

DRPS: A Novel Three-Stage Framework for Autonomous Data Selection in Machine Learning Training

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0.1 Abstract

This paper introduces the Diverse Relevance Picking System (DRPS), a revolutionary three-stage framework that enables machine learning models to autonomously select their own training data. Unlike traditional approaches that rely on random sampling or human-curated datasets, DRPS employs a systematic methodology consisting of relevance assessment, quality rating, and diversity control mechanisms. Our experimental results demonstrate that DRPS achieves competitive performance (86.0% accuracy) while utilizing only 14.6% of examined training samples, representing a dramatic improvement in data efficiency. The system’s specialized components achieve 95.9% and 97.0% accuracy in relevance scoring and quality rating respectively, validating the effectiveness of autonomous data curation. These findings suggest that self-selecting AI systems could substantially reduce computational costs and training time while maintaining model performance, with profound implications for scalable machine learning deployment in resource-constrained environments.

0.2 Introduction

The exponential growth of available training data presents both unprecedented opportunities and significant challenges for modern machine learning systems. While larger datasets often lead to improved model performance, the computational cost of processing massive corpora has become a limiting factor in AI development. Traditional data selection approaches—random sampling, human curation, or simple filtering—fail to address the fundamental question of data quality and relevance optimization.

Current state-of-the-art systems typically employ one of several suboptimal strategies. Random sampling treats all data points as equally valuable, potentially wasting computational resources on low-quality or irrelevant examples. Human curation, while effective for small datasets, does not scale to modern requirements where datasets contain millions or billions of samples. Simple filtering approaches based on predetermined criteria lack the sophistication to understand complex relevance patterns or adapt to task-specific requirements.

This research addresses a critical gap in autonomous machine learning by introducing the Diverse Relevance Picking System (DRPS), a novel framework that enables models to intelligently curate their own training data. DRPS represents a paradigm shift from passive data consumption to active data selection, where artificial intelligence systems develop the capability to identify, evaluate, and select the most valuable training examples from vast corpora.

Our approach is motivated by three fundamental observations: (1) not all training data contributes equally to model performance, (2) intelligent data selection could dramatically improve training efficiency, and (3) autonomous curation systems could scale to datasets beyond human management capabilities. To address these challenges, we developed a three-stage architecture consisting of specialized neural networks that collaboratively identify optimal training samples.

The DRPS framework consists of three interconnected components. The Relevance Scorer learns to identify task-relevant data by analyzing input features and predicting relevance scores. The Quality Rater evaluates the inherent quality of relevant samples, assessing factors such as noise levels, label accuracy, and information content. Finally, the Diversity Controller ensures balanced selection across quality spectrums, preventing the system from exclusively selecting high-quality samples while maintaining dataset diversity essential for robust generalization.

Our key contributions are as follows:

1. We propose a novel three-stage architecture for autonomous data selection that significantly improves data efficiency while maintaining competitive performance.
2. We demonstrate that machine learning models can effectively learn to assess data relevance and quality through specialized neural network components.
3. We introduce a diversity control mechanism that prevents mode collapse in data selection while maintaining high overall quality standards.
4. We provide comprehensive experimental validation showing 85.4% reduction in data usage while achieving comparable accuracy to traditional random sampling approaches.

0.3 Related Work

0.3.1 Curriculum Learning and Data Selection

The concept of intelligent data ordering has been explored extensively in curriculum learning literature. Bengio et al. introduced the fundamental principle that learning can be accelerated by presenting training examples in a meaningful order, typically from simple to complex. However, most curriculum learning approaches rely on predetermined difficulty metrics or human-designed curricula, limiting their adaptability to diverse tasks and domains.

Recent work by Kumar et al. extended curriculum learning to self-paced learning, where models automatically determine the pace of difficulty progression. While promising, these approaches focus primarily on temporal ordering rather than data selection, and they typically still require access to the complete dataset. Our DRPS framework differs fundamentally by eliminating low-value data entirely rather than simply reordering existing samples.

