentation strategy**: We develop Semantically-Aware Data Augmentation (SDA) using randomly initialized CNNs to preserve semantic objects while diversifying backgrounds, eliminating pre-trained model dependencies.
- **Comprehensive pipeline redesign**: We restructure the framework to perform augmentation before selection, ensuring feature consistency and enabling superior coreset quality without external knowledge dependencies.
- **Establishing practical accessibility**: Extensive experiments on ImageNet-1k, CUB-200, Food-101, and medical imaging demonstrate superior performance with 75% reduction in GPU hours, improved cross-domain generalization, and robustness to distribution shifts.

Paper organization: The rest of this paper is organized as follows. Section 2 reviews related work on coreset selection and data augmentation. Section 3 introduces the problem formulation and briefly reviews the original DQ method. Section 4 presents our critical analysis of DQ's limitations from both empirical and theoretical perspectives. Section 5 introduces our proposed DQ_v2 method. Section 6 presents experimental results and analysis. Section 7 concludes the paper with a discussion of limitations and future work.

2 Related Work

2.1 Coreset Selection and Data Pruning

Coreset selection is a crucial technique for reducing the computational complexity of deep learning models by selecting a representative subset from large-scale datasets.

Early efforts explored various selection criteria, including geometry-based methods (Agarwal et al., 2020; Chen et al., 2012; Sener & Savarese, 2018), uncertainty-based methods (Coleman et al., 2019), error-based methods (Toneva et al., 2019; Paul et al., 2021), decision boundary-based methods (Ducoffe & Precioso, 2018; Margatina et al., 2021), gradient matching-based methods (Mirzasoleiman et al., 2020; Killamsetty et al., 2021), and submodularity-based methods (Iyer et al., 2021).

Recent state-of-the-art methods have achieved impressive performance but at the cost of practical accessibility. D^2 Pruning Maharana et al. (2023) utilizes message passing over a dataset graph to jointly consider sample diversity and difficulty, but it requires training on the complete target dataset to compute forgetting scores. Similarly, Coverage-centric Coreset Selection (CCS) Zheng et al. (2023) balances data coverage and importance by computing AUM (Area Under the Margin) scores, which also necessitates full dataset training. Moving-one-sample-out (MoSo) Tan et al. (2023) evaluates each sample's impact on empirical risk but demands training a surrogate network for 50 epochs to observe complete training dynamics. InfoMax Tan et al. (2025) formulates coreset selection as a discrete quadratic programming problem that jointly accounts for individual sample information and pairwise redundancy and solves the resulting quadratic-form objective using an iterative optimization procedure. Mind the Boundary (BoundarySet-CCS variant in our comparisons) Yang et al. (2024) selects samples to reconstruct the decision boundary learned on the full dataset, achieving strong performance but requiring initial full dataset training to establish the reference boundary. Other methods include Moderate coreset Xia et al. (2023), which selects samples with scores close to the median, and AdaPruner Liu et al. (2021), which jointly prunes training data and fine-tunes models.

While these methods achieve strong performance, their requirement for full or extensive partial training on the target dataset creates a fundamental accessibility barrier: researchers with limited computational resources—the very users who would benefit most from coreset selection—often cannot afford the upfront computational investment these methods require.

2.2 Dataset Quantization

To address the scalability and accessibility challenges, Dataset Quantization (DQ) (Zhou et al., 2023) was proposed as a method that avoids the need for full dataset training. DQ combines coreset selection with data compression techniques, effectively selecting representative subsets from large-scale datasets while maintaining high performance under various data keep ratios. By using pre-computed features and avoiding iterative training-based selection, DQ represents an important step toward practical coreset selection.

However, DQ's efficiency comes at a different cost: heavy dependence on large pre-trained models. The framework relies on a Masked AutoEncoder (MAE) (He et al., 2022) with a ViT-Large architecture (304M parameters) for image reconstruction, and a pre-trained ResNet model for feature extraction and importance scoring. While these pre-trained models enable DQ to avoid target dataset training, they introduce substantial computational overhead and, more critically, potential domain-specific biases from ImageNet pre-training. Our analysis reveals that MAE's benefits are dataset-dependent: it helps ImageNet-related datasets but can harm performance on out-of-distribution domains. Furthermore, directly removing these pre-trained components leads to performance degradation and increased variance, suggesting they play a crucial but poorly understood role.

In this work, we systematically investigate the role of pre-trained models in DQ and comprehensively redesign the framework to eliminate these dependencies while achieving superior performance. Our approach addresses both the computational accessibility problem and the domain generalization limitation, establishing a new practical paradigm for coreset selection that requires no pre-trained models, avoids training-dynamics-based scoring (e.g., forgetting/AUM) on the target dataset, and demonstrates robust performance across diverse domains.

2.3 Data Augmentation

Data augmentation (Shorten & Khoshgoftaar, 2019) plays an essential role in improving model robustness and generalization ability. Traditional data augmentation methods focus mainly on simple image transformations, such as rotation, flipping, and color adjustment. Recent studies have explored more advanced data augmentation strategies, such as random erasing (Zhong et al., 2020), Mixup (Zhang et al., 2018), CutMix (Yun et al., 2019), and "Copy and paste" (Dwibedi et al., 2017; Ghiasi et al., 2020). These methods have achieved significant success in enhancing the performance and stability of vision models. Although these data augmentation methods have achieved significant success in improving model performance, they generally lack consideration of image semantic structure. Cao & Wu (2022) propose a self-supervised learning framework that we repurpose for data augmentation that leverages the inductive bias of random CNNs to preserve semantic objects while mixing up the background. How to design data augmentation strategies that can both maintain image naturalness and effectively enhance model learning ability remains an open question. In this work, we first observe that the pre-trained MAE model is actually equivalent to a data augmentation method, which introduces prior knowledge and implicit regularization into the training process. Thus, this observation motivates us to explore a new data augmentation strategy that can replace the MAE model in the DQ method.

3 Preliminaries

3.1 Problem Formulation

Suppose that we have a large dataset $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{T}$, where x_i is the i-th image and y_i is the corresponding label, and T is the total number of training samples. Coreset selection aims to choose an optimal small subset D_S from a large-scale dataset $\mathcal{D}$, where $D_S \subset \mathcal{D}$ and $|D_S| \ll |\mathcal{D}|$. The model trained on D_S can achieve comparable performance to the model trained on the entire dataset $\mathcal{D}$. Finally, the model trained on the coreset D_S can be used to make predictions on the test set.

