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Trustworthy Machine Learning on Imbalance Data

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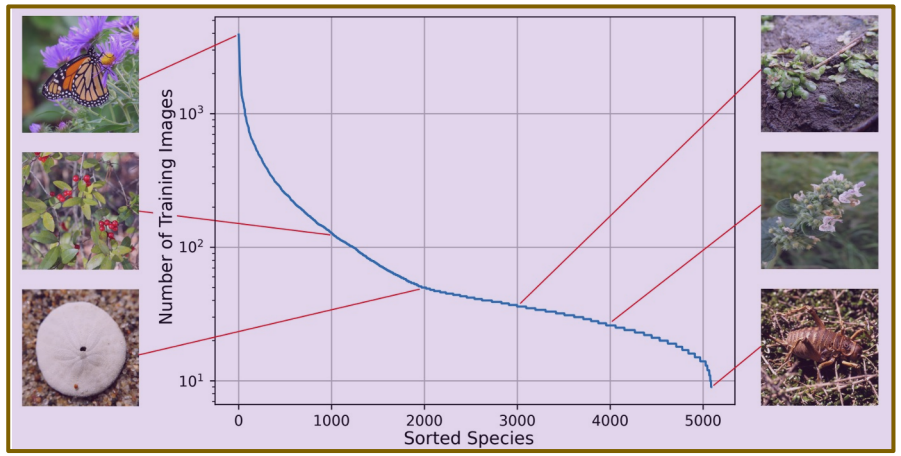
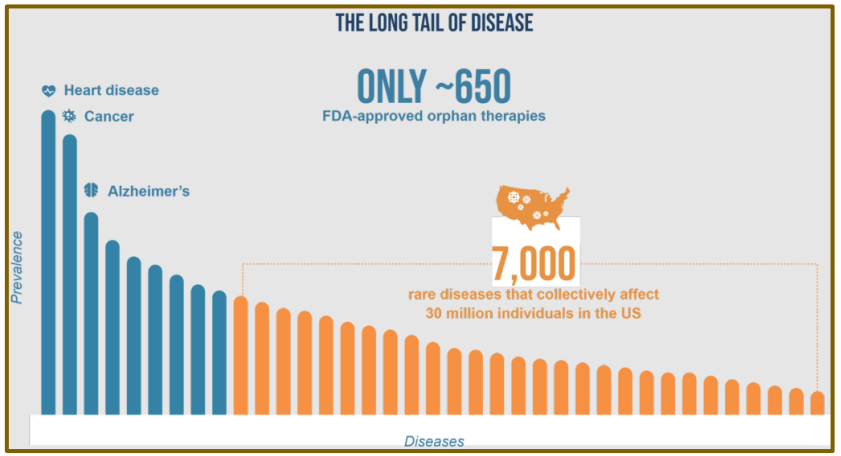
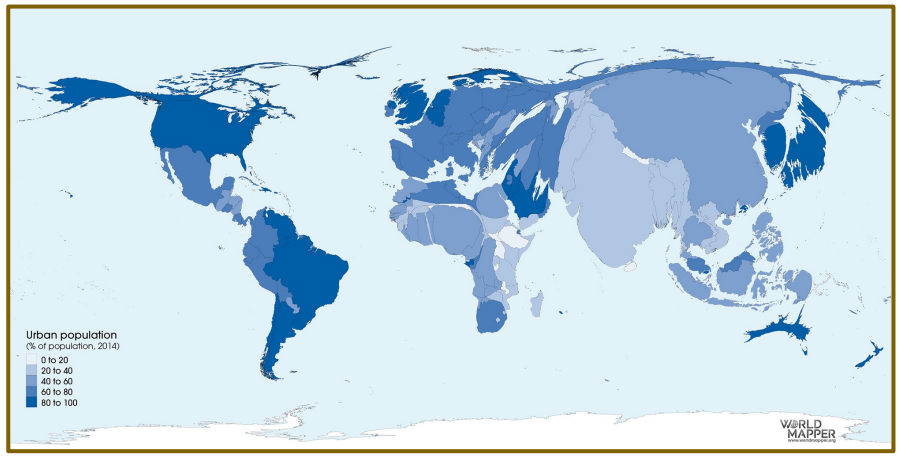
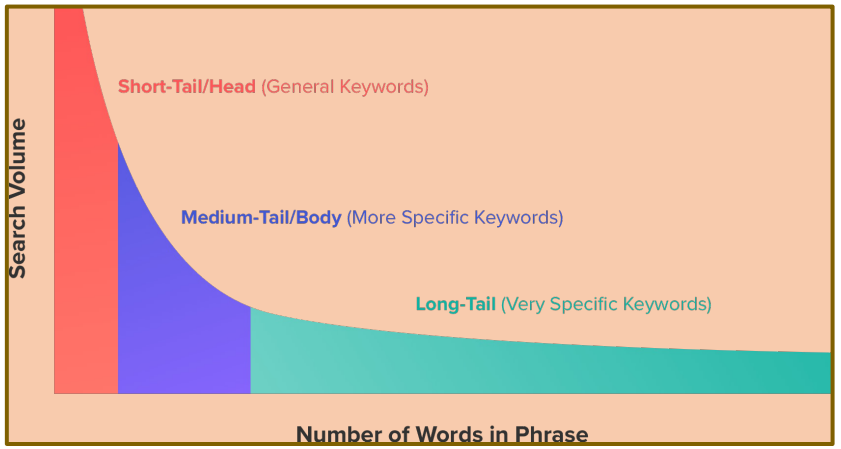
The Imbalance Nature of Data

