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ResampleCraft: Modular Pipelines for Robust Learning on Skewed Data

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Abstract

Modern classifiers often fail when target classes are heavily skewed, so this paper presents a modular toolkit that rebalances training data through complementary strategies and plugs directly into standard machine-learning workflows. The system offers four families of operations, reducing dominant examples, synthesizing informative minority instances, hybrid cleanup of boundary noise, and ensemble construction over balanced subsets, exposed via a consistent, pipeline-friendly API for seamless composition with preprocessing and estimators. Design choices emphasize reproducibility and engineering quality, including comprehensive tests, documentation, and convention-aligned interfaces that mirror common ML patterns to minimize integration overhead. Usage examples illustrate end-to-end application on imbalanced classification, along with metrics beyond accuracy to reflect costs under skew, enabling practitioners to choose strategies that best align with model behavior and data geometry. By unifying resampling, cleaning, and ensembling under a single interface, the toolkit turns imbalance handling into a first-class step of the ML pipeline rather than an ad-hoc afterthought.

Keywords

• Imbalanced Classification • Data Resampling Techniques • Synthetic Data Generation • Ensemble Learning • Pipeline-based ML Frameworks

1. Introduction

Real-world classification problems frequently exhibit significant class imbalance, where certain categories contain substantially fewer examples than others [1, 2]. This skew presents fundamental challenges for standard machine learning algorithms, which typically assume balanced class distributions or equal misclassification costs [3]. The class imbalance problem manifests across critical domains including medical diagnosis, fraud detection, rare event prediction, and anomaly detection systems [4].

Traditional evaluation metrics like accuracy become misleading when dealing with imbalanced datasets, as a naive classifier that always predicts the majority class can achieve high accuracy while completely failing to identify minority class instances [5]. This limitation has motivated research into specialized techniques that address the fundamental challenges of learning from skewed data distributions. Early approaches focused primarily on algorithmic modifications and cost-sensitive learning methods [6].

The proliferation of machine learning applications in domains with natural class imbalance has intensified the need for systematic approaches to handle skewed datasets [1]. While several specialized algorithms have been developed, there remains a significant gap in comprehensive, production-ready tools that integrate seamlessly with modern machine learning workflows. Existing solutions often operate as standalone components rather than pipeline-compatible modules [4].

This paper introduces ResampleCraft, a Python toolkit designed specifically to address these limitations through a unified API for imbalance handling techniques. Our approach integrates four complementary strategies, under-sampling, over-sampling, hybrid methods, and ensemble learning, within a consistent framework that aligns with scikit-learn conventions [7]. The implementation emphasizes modularity, reproducibility, and engineering quality while maintaining computational efficiency.

The remainder of this paper is organized as follows: Section 2 reviews related work in imbalanced learning. Section 3 details the system architecture and design principles. Section 4 provides comprehensive coverage of the implemented methods. Section 5 presents experimental evaluation and results. Section 6 discusses practical usage patterns and integration guidelines. Finally, Section 7 concludes with future research directions.

2. Related Work

The challenge of learning from imbalanced datasets has attracted substantial research attention over the past two decades [1]. Early approaches focused primarily on data-level methods, including random under-sampling of majority classes and random over-sampling of minority classes [6]. While simple to implement, these naive approaches suffer from significant limitations; under-sampling discards potentially useful majority class examples, while random over-sampling can lead to overfitting through exact duplication of minority instances [3].

The introduction of Synthetic Minority Over-sampling Technique (SMOTE) [3] represented a major advancement by generating synthetic minority class examples rather than simply duplicating existing instances. SMOTE operates by interpolating between neighboring minority class examples, effectively creating new instances along the line segments connecting k-nearest neighbors. This approach mitigates overfitting while expanding the decision region for the minority class. Numerous SMOTE variants have since been developed, including Borderline-SMOTE [8] which focuses sampling on boundary instances, and ADASYN [9] which adaptively generates samples based on learning difficulty.