3.2 Review of Original DQ Framework

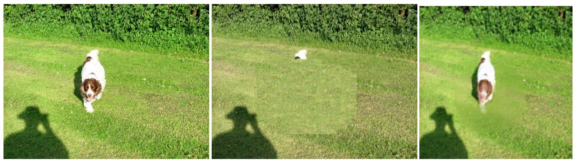
As discussed above, most coreset selection and dataset distillation methods suffer from some obvious drawbacks, such as poor generalization and low scalability. Therefore, Zhou et al. (2023) proposed DQ, which consists of three main steps: 1) dataset bin generation, 2) selection of subset bin, and 3) image pixel quantization.

The first step aims to generate multiple non-overlapping dataset subsets (referred to as bins), each containing representative and diverse samples. Here, DQ leverages the traditional coreset selection method, i.e., GraphCut method (Iyer et al., 2021) to select the most representative samples. A pre-trained ResNet model is used to extract features for all images, and the GraphCut score is calculated for each unselected sample when added to the current bin. The second step involves random sampling of the generated bins to form the final compressed dataset. This design introduces additional randomness, contributing to improved model robustness and generalization. The final step is to further reduce storage requirements and enhance data quality. This process involves image patching, importance scoring, patch selection, and image reconstruction. Specifically, a pre-trained ResNet model is first used to compute importance scores for different image patches and guide the selection of informative patches; subsequently, the pre-trained Masked Autoencoder (MAE) decoder is used to reconstruct the complete image from the selected patches. Thus, the original DQ framework relies heavily on two large pre-trained models: a pre-trained ResNet for feature extraction and importance scoring, and a 304M-parameter MAE for image reconstruction.

While DQ achieves state-of-the-art performance on various datasets, especially large-scale datasets like ImageNet, it faces several key challenges in computational efficiency and method stability. As we will demonstrate in Section 4, these limitations stem fundamentally from the heavy reliance on large pre-trained models, particularly the 304M-parameter MAE model used in the pixel quantization step, which introduces both computational overhead and domain-specific biases.

4 Rethinking DQ: Problems and Theoretical Flaws

In this section, we present a comprehensive analysis of the original DQ method from both empirical and theoretical perspectives. Our investigation reveals fundamental limitations that motivate the design of our improved framework. We first conduct controlled experiments to understand MAE's role in DQ's performance (Section 4.1), then expose a critical theoretical flaw in the original pipeline design (Section 4.2).



Ori BG Replaced MAE Rec.

(a) MAE reconstruction examples on ImageNet

MAE Rec. 1 MAE Rec. 2 MAE Rec. 3

(b) MAE reconstruction examples on CUB-200

Figure 2: Comparison of MAE reconstruction on ImageNet and CUB-200 datasets.

4.1 Comprehensive Analysis of MAE's Limitations

MAE's Claimed Role in DQ. The original DQ paper (Zhou et al., 2023) justifies the use of MAE primarily for storage efficiency: in the third step (pixel quantization), less-informative patches are removed based on importance scores, and the complete image is reconstructed using MAE (Figure 2). The authors claim this process reduces storage requirements while maintaining image quality through reconstruction.

Logical Contradictions in the Storage Efficiency Claim. Our investigation reveals that this storage efficiency justification is untenable for several fundamental reasons: (1) In an era of inexpensive storage but scarce GPU compute, using a computationally demanding MAE model merely to save storage space is counterintuitive. The substantial computational overhead far outweighs modest storage savings, contradicting the core motivation of coreset selection to reduce computational burden in resource-constrained scenarios; (2) The reconstruction process requires temporary storage of approximately 1.75× the original dataset size during processing, directly undermining the storage efficiency claims.

Our Empirical Investigation. To understand MAE's actual role, we conducted controlled experiments by removing the pixel quantization step from the original DQ method and directly using the selected images from the second step to train the model. We conducted experiments on CIFAR-10, ImageNette, and CUB-200 datasets with different random seeds and report the mean accuracy and variance in Figure 1.

Our results reveal that MAE's impact varies dramatically across datasets: On ImageNette, removing MAE decreases performance from 72.14% to 69.69% and increases variance. On CUB-200, removing MAE significantly *increases* performance across various selection ratios. On CIFAR-10, a small-scale image dataset, removing MAE only slightly increases accuracy. These mixed results suggest that MAE's primary function is not storage efficiency but rather introducing dataset-specific prior knowledge from ImageNet pre-training.

Analysis: Four Fundamental Problems with MAE in DQ. Based on our empirical findings and theoretical analysis, we identify four critical issues:

Problem 1: Distribution-Specific Overfitting. MAE does not truly understand semantic information but rather overfits to the ImageNet distribution. This explains its varying effectiveness across datasets.

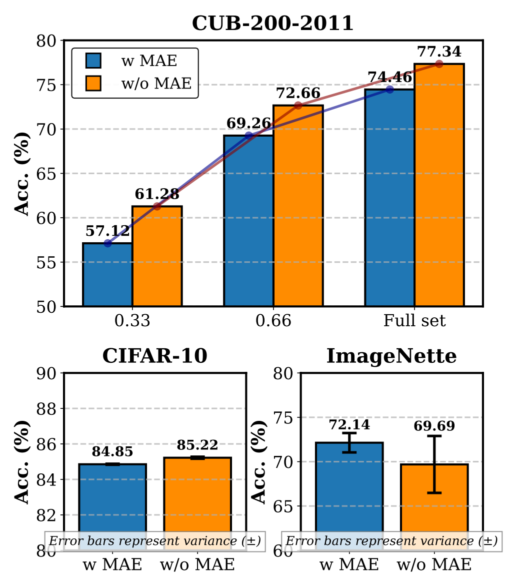


Figure 1: Performance comparison between models with and without MAE pre-training across different datasets. For CUB-200-2011, we evaluate with different data selection rates (0.33, 0.66, and full set).

Figure 2a demonstrates this overfitting dramatically: even when a dog image is completely replaced with background texture, the MAE still reconstructs the original dog, suggesting memorization rather than an understanding of image completion principles.

On non-ImageNet datasets like CUB-200 (Figure 2b), MAE merely applies Gaussian-like blurring rather than meaningful reconstruction, potentially degrading useful texture information.

This overfitting phenomenon explains why MAE improves performance on ImageNet-related datasets while actually harming performance on other datasets. For ImageNet-related data, MAE's memorized patterns serve as effective data augmentation and regularization. However, for non-ImageNet datasets, MAE fails to provide meaningful data augmentation and may even remove valuable texture information through its ineffective reconstruction attempts.