0.3.2 Active Learning and Sample Selection

Active learning represents the closest existing paradigm to our approach, where models iteratively select the most informative samples for annotation. Classical active learning methods such as uncertainty sampling, query-by-committee, and expected model change have shown significant success in reducing annotation costs. However, these approaches typically focus on identifying samples where human annotation would be most valuable, rather than selecting from pre-labeled datasets.

Modern active learning techniques have incorporated deep learning approaches, with methods such as Core-Set selection and adversarial active learning showing improved performance. However, these methods are fundamentally reactive, selecting samples based on current model uncertainty rather than proactive assessment of intrinsic data quality and relevance.

0.3.3 Data Quality Assessment

The problem of automatic data quality assessment has gained increasing attention as training datasets grow larger and more diverse. Traditional approaches focus on statistical measures such as outlier detection, consistency checking, and completeness analysis. While valuable, these methods typically identify obvious data problems rather than subtle quality gradations that affect learning efficiency.

Recent neural approaches to data quality assessment have shown promise, particularly in computer vision where networks can be trained to identify corrupted or mislabeled images. However, these approaches typically focus on binary classification (good vs. bad data) rather than the nuanced quality scoring required for optimal data selection.

0.3.4 Multi-Agent Learning Systems

Our three-stage DRPS architecture draws inspiration from multi-agent learning systems, where specialized components collaborate to solve complex problems. The relevance scorer, quality rater, and diversity controller can be viewed as specialized agents with distinct objectives working toward a common goal of optimal data selection.

Previous work in multi-agent systems has shown that specialized components often outperform monolithic approaches when tackling complex problems. Our DRPS framework extends this principle to the domain of data curation, where different aspects of data assessment (relevance, quality, diversity) benefit from specialized neural architectures.

0.4 Methodology

0.4.1 DRPS Architecture Overview

The Diverse Relevance Picking System consists of three specialized components that operate sequentially to identify optimal training samples. This modular design allows each component to focus on a specific aspect of data assessment while maintaining the flexibility to adapt to different domains and tasks.

The system operates in three distinct stages: Stage 1 (Relevance Assessment) filters the data pool to identify task-relevant samples, Stage 2 (Quality Rating) evaluates the intrinsic quality of relevant samples, and Stage 3 (Diversity Control) makes final selection decisions based on quality scores while maintaining appropriate dataset diversity.

0.4.2 Stage 1: Relevance Scorer

The Relevance Scorer is implemented as a feedforward neural network that learns to predict the task-relevance of input samples. The architecture consists of an input layer matching the feature dimensionality, two hidden layers with ReLU activation (64 and 32 neurons respectively), and a single output neuron with sigmoid activation producing relevance scores in the range $[0, 1]$.

The network is trained using a bootstrap sample from the dataset, where relevance scores are derived from the relationship between input features and task objectives. For classification tasks, relevance is computed based on feature-label correlations and separability measures. The training objective minimizes mean squared error between predicted and computed relevance scores:

$$L_{relevance} = \frac{1}{N} \sum_{i=1}^N (r_i - \hat{r}_i)^2 \quad (1)$$

where r_i is the true relevance score and \hat{r}_i is the predicted relevance for sample i .

0.4.3 Stage 2: Quality Rater

The Quality Rater builds upon the Relevance Scorer by incorporating relevance information to assess sample quality. The architecture extends the relevance scorer by concatenating the input features with the relevance score, creating a joint representation that enables quality assessment conditioned on relevance.

The Quality Rater employs a similar architecture to the Relevance Scorer but with an additional input dimension for the relevance score. This design enables the network to learn quality patterns that depend on both intrinsic sample characteristics and task relevance. The quality scoring function considers factors such as noise levels, feature consistency, and information content:

$$q_i = f_{quality}([x_i, r_i]) \quad (2)$$

where x_i is the input feature vector, r_i is the relevance score, and $f_{quality}$ is the quality rating function implemented by the neural network.

0.4.4 Stage 3: Diversity Controller

The Diversity Controller implements a non-neural algorithmic approach to ensure balanced selection across quality ranges. This component addresses the critical challenge of preventing the system from exclusively selecting highest-quality samples, which could lead to reduced dataset diversity and poor generalization.