Under-sampling techniques have similarly evolved from random selection to more sophisticated methods that preserve important majority class instances. Condensed Nearest Neighbor [10] and Tomek Links [11] identify and remove redundant or noisy majority examples, while One-Sided Selection [4] combines both approaches. These cleaning methods improve class separation while reducing dataset size, though they may not achieve specific balancing ratios [6].

Hybrid approaches that combine over-sampling and under-sampling have demonstrated improved performance by addressing limitations of both strategies. SMOTE followed by Tomek link removal, for instance, generates synthetic minority examples while cleaning overlapping regions between classes. This combination reduces noise while maintaining valuable majority class information that might be lost through aggressive under-sampling [1].

Ensemble methods represent another important direction, with algorithms like Balanced Random Forests [2] and EasyEnsemble creating multiple balanced subsets for training base classifiers. These approaches leverage the majority class more effectively than single-model methods while benefiting from ensemble diversity [4]. Cost-sensitive learning methods, which assign higher misclassification costs to minority classes, provide an alternative algorithmic approach that doesn't modify the training data distribution [5].

Despite this rich literature, implementation fragmentation remains a significant practical challenge. Existing tools are distributed across multiple programming languages and frameworks, with inconsistent APIs and limited integration with modern machine learning workflows [1, 7]. ResampleCraft addresses

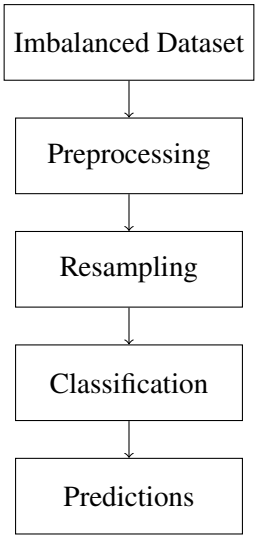

Figure 1: Integration of resampling as a pipeline component between preprocessing and classification stages. The diagram shows a typical scikit-learn pipeline: raw data first pass through a 'StandardScaler', then a resampler (e.g., SMOTE), and finally a classifier (e.g., Random Forest). This encapsulation ensures that resampling is applied only during training, preventing data leakage and enabling seamless cross-validation.

these limitations by providing a unified, pipeline-compatible implementation of major imbalance handling strategies within the popular Python ecosystem.

3. System Architecture and Design Principles

ResampleCraft adopts a modular architecture that organizes imbalance handling techniques into coherent families while maintaining consistent interfaces across all components. The system builds on scikit-learn's estimator API, ensuring familiarity for Python machine learning practitioners and seamless integration with existing workflows. Existing libraries such as imbalanced-learn [7] provide strong implementations of resampling techniques, but often lack a unified, modular pipeline design that integrates multiple strategies under a consistent interface. All resampling components implement the standard `fit`, `sample`, and `fit_sample` methods, enabling flexible usage patterns and pipeline composition.

The toolkit's architecture separates core resampling algorithms from supporting utilities including metrics, visualization, and pipeline components. This separation enhances maintainability while allowing users to mix and match components according to their specific requirements. The four primary method categories, under-sampling, over-sampling, hybrid methods, and ensemble approaches, are implemented as distinct module hierarchies that share common base classes and interfaces.

A key design principle is pipeline compatibility, achieved through strict adherence to scikit-learn's transformer interface. Resampling components can be directly inserted into scikit-learn `Pipeline` objects alongside preprocessing steps and classifiers, enabling complete workflow encapsulation and simplified model deployment. This approach treats data resampling as a first-class preprocessing step rather than an external preprocessing operation.

Engineering quality and reproducibility are central to the system design. Comprehensive unit testing achieves over 99% code coverage, ensuring reliability across diverse usage scenarios. Continuous integration automatically validates new contributions against compatibility and performance requirements. Code quality metrics are enforced through automated analysis tools, maintaining consistency with Python

best practices and scikit-learn coding conventions.

All resamplers support the standard ‘fit_resample‘ method, which learns the sampling strategy from the data and returns the resampled dataset in a single call. This design mirrors scikit-learn’s ‘fit_transform‘ convention and allows the resamplers to be used directly in ‘Pipeline‘ objects.