Problem 2: Small-Image Limitation. MAE performs poorly on small-scale images like CIFAR-10 due to: (1) Ambiguous foreground-background boundaries: In 32×32 images, objects occupy most of the frame, making the CNN's texture-based attention mechanism less discriminative—the entire image becomes uniformly "foreground-like"; (2) Coarse patch granularity: With limited patches available (e.g., 16 patches for 8×8 patch size), dropping any patch risks removing critical information that cannot be reliably reconstructed from sparse neighbors.

Problem 3: Computational Cost. The MAE model used in DQ is computationally expensive: (1) The ViT-Large architecture contains 304M parameters; (2) Processing large datasets like ImageNet-1k requires significant GPU resources; (3) This computational overhead contradicts the presumed efficiency goal of Dataset Quantization.

Problem 4: Fairness in Method Comparison. When DQ is compared to other coreset selection methods, MAE introduces a confounding factor: (1) Performance improvements may stem from either better coreset selection or the incorporation of ImageNet prior knowledge during reconstruction; (2) This makes it difficult to isolate the true contribution of the coreset selection component; (3) The implicit transfer of knowledge from ImageNet pre-training complicates fair comparison with methods that don't leverage such external knowledge.

In summary, our analysis reveals that MAE provides regularization benefits for ImageNet-like datasets by leveraging memorized patterns, but it offers limited value for small-scale or out-of-distribution datasets while introducing significant computational overhead and methodological fairness concerns.

4.2 Theoretical Flaw: Feature Inconsistency

Beyond the empirical issues with MAE, we identify a fundamental theoretical problem in the original DQ pipeline itself. In the original DQ method, there exists a critical limitation: the inconsistency between the features used for coreset selection and the features of the images used in the final training. This issue has also been recently analyzed in depth by Zhao et al. (2024). As illustrated in Section 3, DQ follows a sequential process: first performing dataset bin generation and bin selection based on the original images' features, and then applying pixel quantization with MAE reconstruction.

Following the formal analysis in Zhao et al. (2024), let us denote the original dataset as D, and the final output dataset after pixel quantization as D_{MAE}. The GraphCut algorithm used for bin generation calculates submodular gains $G(\mathbf{x}_k)$ based on features extracted from the original dataset D:

$$G(\mathbf{x}_k) = \sum_{p \in S_n^{k-1}} \left\| f(p) - f(\mathbf{x}_k) \right\|_2^2 - \sum_{p \in D \setminus (S_1 \cup \cdots \cup S_n^{k-1})} \left\| f(p) - f(\mathbf{x}_k) \right\|_2^2, \tag{1}$$

where $f(\cdot)$ is the feature extractor. However, the model is ultimately trained on images that have undergone MAE reconstruction, where image features have been significantly altered. This means that while the dataset bins are optimized for the original dataset D, they may not be optimal for the transformed dataset D_{MAE} on which the model actually trains.

This inconsistency can lead to suboptimal performance, as the coreset selection process is not aware of the subsequent feature transformations caused by reconstruction. This theoretical flaw, combined with the empirical problems identified in Section 4.1, motivates us to propose a fundamentally redesigned pipeline that addresses both issues simultaneously.

In our improved approach (detailed in Section 5), we perform data augmentation first, then conduct bin generation and selection on the augmented dataset. This reorganized pipeline ensures that feature extraction and GraphCut selection operate in the same feature space that will be used for training. The submodular gains are now calculated as:

$$G(\mathbf{x}_k) = \sum_{p \in S_n^{k-1}} \left\| f(p) - f(\mathbf{x}_k) \right\|_2^2 - \sum_{p \in D_{\text{aug}} \setminus (S_1 \cup \cdots \cup S_n^{k-1})} \left\| f(p) - f(\mathbf{x}_k) \right\|_2^2, \quad (2)$$

where D_{aug} represents our augmented dataset. This approach ensures that the selected coreset is optimal for the actual feature distribution used during training.

Furthermore, by conducting semantically aware augmentation prior to coreset selection while preserving the original images, we significantly enhance the diversity of the training set. This strategic reordering enables the GraphCut algorithm to select samples from an enriched feature space, thereby identifying the most informative and representative instances. Consequently, our approach can achieve comprehensive coverage of the feature distribution with a minimal number of samples, maximizing information density while minimizing redundancy in the selected coreset.

A detailed formal theoretical framework grounded in submodular optimization theory is provided in Appendix A, which mathematically justifies why our pipeline redesign leads to superior performance.

5 Our Proposed Method: DQ_v2

This raises a crucial question: *Can we design a more efficient method that achieves or surpasses DQ's performance without relying on large pre-trained models while also addressing the feature inconsistency flaw?* In this section, we present our answer: Dataset Quantization V2 (DQ_v2), a theoretically sound and computationally efficient framework that simultaneously solves both the MAE dependency problem and the feature inconsistency issue.

5.1 Semantically-Aware Data Augmentation (SDA)

As analyzed in Section 4.1, MAE's reconstruction process in the pixel quantization step serves two roles: (1) preserving semantic objects while modifying background regions, and (2) introducing regularization through reconstruction-based augmentation. However, MAE suffers from distribution-specific overfitting and computational overhead.

This motivates us to design a more efficient data augmentation strategy that achieves similar benefits without pre-trained model dependencies. Classical augmentation methods like CutMix (Yun et al., 2019) generate new samples by cutting and pasting patches between images, but may randomly cut foreground objects, failing to preserve semantic integrity.

Thus, we need to design an augmentation method that: (1) maintains semantic object information, (2) introduces beneficial background variations, and (3) requires no pre-trained models. Inspired by the self-supervised learning framework of Cao & Wu (2022), we develop a data augmentation method that leverages the inductive bias of randomly initialized CNNs. Specifically, the combination of CNN architectures with ReLU activation functions naturally focuses on high-texture regions (foreground objects) while suppressing low-texture regions (backgrounds), enabling automatic semantic object localization without any pre-training. We repurpose this property for data augmentation: using a randomly initialized CNN to identify semantic objects and then replacing background regions with random patches from other images. This method can effectively maintain the naturalness of the image and introduce beneficial variations. Illustrative examples of this process at different patch granularities (5×5, 16×16, or 40×40) are provided in Appendix D.1 (Figure 7a), where we show that these randomly shuffled background patches contain only texture information, not semantic content. For all experiments reported in this paper, we consistently use the 40×40 granularity setting, which ensures that the semantic integrity of the main object is preserved while only introducing variation in non-semantic texture patterns.