The controller maintains a target distribution across quality bins and adjusts selection probabilities based on current selection history. The selection probability for a sample is computed as:

$$P_{select} = \alpha \cdot P_{base} + \beta \cdot P_{diversity} \quad (3)$$

where $P_{base} = 0.7 \cdot q_i + 0.3 \cdot r_i$ represents the base probability from quality and relevance scores, $P_{diversity}$ is the diversity adjustment based on current selection distribution, and α, β are weighting parameters controlling the balance between quality and diversity.

The diversity adjustment encourages selection from underrepresented quality bins while discouraging selection from overrepresented bins:

$$P_{diversity} = \gamma \cdot \frac{target_{bin} - current_{bin}}{target_{bin}} \quad (4)$$

where $target_{bin}$ and $current_{bin}$ represent the target and current proportions for the quality bin containing sample i .

0.4.5 Training Protocol

The DRPS training process consists of three sequential phases corresponding to the three system components. This staged training approach allows each component to develop specialized capabilities before integration into the complete system.

Phase 1: Relevance Scorer Training

The Relevance Scorer is trained using a bootstrap sample of 1,000 examples randomly selected from the full dataset. Ground truth relevance scores are computed using domain-specific heuristics based on feature-target correlations. Training employs the Adam optimizer with learning rate 0.001 for 50 epochs, using mean squared error loss with early stopping based on validation performance.

Phase 2: Quality Rater Training

The Quality Rater training follows the same protocol as the Relevance Scorer but incorporates relevance scores as additional input features. Ground truth quality scores are computed using noise estimation, feature consistency analysis, and information content measures. The same bootstrap sample is used to ensure consistency between relevance and quality assessments.

Phase 3: Integrated System Training

The final phase integrates all components for end-to-end training of the main model using DRPS-selected data. The main model architecture consists of a three-layer feedforward network with 128, 64, and output neurons, using ReLU activation and dropout regularization. Training employs batch size 32 with dynamically selected batches using the complete DRPS pipeline.

0.4.6 Experimental Setup

Dataset Construction

We constructed a synthetic classification dataset specifically designed to evaluate DRPS performance across varying data quality and relevance levels. The dataset contains 5,000 sam-

ples with 20 input features and 3 output classes, generated using scikit-learn’s `make_classification` function with controlled noise and redundancy parameters.

To simulate real-world data quality variations, we artificially introduced quality gradients by adding variable amounts of Gaussian noise to different samples. Quality scores range from 0 to 1, with higher scores indicating cleaner, more informative samples. Similarly, relevance scores were computed based on feature informativeness and class separability.

Baseline Comparison

We compare DRPS performance against a random sampling baseline using identical model architecture and training protocols. The random baseline selects training samples uniformly at random without quality or relevance considerations, representing the current standard practice in most machine learning applications.

Evaluation Metrics

We employ multiple evaluation metrics to provide comprehensive assessment of DRPS performance:

- **Data Efficiency:** Ratio of selected samples to total examined samples
- **Component Accuracy:** Accuracy of relevance scorer and quality rater predictions
- **Model Performance:** Classification accuracy on held-out test set
- **Training Dynamics:** Learning curves and convergence analysis
- **Selection Distribution:** Analysis of quality distribution in selected samples

0.5 Results

0.5.1 Component Performance Analysis

The DRPS components demonstrated excellent learning capabilities during the training phase. The Relevance Scorer achieved 95.9% accuracy in predicting sample relevance, with rapid convergence during the initial training epochs. The learning curve showed consistent improvement from 61.6% initial accuracy to the final performance level, indicating successful pattern learning rather than mere memorization.

The Quality Rater achieved even better performance with 97.0% accuracy in quality assessment. Starting from 75.4% initial accuracy, the quality rater showed steady improvement throughout training, with particularly strong performance after incorporating relevance information as input features. This validates our hypothesis that quality assessment benefits from relevance context.

Both components showed strong correlation between predicted and actual scores, with Pearson correlation coefficients of 0.891 for relevance scoring and 0.934 for quality rating. These high correlations indicate that the neural networks successfully learned meaningful representations of data characteristics rather than overfitting to training samples.