Large-scale natural sources are very imbalance, usually following a long-tailed distribution.









[1] Van Horn et al. The iNaturalist Species Classification and Detection Dataset. CVPR 2018.

[2] Gregory et al. CXR-LT challenge. ICCV CVAMD 2023.

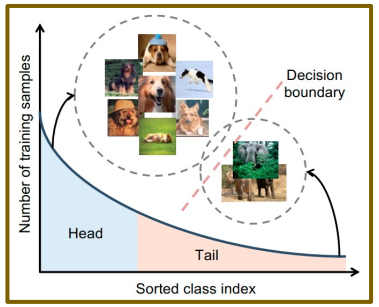
[3] https://worldmapper.org/maps/urban-population-relative-2014/

[4] https://seopressor.com/blog/short-tail-or-long-tail-keywords/

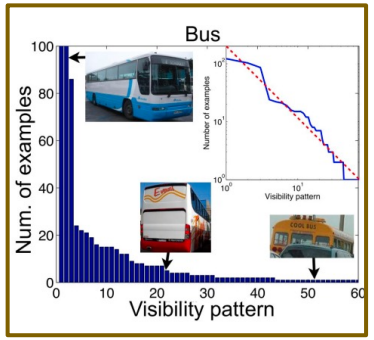
How Imbalance Data Matters in Machine Learning

A direct decomposition on the risk minimization

$$\min_f R(f) = E_{P(x,y)}[\ell(f(x), y)] = \sum_{k=1}^{K} \boldsymbol{P(y=k)} E_{P(x|y=k)}[\ell(f(x), y)]$$



Minority ("generalized" conceptual) classes have weak importance for training, which will be easily ignored in the early phase especially for overparameterized DNNs [1] *(or namely, will be sacrificed first if it is not sufficient for the model to learn)*.