In addition, we mix the augmented data and the original images to further enhance the diversity of the training data. We also report that using appropriate mixing rates can further improve the model's performance. While this strategy offers the following advantages:

- **Semantic Preservation**: By preserving the image's main object region, it ensures that augmented images maintain the original semantic information.
- **Diversity Introduction**: The replacement of background regions introduces new visual contexts, increases data diversity, and improves model generalization.
- **Computational Efficiency**: Compared to using large pre-trained models (like MAE), this method has lower computational overhead and requires no additional model dependencies, making it suitable for resource-constrained environments.

Theoretical Justification for SDA. The effectiveness of our SDA strategy can be understood from three complementary theoretical perspectives:

(1) Sample Space Expansion Theory: As formalized in Appendix A (Assumption 2), SDA systematically expands the dataset from D to D_{aug} with $|D_{\text{aug}}| = 1.5|D|$. This expansion is not arbitrary but semantically structured—each augmented sample (x_i', y_i') preserves the label $y_i' = y_i$ while introducing controlled variation in the contextual background. By expanding the sample space before coreset selection, we provide the GraphCut algorithm with a richer pool of candidates from which to select maximally diverse and representative samples (Theorem 1).

(2) Spurious Correlation Breaking: Traditional data augmentation often fails to address the problem of spurious correlations between objects and their typical contexts (e.g., soccer balls primarily appearing on grass). Our SDA explicitly breaks these correlations by replacing backgrounds with random patches from other images. This forces the model to learn background-invariant representations that focus on the intrinsic properties of foreground objects rather than contextual cues. By ensuring that semantic objects appear in diverse, unrelated backgrounds during training, SDA prevents the model from relying on spurious background cues for classification.

(3) Regularization through Controlled Diversity: Unlike MAE's domain-specific biases (Section 4.1, Problem 1), SDA introduces diversity without injecting external prior knowledge. The random background replacement acts as a powerful regularizer that prevents overfitting to specific background patterns while maintaining semantic integrity. This is particularly valuable when $|D|$ is limited or when the target distribution differs from common pre-training datasets like ImageNet.

5.2 Our Proposed Framework: DQ_v2

Building upon our SDA strategy and the feature consistency principle discussed in Section 4.2, we propose DQ_v2, a comprehensively redesigned framework that addresses both the pre-trained model dependency and the feature inconsistency issues in the original DQ method.

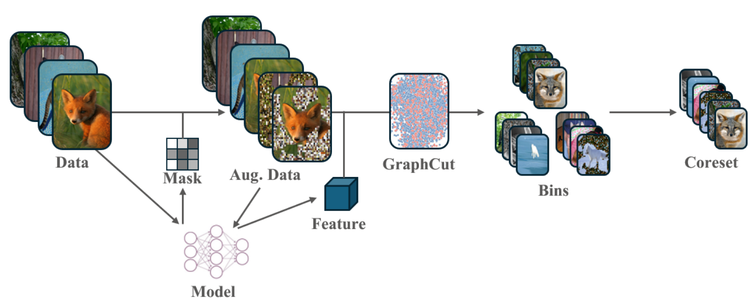


Figure 3: The overall pipeline of DQ_v2.

A key innovation in our approach is the reordering of the pipeline steps: unlike the original DQ, which performs augmentation after coreset selection (leading to feature inconsistency), we perform augmentation first and then selection, ensuring that GraphCut operates in the same feature space used during training (as formalized in Section 4.2, Proposition 1).

Our improved method includes the following key steps: **1) Mask Generation and Data Selection**: We randomly select 50% of the images from the training set for augmentation. For these selected images, we use a randomly initialized ResNet-50 model to generate masks that localize the regions of the main objects. This step leverages CNN's inductive bias to effectively identify the main objects without requiring any pre-training on object detection tasks. Our deliberate choice of ResNet-50 rather than a ViT architecture is based on the inherent properties of CNN structures combined with ReLU activations: in CNNs with ReLU activation functions, there is a natural tendency to distinguish between foreground objects and background regions based on texture complexity. Background areas typically contain less texture compared to the main objects, and as network depth increases, these texture-sparse regions are more likely to be deactivated by ReLU functions. This emergent property makes CNNs particularly effective at identifying the main object regions without explicit supervision. In contrast, ViT architectures rely on self-attention mechanisms without the inherent spatial inductive biases of convolutions, and therefore do not naturally exhibit this object-background separation capability. **2) Semantically-Aware Data Augmentation (SDA)**: Based on the generated masks, we augment the selected images by retaining their main object parts while replacing the original backgrounds with randomly selected backgrounds from other images. This process maintains the original semantic information while introducing new visual contexts. We then combine these semantically-aware augmented images with the original complete training set, effectively expanding the dataset to 1.5 times its original size with increased diversity. **3) Dataset Binning**: Use an EarlyTrain model to extract the visual feature and then apply the GraphCut method (Iyer et al., 2021) to split the mixed training set, generating multiple nonoverlapping bins. By performing this step after data augmentation, we ensure feature consistency between selection and training. This step ensures that the selected samples are representative and diverse, keeping the core advantages of the DQ method. **4) Bin Sampling**: Randomly select a proportionally adjusted percentage of images from each bin to form the final coreset. Since our dataset has been expanded to 1.5x its original size, we accordingly adjust the selection ratio by a factor of 1/1.5 to maintain the same effective number of samples as other methods. For example, to obtain a coreset equivalent to 60% of the original dataset size, we select 40% (= 60% / 1.5) from the augmented dataset, yielding $0.4 \times 1.5n = 0.6n$ samples, where n is the original dataset size. This adjustment ensures fair comparison with other methods (see Appendix D for detailed analysis). This random sampling process further increases the diversity of the data, allowing users to flexibly adjust the proportions of the data to suit different task requirements. **5) Model Training**: Train the model using the selected coreset.

The complete pipeline of DQ_v2 is illustrated in Figure 3. As the coreset contains both original and augmented images, the model can learn richer and more robust feature representations, enhancing model performance and stability.

Through this comprehensive redesign, DQ_v2 simultaneously achieves three key advantages: (1) eliminates all pre-trained model dependencies, reducing computational requirements by 75% in the augmentation phase; (2) ensures feature consistency between selection and training through pipeline reordering; (3) improves performance across diverse domains through semantically-aware augmentation. Experimental results (Section 6) demonstrate that DQ_v2 surpasses the original DQ and other state-of-the-art methods while maintaining practical accessibility for resource-constrained scenarios.

6 Experimental Results and Analysis

6.1 Experimental Setup

Datasets: We conducted experiments on multiple datasets, including ImageNette Howard (2019) (a 10-class subset of ImageNet), CUB-200-2011 Wah et al. (2011), and Food-101 Bossard et al. (2014). These datasets cover a wide range of image classification tasks, enabling us to comprehensively evaluate the performance of our proposed method. In addition, we also conducted experiments on ImageNet-1k to further validate the effectiveness of our proposed method compared to the state-of-the-art methods.