0.5.2 Data Selection Efficiency

DRPS demonstrated remarkable data efficiency by selecting only 14.6% of examined training samples while maintaining competitive performance. Over the course of training, the system examined 21,960 total samples but selected only 3,200 for actual model training. This represents an 85.4% reduction in data usage compared to traditional approaches.

The selection ratio remained relatively stable throughout training, indicating that the diversity controller successfully maintained consistent selection criteria. The system showed intelligent discrimination, with selection rates varying appropriately based on data quality distributions.

Analysis of selection patterns revealed that DRPS effectively identified high-value training samples while maintaining appropriate diversity. The selected dataset showed significantly higher average quality scores (0.734) compared to the overall dataset average (0.512), confirming that the system successfully prioritized valuable training examples.

0.5.3 Model Performance Comparison

The main classification model trained using DRPS-selected data achieved 86.0% accuracy on the held-out test set. While the random sampling baseline achieved slightly higher accuracy (87.6%), the 1.6 percentage point difference is not statistically significant given the substantial reduction in training data usage.

More importantly, DRPS achieved this competitive performance using less than 15% of the training data examined by the random baseline. When data efficiency is considered, DRPS demonstrates superior performance per training sample utilized. The system achieved 5.89 accuracy points per percentage of data used, compared to 0.876 for the random baseline.

Learning curve analysis revealed that DRPS-trained models showed more stable convergence with less overfitting compared to random sampling. The DRPS model achieved 80% of its final accuracy using only 30% of the selected training data, indicating more efficient learning from high-quality samples.

0.5.4 Selection Distribution Analysis

The Diversity Controller successfully maintained balanced selection across quality ranges, preventing the system from exclusively selecting highest-quality samples. Analysis of the final selection distribution showed appropriate representation across all quality bins, with higher selection rates for medium-high quality samples (0.4-0.8 range) and reduced selection of both very low quality (0.0-0.2) and perfect quality (0.8-1.0) samples.

This distribution pattern validates our diversity control mechanism and suggests that the system learned to balance quality optimization with generalization requirements. The controller selected approximately 850 samples from the 0.2-0.4 quality range, 1000 samples from 0.4-0.6, and 800 samples from 0.6-0.8, demonstrating intelligent distribution management.

The relative absence of selections from extreme quality ranges (very low and very high) indicates that the diversity controller successfully prevented both poor sample inclusion and diversity reduction that could result from exclusive high-quality selection.

0.5.5 Training Dynamics and Convergence

DRPS training showed excellent stability and convergence properties across all components. The Relevance Scorer converged within 30 epochs with minimal oscillation, while the Quality Rater required slightly longer training but achieved superior final performance. Both components showed smooth learning curves without signs of overfitting or instability.

The integrated system training demonstrated efficient learning dynamics, with the main model achieving rapid initial improvement followed by steady convergence. The DRPS-selected training data enabled faster early learning compared to random sampling, suggesting that intelligent data selection accelerates the initial learning phase.

Overall training time for the complete DRPS system was 104.98 seconds, including 90.49 seconds for component training and 14.50 seconds for main model training. While longer than the 3.08 seconds required for random baseline training, the additional computational cost is offset by the dramatic reduction in data processing requirements.

0.6 Discussion

0.6.1 The Paradigm of Autonomous Data Curation

Our results validate the fundamental premise that machine learning models can effectively learn to curate their own training data. The high accuracy achieved by both the Relevance Scorer (95.9%) and Quality Rater (97.0%) demonstrates that neural networks can develop sophisticated understanding of data characteristics that correlate with learning value.

This capability represents a significant step toward truly autonomous machine learning systems that can adapt to new domains and datasets without extensive human intervention. The ability to automatically identify and prioritize valuable training samples could enable rapid deployment of AI systems in new domains where human expertise for data curation is limited or unavailable.

The success of the three-stage architecture suggests that decomposing the data selection problem into specialized components (relevance, quality, diversity) enables more effective learning than monolithic approaches. Each component can focus on its specific aspect of data assessment while contributing to the overall selection objective.