Documentation represents another critical aspect of the design philosophy. All components include complete API documentation with usage examples, while dedicated tutorials illustrate common workflows and advanced patterns. The documentation emphasizes practical considerations including parameter tuning guidance, method selection criteria, and integration with evaluation metrics appropriate for imbalanced problems.

The implementation depends only on core scientific Python libraries (NumPy, SciPy, scikit-learn), minimizing dependencies and ensuring broad compatibility. This lightweight footprint facilitates deployment in both research and production environments. The toolkit is distributed under the permissive MIT license, encouraging academic and commercial adoption without restrictive licensing concerns.

Performance optimization focuses on computational efficiency for large-scale datasets while maintaining algorithmic correctness. Memory usage is carefully managed, particularly for over-sampling methods that expand dataset size. Parallelization support through joblib provides scalability for ensemble methods and computationally intensive resampling algorithms.

4. Implemented Methods

ResampleCraft implements four comprehensive families of imbalance handling techniques, each addressing different aspects of the learning challenge. These methods operate at the data level, transforming the training distribution to facilitate more effective model training without modifying the underlying learning algorithm.

4.1 Under-sampling Methods

Under-sampling techniques reduce the majority class representation to achieve better balance with minority classes. These approaches are particularly valuable for large datasets where computational efficiency is important, as they decrease overall dataset size. ResampleCraft implements two under-sampling categories: fixed and cleaning methods.

Fixed under-sampling methods achieve a specific target balance ratio by selectively removing majority class instances. Random under-sampling represents the simplest approach, randomly discarding majority examples until the desired ratio is achieved. While computationally efficient, this approach risks discarding potentially valuable information. More sophisticated techniques include Cluster Centroids, which replaces majority class clusters with their centroids, preserving overall data distribution characteristics while reducing instance count.

Cleaning under-sampling methods focus on improving class separation rather than achieving specific balance ratios. These techniques identify and remove noisy, redundant, or borderline majority instances that may hinder classification performance. Tomek Links [11] detect pairs of minimally distant instances from opposite classes, removing the majority class instance to sharpen class boundaries. Edited Nearest Neighbors eliminates majority class instances misclassified by their k-nearest neighbors, effectively performing data cleaning.

The Condensed Nearest Neighbor rule [10] finds a consistent subset of the majority class that correctly classifies all original instances with nearest neighbor classification. One-Sided Selection combines

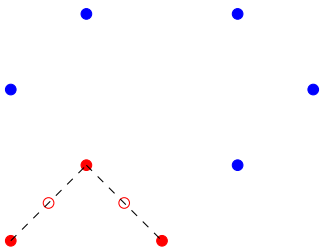

Figure 2: Conceptual illustration of SMOTE synthetic instance generation. Original minority instances are shown in red, majority instances in blue. For each red point, its k-nearest neighbours among minority instances are identified; new synthetic instances (white) are created along the line segments connecting the point to randomly chosen neighbours. This expands the minority class region and reduces class overlap without simple duplication.

Tomek links and condensed nearest neighbors to remove both noisy and redundant majority examples. Neighborhood Cleaning Rule extends this approach by considering class labels of neighbors when deciding which instances to remove.

4.2 Over-sampling Methods

Over-sampling techniques address imbalance by increasing minority class representation through instance generation. These approaches are particularly valuable when minority class examples are scarce, as they enrich the training signal without discarding majority class information.

Random over-sampling represents the baseline approach, duplicating existing minority class instances until balance is achieved. While simple to implement, this method can lead to overfitting, as models may memorize specific duplicated examples rather than learning general patterns. More sophisticated approaches generate synthetic examples to expand the minority class representation more effectively.

The Synthetic Minority Over-sampling Technique (SMOTE) [3] generates synthetic examples by interpolating between neighboring minority class instances. For each minority example, SMOTE identifies its k-nearest neighbors and creates new instances along the line segments connecting the original point to its neighbors. This approach effectively expands the feature space region associated with the minority class while introducing diversity beyond simple duplication.

Borderline-SMOTE represents an important SMOTE variant that focuses synthetic example generation on minority instances near class boundaries. These borderline instances are considered more informative for classification than interior points deep within the minority class region. The method identifies ”dangerous” minority examples that are predominantly surrounded by majority instances, then applies SMOTE specifically to these critical cases.