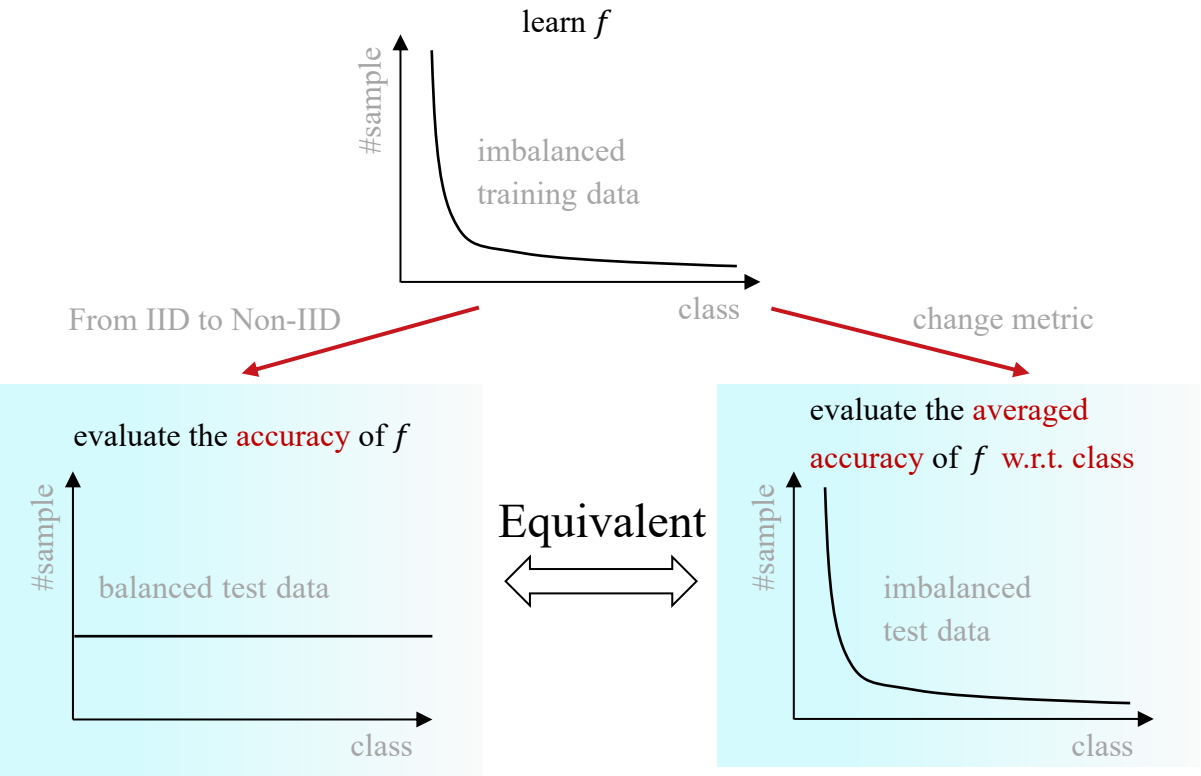
However, in real applications, the value of classes cannot be absolutely characterized by their quantity, and instead, sometimes **less is more** for sustainable long-term development.

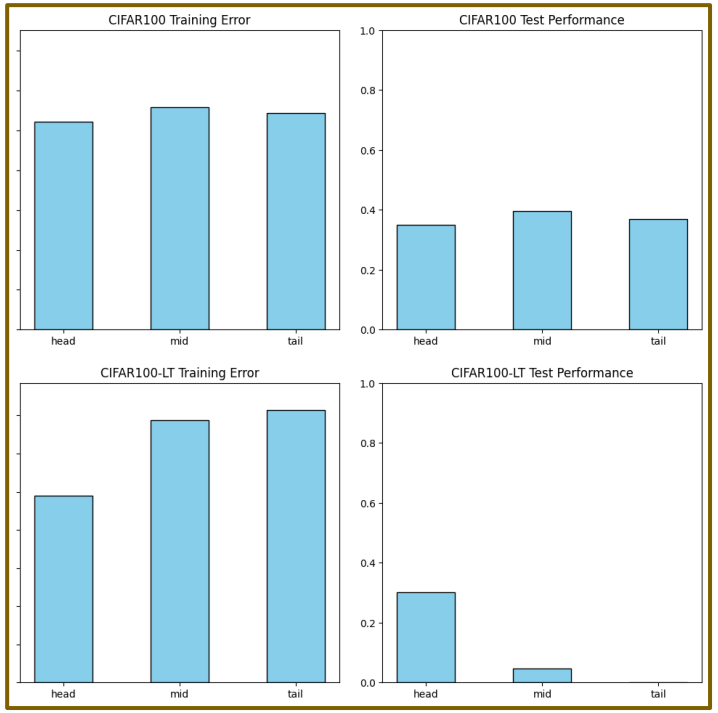
- **Fairness** w.r.t. diversity e.g., small populations of gender, race and consumers
- **Cost-sensitive scenarios** e.g., medical disease diagnosis and treatment (COVID-19)

[1] Vitaly Feldman. "Does Learning Require Memorization? A Short Tale about a Long Tail." SIGACT 2020.

Why the Resulted Imbalanced Learning is Special

A critical highlight on the evaluation, different from the ordinary IID learning





The change in evaluation metric induces **an statistical consistency problem** on applying conventional learning methods, that is,

What we design during training should be statistically consistent with what we pursue about the evaluation.