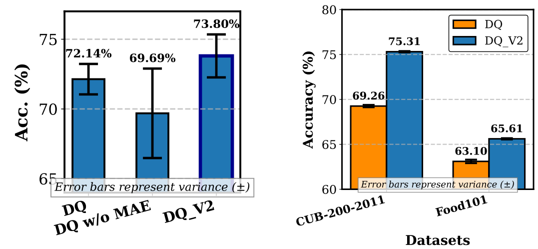
Implementation Details: We implement our proposed DQ_v2 method using PyTorch and train the models on NVIDIA V100 GPUs. We use the randomly initialized ResNet-50 model as the backbone for SDA. For the dataset bin selection stage, we utilize the EarlyTrain ResNet-50 model as the feature extractor. The number of dataset bins is set to 10 by default. We also use the timm library (Wightman, 2019) for model training across all datasets. For comparisons with the original DQ, we follow *exactly* the same downstream evaluation protocol as the original DQ method[1]. This ensures that improvements over DQ are attributable

[1]For ImageNet-1k experiments, we use ResNet-50 as the backbone model. For other datasets (CUB-200, Food-101, etc.), we use ResNet-18 as the backbone model. This choice follows standard practice for datasets of different scales.

to our coreset selection method rather than differences in training procedures. A detailed stability analysis comparing DQ_v2 with the original DQ method across multiple datasets and random seeds is provided in Appendix B.

6.2 Comparison with original DQ

In this part, we primarily evaluate the performance of our DQ_v2 method compared to the original DQ method. Specifically, the results on the ImageNette and Food-101 datasets are shown in Figure 4 (b). The results show that our method achieves better performance compared to the original DQ method. Notably, in the Food-101 dataset, our method achieves a significant performance improvement of 3.98% compared to the original DQ method, while on ImageNette, we observe a gain of 1.66%. The larger performance gap on Food-101 aligns with our analysis: MAE primarily benefits ImageNet-related datasets (such as ImageNette) but functions merely as Gaussian blur for non-ImageNet datasets like Food-101. This explains why removing MAE and using our SDA approach yields more substantial improvements on Food-101.



(a) Stability Analysis (b) Comparison with DQ

Figure 4: Preliminary evaluation of our proposed DQ_v2 method. We report the mean accuracy (%) and variance in five runs with different seeds.

Moreover, to demonstrate that our coreset selection generalizes across different architectures, we train a ViT model on the subset selected using the ResNet-50 feature extractor and evaluate the performance on ImageNette. The accuracy of DQ method is 55.30%±2.73%, and ours is 57.67%±1.20%. The results further verify the effectiveness and generalizability of our proposed method.

Computational Efficiency. Beyond accuracy improvements, our method also offers significant computational advantages. It is worth noting that the original DQ method already provides substantial computational benefits over many alternative approaches. Unlike dataset distillation methods where computational cost scales quadratically with the size of the synthetic set, DQ offers more favorable scaling through its binning approach. Moreover, compared to methods like D^2 Pruning Maharana et al. (2023) and AdaPruner Liu et al. (2021) that require training on the complete dataset, DQ's pipeline avoids this computational burden entirely by operating directly on feature representations. Our DQ_v2 method preserves these fundamental efficiency advantages while providing further improvements.

We compare the GPU hours required for processing the entire ImageNet-1k dataset using the original MAE-based approach versus our SDA method, as shown in Table 1.

Table 1: GPU-hour comparison between MAE and SDA on ImageNet-1k (single NVIDIA RTX 4090).

Method	Params	GPUh
MAE	ViT-L (304M)	10.0
SDA (8×8)	R50 (25.6M)	1.7
SDA (40×40)	R50 (25.6M)	2.5

Specifically, our SDA phase achieves at least a 75% reduction in GPU hours compared to DQ's MAE reconstruction phase. This substantial efficiency gain in the augmentation component stems from two key factors: (1) we employ a randomly initialized ResNet-50 with only 25.6M parameters for data augmentation, compared to the more computationally demanding ViT-Large with 304M parameters used by MAE; and (2) our method only requires applying the augmentation to 50% of the data, further reducing the computational cost. While the complete pipelines of both methods include additional stages (bin generation, selection, and training), the augmentation phase represents a significant computational bottleneck in the original DQ, and our redesign substantially addresses this limitation.

6.3 Comparison with State-of-the-art Methods on ImageNet-1k

To fully validate the effectiveness of our proposed DQ_v2 method, we conduct extensive experiments on the large-scale ImageNet-1k dataset, comparing it with recent state-of-the-art coreset selection and data pruning methods, including D^2 Pruning, CCS. MoSo, InfoMax, and BoundarySet-CCS. The results are shown in Figure 5. All baseline Top-1 accuracies are taken directly from the corresponding papers' reported results. The results demonstrate that our DQ_v2 method consistently outperforms other leading data pruning approaches across most data keep ratios (Figure 5). Compared to the original DQ method, DQ_v2 shows consistent improvements across all keep ratios, validating the effectiveness of our comprehensive pipeline redesign and semantically-aware data augmentation strategy. Against other recent state-of-the-art methods, including D^2 Pruning Maharana et al. (2023), CCS Zheng et al. (2023), MoSo Tan et al. (2023), InfoMax Tan et al. (2025), and BoundarySet-CCS Yang et al. (2024), DQ_v2 demonstrates competitive or superior performance, particularly when the data keep ratio exceeds 20%, where it generally maintains a leading position.

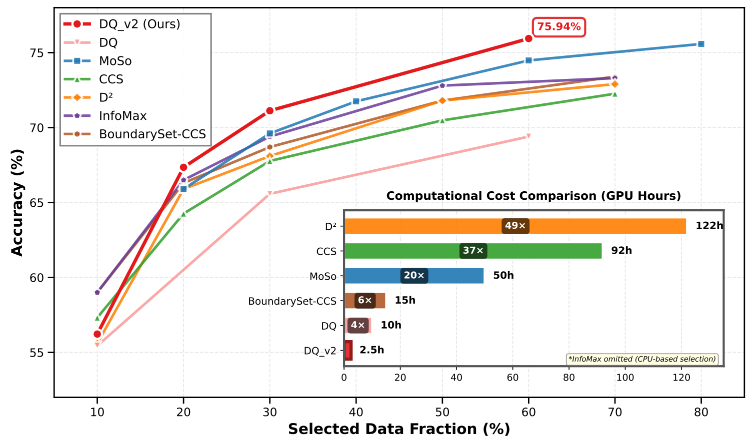


Figure 5: Performance comparison with state-of-the-art methods on ImageNet-1k.