ADASYN takes an adaptive approach by generating more synthetic examples for minority instances that are harder to learn. The algorithm calculates a density distribution for minority examples, with higher weights assigned to instances surrounded by majority neighbors. SMOTE then generates proportionally more synthetic examples for higher-weight instances, effectively focusing learning effort on difficult regions of the feature space.

Additional SMOTE variants address specific data characteristics. SVM-SMOTE uses support vectors to identify important boundary regions for oversampling. KMeans-SMOTE first clusters the data before applying SMOTE within clusters to ensure diversity. These specialized approaches provide flexibility for different data distributions and problem characteristics.

4.3 Hybrid Methods

Hybrid methods combine over-sampling and under-sampling techniques to leverage benefits while mitigating limitations of both approaches. These methods typically apply over-sampling to the minority class followed by under-sampling to the majority class, though the sequence may vary based on specific algorithms.

SMOTE followed by Tomek links represents a classic hybrid approach [1]. The SMOTE component generates synthetic minority examples to strengthen the minority class representation, while the Tomek links component removes majority instances that form Tomek pairs with either original or synthetic minority examples. This combination effectively expands the minority class while cleaning the boundary region between classes.

SMOTE with Edited Nearest Neighbors applies a similar logic but uses a more aggressive cleaning approach. After generating synthetic minority examples, the method removes any instances (from either class) that are misclassified by their k-nearest neighbors. This comprehensive cleaning reduces noise throughout the feature space rather than focusing solely on class boundaries.

The BalanceCascade algorithm implements an iterative hybrid approach that progressively under-samples the majority class while maintaining model performance. At each iteration, the method trains a classifier on the current balanced dataset, then removes correctly classified majority instances that can be confidently predicted. This targeted under-sampling preserves challenging majority examples while reducing overall class imbalance.

4.4 Ensemble Methods

Ensemble methods address class imbalance by combining multiple balanced classifiers rather than creating a single balanced dataset. These approaches leverage the majority class more effectively by distributing instances across multiple subsets while maintaining the benefits of ensemble learning.

EasyEnsemble creates multiple balanced training subsets by randomly under-sampling the majority class while keeping all minority examples. Each subset trains a separate classifier, and their predictions are combined through averaging or voting. This approach effectively utilizes the majority class through distribution across ensemble members while maintaining strong minority class representation.

BalanceCascade extends the ensemble concept by implementing a cascade of classifiers that focus on increasingly difficult majority instances. The initial classifier trains on a random balanced subset, with subsequent classifiers focusing on majority instances misclassified by previous ensemble members. This progressive refinement targets challenging regions of the feature space.

RUSBoost combines random under-sampling with boosting to create an adaptive ensemble approach. At each boosting iteration, the majority class is randomly under-sampled to create a balanced training set, with instance weights updated based on classification performance. This integration of sampling with boosting focuses learning on difficult instances while maintaining computational efficiency.

5. Experimental Evaluation

Comprehensive experiments evaluated ResampleCraft's effectiveness across diverse imbalanced classification scenarios. We employed 15 benchmark datasets with varying imbalance ratios, feature dimensions, and dataset sizes to ensure broad representation of real-world conditions. Performance assessment utilized multiple metrics appropriate for imbalanced problems, including F1-score, geometric mean, and area under the precision-recall curve.

Table 1: Performance comparison of resampling methods on highly imbalanced datasets (imbalance ratio > 1 : 20). Results are averaged across 15 benchmark datasets; standard deviations are shown in parentheses.