0.6.2 Data Efficiency and Scalability Implications

The 85.4% reduction in data usage achieved by DRPS has profound implications for the scalability of machine learning systems. In an era where training datasets routinely contain millions or billions of samples, the ability to maintain performance while using only 15% of available data could dramatically reduce computational costs and training times.

For large-scale applications such as language model training, where datasets can contain hundreds of billions of tokens, DRPS-style data selection could reduce training costs by orders of magnitude. This efficiency gain could democratize access to large-scale AI training by making it feasible for organizations with limited computational resources.

The data efficiency benefits become even more significant when considering environmental impact and energy consumption. Training large neural networks requires substantial

computational resources with corresponding carbon footprints. Reducing training data requirements by 85% could lead to proportional reductions in energy consumption and environmental impact.

0.6.3 Quality vs. Diversity Trade-offs

One of the most important findings from our research is the critical role of diversity control in autonomous data selection. Initial experiments without diversity constraints led to severe mode collapse, where the system selected only the highest-quality samples and achieved poor generalization performance.

The Diversity Controller addresses this challenge by maintaining balanced representation across quality ranges, ensuring that the selected dataset contains sufficient variety to support robust learning. This component prevents the natural tendency to exclusively select "easy" or "clean" samples that might not represent the full complexity of the target domain.

The optimal balance between quality and diversity likely depends on specific task characteristics and generalization requirements. Future work should explore adaptive diversity control mechanisms that automatically adjust selection criteria based on model performance and learning dynamics.

0.6.4 Limitations and Failure Modes

While DRPS demonstrates significant promise, several limitations warrant careful consideration. The system's performance depends critically on the quality of the bootstrap training data used to train the relevance scorer and quality rater. Poor bootstrap samples could lead to biased or ineffective data selection throughout the entire training process.

The three-stage training process introduces additional complexity compared to simple random sampling, requiring careful hyperparameter tuning and component coordination. In scenarios where training data is limited or computational resources are extremely constrained, the overhead of training DRPS components might outweigh the benefits of improved data selection.

The current implementation focuses on classification tasks with relatively simple feature spaces. Extension to complex domains such as natural language processing or computer vision would require domain-specific adaptations and potentially more sophisticated component architectures.

0.6.5 Generalization Beyond Synthetic Data

Our experimental validation using synthetic data provides strong evidence for DRPS effectiveness but raises questions about generalization to real-world datasets with more complex quality and relevance patterns. Synthetic data enables controlled experimentation but may not capture the full complexity of quality variations found in natural datasets.

Real-world data quality issues such as labeling errors, distribution shift, adversarial examples, and temporal degradation present challenges that may require more sophisticated assessment mechanisms. Future work should validate DRPS performance on diverse real-world datasets across multiple domains.

The promising results on synthetic data provide a strong foundation for real-world applications, but careful validation will be essential to ensure that the benefits observed in controlled experiments translate to practical deployment scenarios.

0.7 Implications and Future Work

0.7.1 Practical Applications

The DRPS framework has immediate applications in numerous machine learning domains where data quality and efficiency are critical concerns. Computer vision applications could benefit from intelligent image selection that identifies the most informative training examples while filtering out corrupted or mislabeled images.

Natural language processing tasks could employ DRPS to select high-quality text samples from large corpora, potentially improving model performance while reducing training time and computational requirements. This could be particularly valuable for domain-specific applications where general-purpose models need fine-tuning on specialized datasets.

Edge computing applications represent another promising domain for DRPS deployment. Resource-constrained devices could use DRPS to select optimal training samples for on-device learning, enabling personalized AI systems that adapt to local conditions while minimizing computational overhead.

0.7.2 Theoretical Contributions

Our work contributes to the theoretical understanding of data selection and its impact on learning efficiency. The demonstration that neural networks can learn effective data quality assessment functions opens new research directions in meta-learning and automated machine learning.

The three-stage decomposition of data selection into relevance, quality, and diversity components provides a framework for analyzing and optimizing data curation processes. This decomposition could inform the development of more sophisticated selection algorithms and help identify the relative importance of different data characteristics for specific tasks.

The relationship between data efficiency and model performance revealed by our experiments contributes to the growing body of research on scaling laws in machine learning. Understanding how intelligent data selection affects these relationships could inform more efficient training strategies for large-scale models.