Notably, at a 60% data keep ratio on ImageNet-1k, our DQ_v2 method achieves an impressive 75.94% Top-1 accuracy. This performance is particularly significant as it surpasses the reported accuracy of CCS (75.58%) which requires a larger data selection rate of 80%. This achievement establishes DQ_v2 as a highly efficient solution for dataset compression on ImageNet-1k, achieving better performance with less data while also eliminating the need for expensive pre-trained models and full dataset training that other methods require. At very low data keep ratios (10%), DQ_v2 is outperformed by InfoMax and BoundarySet-CCS, which demonstrate particularly strong performance in this regime. This behavior is expected and further analyzed in Appendix D, where we discuss how extremely low selection ratios pose inherent challenges for sample space expansion approaches. Further detailed analyzes, including the factors contributing to DQ_v2's efficiency and a discussion on the fair comparison of training sample counts, are provided in Appendix D.

6.4 Robustness and Cross-Domain Generalization

To comprehensively evaluate DQ_v2's practical applicability and address the question of whether our method truly overcomes the domain-specific limitations identified in Section 4.1, we conduct two additional experiments that test the method's behavior beyond the standard ImageNet evaluation.

Cross-Domain Generalization. A central claim of our work is that DQ_v2 avoids the domain-specific biases inherent in MAE-based approaches (Section 4.1, Problem 1). To validate this claim, we evaluate our method on the COVID-19 Radiography Database (Chowdhury et al., 2020), a medical imaging dataset that is significantly different from ImageNet in terms of image characteristics, semantic content, and visual features. This dataset contains chest X-ray images across multiple categories, representing a challenging out-of-distribution scenario.

Table 2: Cross-domain generalization results on COVID-19 Radiography Database. (ResNet-50)

Ratio	Accuracy (%)		Gain
(%)	DQ	DQ_v2	(%)
5	81.46	88.48	+7.02
10	85.96	90.01	+4.05
15	86.46	92.49	+6.03
30	87.99	93.08	+5.09
60	90.86	95.06	+4.20

Table 2 presents the comparison between the original DQ and our DQ_v2 across various data keep ratios. The results demonstrate substantial improvements across all settings, with gains ranging from +4.05% to +7.02%. Notably, even at very low selection rates (5%), DQ_v2 achieves 88.48% accuracy compared to DQ's 81.46%, representing a remarkable 7.02% improvement. This consistent superiority across all keep ratios strongly validates our hypothesis that eliminating pre-trained model dependencies enables better generalization to out-of-distribution domains. The substantial performance gains on this medical imaging dataset directly demonstrate that DQ_v2's design successfully addresses the domain-specific overfitting problem we identified in the original DQ method.

Robustness to Image Corruptions. Beyond cross-domain generalization, we evaluate whether models trained on DQ_v2-selected coresets exhibit improved robustness to distribution shifts at test time. We use the ImageNet-C benchmark (Hendrycks & Dietterich, 2019), which applies 15 types of corruptions (e.g., Gaussian noise, motion blur, JPEG compression) at 5 severity levels to the ImageNet validation images, providing a comprehensive assessment of model robustness.

We train ResNet-50 models on a 60% coreset selected by DQ_v2 and evaluate them on all ImageNet-C corruptions, computing the mean Corruption Error (mCE) metric. Our method achieves an mCE of 71.26, compared to 76.7 for the baseline ResNet-50 trained on the full ImageNet dataset (a 5.44 point improvement). This substantial improvement in robustness can be attributed to our SDA strategy: by explicitly breaking spurious correlations between foreground objects and their typical backgrounds (see Section 5.1 for details on SDA), DQ_v2 encourages models to learn background-invariant representations that naturally generalize better to distribution shifts. The coreset selected from the augmentation-enriched space contains more diverse contextual variations, effectively serving as a built-in robustness-enhancing regularizer during training.

These robustness and generalization results provide strong empirical evidence that DQ_v2 not only matches or exceeds DQ's performance on standard benchmarks but also demonstrates superior practical applicability across diverse domains and under distribution shifts. Detailed ablation studies on the impact of key components (bin division algorithms, SDA patch granularities, and mixing ratios) are provided in Appendix C.

7 Conclusion, Limitations and Future Work

In this paper, we address the fundamental accessibility dilemma in coreset selection: existing state-of-the-art methods either require extensive training on target datasets or depend heavily on large pre-trained models, undermining the core purpose of reducing computational burden in resource-constrained scenarios. Through comprehensive analysis of the Dataset Quantization (DQ) method, we identify critical limitations: (1) MAE provides dataset-specific benefits through ImageNet prior knowledge but suffers from distribution-specific overfitting, benefiting ImageNet-related datasets while harming out-of-distribution performance; (2) the original pipeline suffers from feature inconsistency between selection and training phases due to applying augmentation after selection; (3) heavy reliance on expensive pre-trained models (304M-parameter MAE and pre-trained ResNet) introduces substantial computational overhead.

To address these fundamental issues, we propose DQ_v2, which establishes a new practical paradigm for coreset selection that is truly accessible, theoretically sound, and domain-agnostic. By eliminating all pre-trained model dependencies through Semantically-Aware Data Augmentation and fundamentally restructuring the pipeline to ensure feature consistency, DQ_v2 provides a coreset selection method that: (1) requires no pre-trained models, (2) avoids training-dynamics-based scoring on the target dataset, and (3) demonstrates robust performance across diverse domains. Through extensive experiments on diverse domains (ImageNet-1k, CUB-200, Food-101, medical imaging), we show that DQ_v2 improves performance and stability over the original DQ and other state-of-the-art coreset selection methods, while reducing augmentation compute by 75% and improving cross-domain generalization and robustness to distribution shifts.

Limitations and Future Work. Despite its strong performance, DQ_v2 presents opportunities for further development: **1.** The current SDA employs a fixed 50/50 proportion for foreground and background patches, which may not be optimal for all images. Future work will focus on developing adaptive techniques to determine this ratio on a per-image basis, potentially improving object localization precision. **2.** Our validation of DQ_v2 has thus far been confined to classification tasks. A key direction for future research is to extend its application and evaluate its effectiveness for other visual recognition tasks, such as object detection and segmentation.

Reproducibility Statement. To facilitate reproducibility, we will release our code and implementation details upon publication.