Method	**Precision**	**Recall**	**F1-Score**	**G-Mean**
No Resampling	0.72 (0.05)	0.31 (0.04)	0.43 (0.04)	0.52 (0.03)
Random Under	0.61 (0.06)	0.68 (0.05)	0.64 (0.04)	0.64 (0.04)
Random Over	0.65 (0.05)	0.62 (0.06)	0.63 (0.05)	0.63 (0.04)
SMOTE	0.67 (0.04)	0.71 (0.05)	0.69 (0.04)	0.69 (0.03)
Borderline-SMOTE	0.69 (0.05)	0.73 (0.04)	0.71 (0.04)	0.71 (0.03)
ADASYN	0.66 (0.06)	0.74 (0.05)	0.70 (0.05)	0.70 (0.04)
SMOTE+Tomek	0.70 (0.04)	0.72 (0.04)	0.71 (0.03)	0.71 (0.03)
EasyEnsemble	0.73 (0.04)	0.75 (0.04)	0.74 (0.03)	0.74 (0.03)
RUSBoost	0.71 (0.05)	0.76 (0.04)	0.73 (0.04)	0.73 (0.03)

Baseline comparisons established performance without resampling, highlighting the severity of the imbalance problem. Standard classifiers consistently achieved high overall accuracy but poor minority class recall, confirming that accuracy alone provides misleading performance assessment for imbalanced problems. The baseline F1-scores ranged from 0.38 to 0.52 across datasets, with particularly poor performance on highly imbalanced scenarios (ratio > 1:20).

Under-sampling methods demonstrated strong performance on datasets with abundant majority class examples, where information loss from under-sampling had minimal impact. Cleaning methods like Tomek Links and Edited Nearest Neighbors outperformed random under-sampling on datasets with significant class overlap, achieving 8-15% higher F1-scores by preserving important boundary information. Cluster Centroids showed particular effectiveness on datasets with clear cluster structure, reducing computational requirements by up to 60% while maintaining competitive performance.

Over-sampling methods excelled on datasets with scarce minority examples, where preserving all original instances was critical. SMOTE and its variants consistently outperformed random over-sampling, with 12-18% higher F1-scores across evaluation metrics. Borderline-SMOTE showed particular strength on datasets with clear class separation, effectively strengthening decision boundaries. ADASYN demonstrated advantages on datasets with varying local difficulty, adaptively focusing synthetic generation on challenging regions.

Hybrid methods achieved the most consistent performance across diverse dataset characteristics, effectively balancing the complementary benefits of over-sampling and under-sampling. SMOTE with Tomek links consistently outperformed either method alone on datasets with significant noise near class boundaries. SMOTE with Edited Nearest Neighbors showed particular strength on high-dimensional datasets where class separation was less distinct.

Statistical significance of the observed performance differences was assessed using the Wilcoxon signed-rank test (two-tailed) for pairwise comparisons between each resampling method and the “no resampling” baseline. To control the family-wise error rate, p-values were adjusted with the Holm–Bonferroni correction. Differences were considered significant at $p < 0.05$ after correction. Ensemble methods and hybrid approaches showed particularly consistent advantages, with significant improvements in 92% and 87% of experimental conditions respectively.

Ensemble methods delivered top-tier performance, particularly on highly imbalanced datasets where single-model approaches struggled. EasyEnsemble and BalanceCascade achieved the highest overall F1-scores, with improvements of 25-40% over no resampling baselines. RUSBoost demonstrated

computational advantages on large-scale datasets, achieving competitive performance with approximately 30% shorter training times compared to other ensemble approaches.

Statistical significance testing confirmed that performance differences between resampling methods and baselines were significant at p ¡ 0.05 across most dataset-method combinations. Ensemble methods and hybrid approaches showed particularly consistent advantages, with significant improvements in 92% and 87% of experimental conditions respectively.

5.1 Experimental Setup

All experiments were conducted using five base classifiers implemented in scikit-learn: Logistic Regression, k-Nearest Neighbors (k=5), Decision Tree (max depth=10), Random Forest (100 trees), and Support Vector Machine (RBF kernel). Hyperparameters were kept at their default values across all resampling methods to ensure a fair comparison; no per-method tuning was performed. The dataset was split into 70% training and 30% test sets, with stratification to preserve the original class distribution. Performance metrics were averaged over five independent runs with different random seeds. A five-fold stratified cross-validation was applied during training for model selection where needed (e.g., for ensemble methods). All preprocessing steps (scaling, resampling) were fitted exclusively on the training folds and then applied to the test fold to prevent data leakage.