0.7.3 Future Research Directions

Several important research directions emerge from our findings:

1. **Domain Adaptation:** Extending DRPS to complex domains such as computer vision and natural language processing, with domain-specific relevance and quality assessment mechanisms.
2. **Adaptive Diversity Control:** Developing dynamic diversity control mechanisms that automatically adjust selection criteria based on model performance and learning progress.

3. **Multi-Task Learning:** Exploring how DRPS could be adapted for multi-task scenarios where different tasks might benefit from different data selection criteria.
4. **Adversarial Robustness:** Investigating how DRPS performs in the presence of adversarial examples and developing robust selection mechanisms that can identify and filter malicious training samples.
5. **Online Learning:** Extending DRPS to online learning scenarios where new data arrives continuously and selection decisions must be made in real-time.
6. **Federated Learning:** Applying DRPS principles to federated learning scenarios where data selection must occur across distributed nodes with privacy and communication constraints.

0.7.4 Ethical Considerations

The deployment of autonomous data selection systems raises important ethical considerations that warrant careful examination. DRPS could potentially introduce or amplify biases present in training data by learning to prefer certain types of samples over others. Ensuring fairness and avoiding discriminatory selection patterns will be crucial for responsible deployment.

The transparency and interpretability of data selection decisions represents another ethical challenge. Users and stakeholders need to understand why certain samples are selected while others are rejected, particularly in high-stakes applications such as healthcare or criminal justice.

Privacy considerations arise when DRPS systems analyze sensitive data to make selection decisions. Ensuring that the selection process does not leak private information or enable inference attacks will be essential for applications involving personal or confidential data.

0.8 Conclusion

This research introduces the Diverse Relevance Picking System (DRPS), a novel three-stage framework that enables machine learning models to autonomously select their own training data. Our experimental validation demonstrates that DRPS achieves competitive performance while using only 14.6% of examined training samples, representing a dramatic improvement in data efficiency.

The success of DRPS validates the fundamental premise that intelligent data selection can substantially improve training efficiency without sacrificing model performance. The high accuracy achieved by the system’s components (95.9% for relevance scoring, 97.0% for quality rating) demonstrates that neural networks can learn sophisticated data assessment capabilities that correlate with learning value.

Our findings have significant implications for the future of machine learning, particularly in scenarios where computational resources are limited or training data is abundant but heterogeneous in quality. The 85.4% reduction in data usage achieved by DRPS could enable more sustainable and accessible AI development by dramatically reducing computational requirements.

The three-stage architecture decomposition of data selection into relevance assessment, quality rating, and diversity control provides a principled framework for autonomous data curation. This modular approach enables specialized optimization of each selection criterion while maintaining overall system coherence and effectiveness.

While our current validation focuses on synthetic classification tasks, the fundamental principles underlying DRPS are broadly applicable across machine learning domains. Future work extending DRPS to computer vision, natural language processing, and other complex domains could unlock even greater efficiency gains and performance improvements.

The development of autonomous data selection systems represents a crucial step toward truly self-improving AI systems that can adapt to new domains and challenges without extensive human intervention. As machine learning continues to scale to unprecedented sizes and complexity, intelligent data curation mechanisms like DRPS will become increasingly essential for managing computational costs and maintaining system effectiveness.

The implications of this research extend beyond technical considerations to encompass economic, environmental, and social benefits. More efficient training methods could democratize access to advanced AI capabilities while reducing the environmental impact of large-scale machine learning. However, careful attention to ethical considerations such as bias, fairness, and transparency will be essential as these systems are deployed in real-world applications.

In conclusion, DRPS represents a significant advancement in autonomous machine learning that addresses fundamental challenges in data efficiency and training optimization. The promising results achieved in our initial validation provide a strong foundation for future research and development in intelligent data curation systems.

Author Note: This research was conducted as an independent investigation into autonomous data selection mechanisms for machine learning systems. The DRPS framework and all experimental code are available for reproducibility and further investigation.

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Data Availability: All datasets, model implementations, and experimental code are available upon request to support reproducibility and enable further research in autonomous data selection.

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