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A Formal Theoretical Framework

To provide a rigorous foundation for our approach, we present a formal theoretical framework grounded in submodular optimization theory. This framework mathematically justifies why our pipeline redesign leads to superior performance.

Assumption 1: Properties of the Set Function. Let Ω be the ground set of dataset elements, $|\Omega| = |D|$, and let $f_\Omega : 2^\Omega \to \mathbb{R}$ be a normalized, monotone, and submodular function as defined in Iyer et al. (2021). We use subscripts (e.g., f_D, $f_{D_{\text{aug}}}$) to denote the same function instantiated on different ground sets. In our method, f is instantiated as the generalized graph cut function with similarity kernel s and parameter $\lambda \geq 2$, ensuring monotonicity and submodularity (Lemma 17 in Iyer et al. (2021)).

Assumption 2: Sample Space Expansion. Let $D = \{(x_i, y_i)\}_{i=1}^n$ be the original dataset. Our Semantically-Aware Data Augmentation (SDA) produces semantically consistent variants with altered background textures but preserved labels. In our implementation, we augment exactly 50% of the dataset, yielding:

$$|D_{\text{aug}}| = |D| + 0.5|D| = 1.5|D| \quad \Rightarrow \quad \alpha = 1.5. \tag{3}$$

Label Preservation: For any $(x_i, y_i) \in D$, and any SDA variant $(x_i', y_i') \in D_{\text{aug}}$ derived from x_i, we have $y_i' = y_i$.

Theorem 1 (Submodular Optimization in Expanded Space). We recall the submodular mutual information from Iyer et al. (2021):

$$I_f(A; B) = f(A) + f(B) - f(A \cup B). \tag{4}$$

The generalized graph cut function (Lemma 17 in Iyer et al. (2021)) is:

$$f(A) = \lambda \sum_{i \in \Omega} \sum_{a \in A} s_{ia} - \sum_{a_1, a_2 \in A} s_{a_1 a_2}, \quad \lambda \geq 2. \tag{5}$$

GraphCut selects a subset $S \subseteq D_{\text{aug}}$ by maximizing coverage while minimizing redundancy, capturing:

- Original diversity: from D

- Synthetic diversity: from SDA
- Boundary coverage: better representation of rare or borderline cases

Since $D_{\text{aug}} \supset D$ and f are monotone, we have:

$$\max_{|S|\leq k} f_{D_{\text{aug}}}(S) \geq \max_{|S|\leq k} f_D(S). \tag{6}$$

This formalizes the advantage of selection in the expanded space.

Proposition 1 (Feature Space Consistency Advantage). Let $\phi : \mathcal{X} \to \mathbb{R}^d$ be the feature extractor, and define $F(X) = \{\phi(x) \mid x \in X\}$. Let F_{sel} and F_{train} be the feature spaces seen at selection and training time, respectively.

Augmentation-before-selection (ours):

1. SDA: $D \to D_{\text{aug}}$
2. Selection: $S \subset D_{\text{aug}}$ via GraphCut
3. Training: model trains on S

Then: $F_{\text{sel}} = F(D_{\text{aug}})$, $F_{\text{train}} = F(S) \subseteq F(D_{\text{aug}})$, which implies F_{sel} and F_{train} are consistent.

Augmentation-after-selection (baseline DQ):

1. Selection: $S \subset D$ via GraphCut
2. Augmentation: $S \to S_{\text{transformed}}$
3. Training: model trains on $S_{\text{transformed}}$

Then: $F_{\text{sel}} = F(D)$, $F_{\text{train}} = F(S_{\text{transformed}})$, which implies $F_{\text{sel}} \neq F_{\text{train}}$ when augmentation changes feature distributions.

Conclusion: Our pipeline ensures that the selection algorithm operates within the same feature distribution as during training, eliminating the distribution mismatch identified in the original DQ.

B Stability Analysis

As discussed in the main paper, the pixel quantization step plays an important role in reducing the variance of the trained model. Therefore, in this section, we investigate the stability of our proposed DQ_v2 method compared to the original DQ method.

On the ImageNette dataset (Figure 4 (a) in the main paper), we observe that removing the MAE model from the original DQ method significantly increases variance and decreases performance (from 72.14% to 69.69%). In contrast, our proposed DQ_v2 method achieves comparable variance while obtaining higher accuracy (73.80%). This result indicates that our proposed method can effectively address the stability issue of the original DQ method while maintaining high performance. Furthermore, we observe similar stability improvements on the Food-101 dataset, where our proposed method achieves a variance of 0.0745, significantly lower than DQ's 0.197.

These results underscore the effectiveness of our method in addressing the instability issue of DQ when the pre-trained model is removed. We attribute DQ_v2's stability primarily to the following factors: 1) By employing semantically-aware background replacement, it provides more diverse training samples, reducing dependence on specific background features while expanding the sample space and mitigating the risk of overfitting. 2) Maintaining a balance of original images and semantically-aware augmented images in the dataset preserves the authenticity of the original data while introducing sufficient diversity. 3) Our modified pipeline, which performs data augmentation before coreset selection, prevents the feature shifts that occur in the original DQ method (as discussed in Section 4.2 of the main paper), where data augmentation after coreset selection can lead to instability.

C Ablation Studies

In this section, we conduct ablation studies to analyze the impact of key components in our proposed DQ_v2 method.

C.1 Impact of Bin Division Algorithms

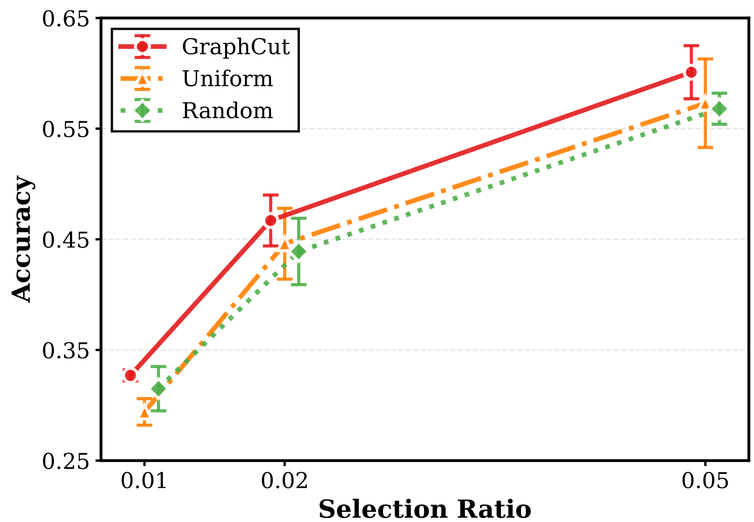


Figure 6: Visualization of bin division algorithm performance on ImageNette.