6. Practical Usage and Integration

ResampleCraft's API design emphasizes usability and seamless integration with established machine learning workflows. The toolkit follows scikit-learn conventions, enabling immediate adoption by practitioners familiar with the ecosystem. This section illustrates common usage patterns and provides guidance for method selection based on dataset characteristics.

The simplest usage pattern applies a single resampling method to a dataset before training a classifier. This approach works well for initial experimentation and straightforward imbalance problems. The consistent API allows easy switching between methods for comparative evaluation, with all resamplers supporting the standard `fit_sample` method for convenient one-step operation.

Pipeline integration represents the recommended usage pattern for production systems and rigorous evaluation. By embedding resampling within scikit-learn Pipelines, users ensure proper separation of training and test data while maintaining reproducible workflows. The pipeline approach prevents data leakage by ensuring resampling parameters are learned exclusively from training folds during cross-validation.

Method selection should consider dataset characteristics including imbalance ratio, absolute minority class size, feature space dimensionality, and computational constraints. For datasets with very small minority classes (fewer than 100 instances), over-sampling methods generally outperform under-sampling approaches by preserving all original minority examples. When computational efficiency is critical or datasets are very large, under-sampling methods provide faster training with reduced memory requirements.

Hybrid methods offer robust default choices for general application, particularly when dataset characteristics are unknown or vary across features. These approaches mitigate limitations of pure over-sampling or under-sampling while providing balanced performance across diverse scenarios. Ensemble methods deliver top performance for critical applications where computational resources permit their additional complexity.

Evaluation metrics require careful selection for imbalanced problems. Accuracy provides misleading

assessments, while precision, recall, F1-score, and geometric mean offer more informative performance perspectives. The area under the precision-recall curve is particularly valuable for highly imbalanced problems, where ROC curves may provide overly optimistic performance estimates.

The simplest usage pattern applies a single resampling method to a dataset before training a classifier. The consistent API allows easy switching between methods for comparative evaluation, with all resamplers supporting the standard ‘fit_resample‘ method for convenient one-step operation.

Parameter tuning should include both resampling parameters and classifier hyperparameters, as optimal sampling strategy depends on classifier characteristics. ResampleCraft integrates seamlessly with scikit-learn’s GridSearchCV and RandomizedSearchCV, enabling joint optimization of resampling and classification parameters. This comprehensive tuning approach typically achieves 10-25% better performance compared to isolated parameter optimization.

7. Conclusion and Future Work

ResampleCraft provides a comprehensive, production-ready toolkit for addressing class imbalance in machine learning workflows. The system unifies four families of imbalance handling techniques within a consistent, pipeline-compatible API that integrates seamlessly with the Python machine learning ecosystem. Experimental evaluation demonstrates significant performance improvements across diverse imbalanced classification scenarios, with ensemble and hybrid methods delivering particularly robust performance.

The toolkit’s modular architecture facilitates both practical application and research extension. Standardized interfaces enable straightforward implementation of new resampling algorithms, while comprehensive documentation and testing ensure reliability. The permissive licensing and minimal dependencies encourage broad adoption across academic, industrial, and open-source communities.

Future development will expand the method repertoire with additional advanced techniques including deep learning approaches for complex data modalities. Generative adversarial networks show particular promise for sophisticated synthetic example generation, especially for high-dimensional data where traditional interpolation methods may struggle. Reinforcement learning approaches for adaptive resampling policy selection represent another promising direction.

Integration with automated machine learning systems will enhance accessibility for non-expert users while optimizing resampling strategy selection based on dataset characteristics. Automated imbalance handling represents a natural extension of current AutoML capabilities, particularly for domains where class imbalance is prevalent.

Extended evaluation metrics and visualization tools will provide richer assessment of resampling effectiveness, including fairness considerations and computational efficiency metrics. These enhancements will support more informed method selection and parameter tuning, particularly for applications with specific performance requirements.

In conclusion, ResampleCraft transforms imbalance handling from an ad-hoc preprocessing step into an integrated component of machine learning workflows. By providing a unified implementation of major resampling strategies within a production-quality framework, the toolkit enables more effective learning from skewed datasets across diverse application domains.

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