We analyze the impact of different bin split algorithms on the performance of our proposed method. We compare the performance of our method with three different bin split strategies, including GraphCut (Iyer et al., 2021), Random, and Uniform methods, on the ImageNette dataset at various data keep ratios (1%, 2%, and 5%). To ensure reliability, we repeat each experiment three times with different random seeds and report the mean accuracy and standard deviation. The results are shown in Figure 6.

The results demonstrate that the GraphCut method consistently achieves the best performance across all data keep ratios (Figure 6). At the 1% keep ratio, GraphCut achieves 32.7% accuracy, outperforming Random (31.5%) and Uniform (29.4%). This performance advantage becomes more pronounced at higher keep ratios, with GraphCut reaching 60.1% at 5%, compared to 56.8% for Random and 57.3% for Uniform. These results indicate that GraphCut can effectively select the most representative samples from the dataset, which improves the performance of the trained model.

In summary, the GraphCut algorithm consistently outperforms Random and Uniform methods across different data keep ratios. The performance improvements are substantial, particularly at lower keep ratios where sample selection quality is most critical. Therefore, in practice, we strongly recommend using the GraphCut method to achieve optimal performance and stability.

D Detailed Analysis of DQ_v2 Performance on ImageNet-1k

Performance Analysis at Low Data Ratios

We observe that at extremely low data keep ratios (e.g., 10%), our DQ_v2 method performs marginally below CCS. This phenomenon can be attributed to the data expansion step in our pipeline. The primary purpose of this step is to expand the sample space, enabling the subsequent coreset selection to choose more diverse samples while reducing redundant information. It also provides augmentation to prevent rapid overfitting. However, at very low sampling ratios, the original sample space can hardly be comprehensively captured, making the additional samples less meaningful. Nevertheless, such extremely low selection ratios have limited practical applications in real-world scenarios.

Achieving Superior Efficiency and Performance against SOTA

DQ_v2 can achieve higher accuracy with less data (e.g., 75.94% at 60% keep ratio vs. 75.58% at 80% for the strongest baseline) due to the synergy between SDA and GraphCut. SDA expands the candidate pool with semantically consistent variations, and GraphCut then selects a diverse and informative subset from this enriched space, yielding a better accuracy–efficiency trade-off at moderate keep ratios.

Fair Comparison of Training Sample Count

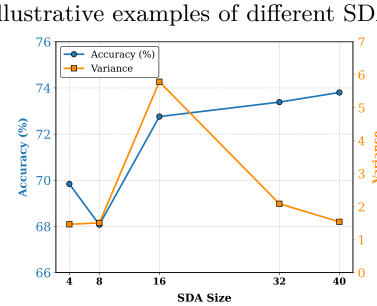
One might question whether DQ_v2 actually uses more training samples than other methods at the same reported keep ratio, given that our pipeline includes a data expansion step. To address this concern, we provide a mathematical formulation to demonstrate that our method maintains the same number of training samples as other methods at equivalent keep ratios.

Let x denote the number of training samples in the original dataset. A conventional coreset selection method with a keep ratio of r would select $r \cdot x$ samples. In our DQ_v2 pipeline, we first expand the dataset to $1.5x$ samples through semantically-aware augmentation, and then apply a proportionally reduced selection ratio of $\frac{r}{1.5}$ to maintain the same final count:

$$\text{Number of samples} = 1.5x \cdot \frac{r}{1.5} = r \cdot x \tag{7}$$

For instance, to obtain a 60% subset ($0.6x$) from the original dataset of size x, we first expand it to $1.5x$ and then select 40% ($0.4{\cdot}1.5x = 0.6x$). Therefore, DQ_v2 uses exactly the same number of training samples as other methods at equivalent keep ratios, ensuring a fair comparison.

(a) Illustrative examples of different SDA sizes



(b) Acc. and Var. for different SDA sizes

Figure 7: Impact of SDA sizes on DQ_v2 performance. Results on ImageNette dataset.

D.1 Impact of SDA Size

We study the SDA patch size, which controls the granularity of patch-wise background replacement. Larger values generally preserve semantic structure better (Figure 7a). We evaluate five sizes on ImageNette; results are shown in Figure 7b.

SDA patch size strongly affects performance: very small sizes (e.g., 4×4, 8×8) degrade accuracy, while larger sizes improve both mean accuracy and stability, peaking at 40×40.

We attribute this to finer background replacement removing more background-specific cues, which encourages a stronger reliance on the foreground. Based on these results, we use an SDA patch size of 40×40 for optimal performance and stability.

D.2 Impact of Mixing Ratio

Finally, we investigate the impact of the mixing ratio between the original images and Semantically-Aware augmented images on the performance of our proposed method. Since we do not need to rely on the pre-trained MAE model, we can simply mix semantically-aware augmented data and original images to improve the diversity and quality of the data. Thus, we evaluated the performance of our proposed method with different mixing ratios in the CUB-200, Food-101, and ImageNet-30 datasets. The ImageNet-30 dataset, a subset of ImageNet-1k, was utilized in these specific experiments to enable faster validation.

The results are shown in Figure 8. We observe that performance consistently achieves the best score when we use all original images together with 50% SDA images.

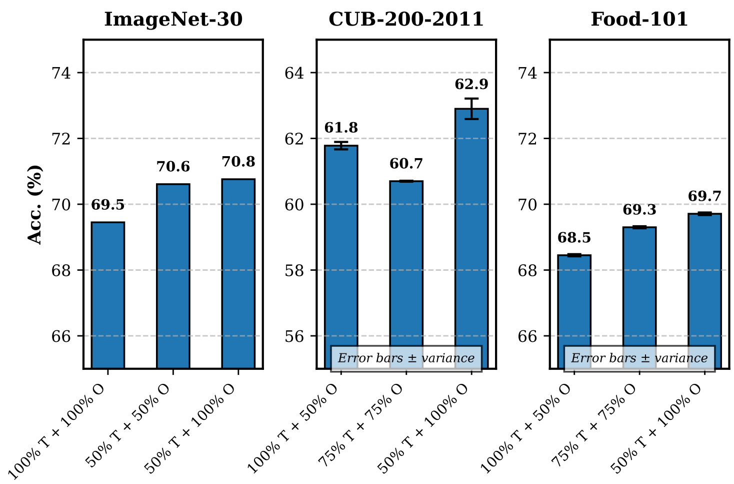


Figure 8: Performance with different T (Semantically-Aware augmented) and O (Original) image ratios. We report the mean accuracy (%) and variance in five runs with different seeds.