The Historical Development

The development of imbalance learning

1998 → methods → 2009 → Applications → 2018 → Deep learning → 2023

Optimizing Classifiers for Imbalanced Training Sets

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Abstract

Following recent results [9, 8] showing the importance of the fat-shattering dimension in explaining the beneficial effect of a large margin on generalization performance, the current paper investigates the implications of these results for the case of imbalanced datasets and develops two approaches to setting the threshold. The approaches are incorporated into ThetaBoost, a boosting algorithm for dealing with unequal loss functions. The performance of ThetaBoost and the two approaches are tested experimentally.

Keywords: Computational Learning Theory, Generalization, fat-shattering, large margin, pac estimates, unequal loss, imbalanced datasets

1 Introduction

Shawe-Taylor [8] demonstrated that the output margin can also be used as an estimate of the confidence with which a particular classification is made. In other words if we example has an output value well clear of the threshold we can be more confident of the associated classification than when the output value is closer to the threshold. The current paper applies this result to the case where there are different losses associated with a false positive, than with a false negative. If a significant number of data points are misclassified we can use the criterion of minimizing the empirical loss. If, however, the data is correctly classified the empirical loss is zero for all correctly separating hyperplanes. It is in this case that the approach can provide insight into how to choose the hyperplane and threshold. In summary, the paper suggests a way in which a hyperplane should be optimised for imbalanced datasets where the loss associated with misclassifying the less prevalent class is higher.

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Learning from Imbalanced Data

Haibo He, Member, IEEE, and Edwardo A. Garcia

Abstract—With the continuous expansion of data availability in many large-scale, complex, and networked systems, such as surveillance, security, Internet, and finance, it becomes critical to advance the fundamental understanding of knowledge discovery and analysis from raw data to support decision-making processes. Although existing knowledge-discovery and data engineering techniques have shown great success in many real-world applications, the problem of learning from imbalanced data (the imbalanced learning problem) is a relatively new challenge that has attracted growing attention from both academia and industry. The imbalanced learning problem is concerned with the performance of learning algorithms in the presence of underrepresented data and severe class distribution skews. Due to the inherent complex characteristics of imbalanced data sets, learning from such data requires new understandings, principles, algorithms, and tools to transform vast amounts of raw data efficiently into information and knowledge representation. In this paper, we provide a comprehensive review of the development of research in learning from imbalanced data. Our focus is to provide a critical review of the nature of the problem, the state-of-the-art technologies, and the current assessment metrics used to evaluate learning performance under the imbalanced learning scenario. Furthermore, in order to stimulate future research in this field, we also highlight the major opportunities and challenges, as well as potential important research directions for learning from imbalanced data.

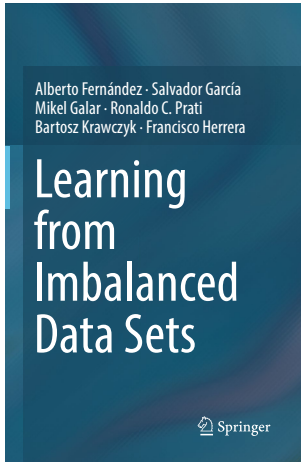
Index Terms—Imbalanced learning, classification, sampling methods, cost-sensitive learning, kernel-based learning, active learning, assessment metrics.

1 Introduction

Recent developments in science and technology have enabled the growth and availability of raw data to occur at an explosive rate. This has created an immense opportunity for knowledge discovery and data engineering research to play an essential role in a wide range of applications from daily civilian life to national security, from enterprise information processing to governmental decision-making support systems, from microscale data analysis to macroscale knowledge discovery. In recent years, the imbalanced learning problem has drawn a significant amount of attention from both academia and government funding agencies. The fundamental issue with the imbalanced learning problem is the ability of imbalanced data to significantly compromise the performance of most standard learning algorithms. Most standard algorithms assume or expect balanced class distributions or equal misclassification costs. Therefore, when presented with complex imbalanced data sets, these algorithms fail to properly represent the distributive characteristics of the data and resultantly provide unfavorable accuracies across the classes of the data. When translated to real-world domains, the imbalanced learning problem represents a recurring problem of high importance with wide-ranging implications, warranting increasing exploration. This increased interest is reflected in the recent installment of several major workshops, conferences, and special issues including the American Association for Artificial Intelligence (now the Association for the Advancement of Artificial Intelligence) workshop on Learning from Imbalanced Data Sets (AAAI '00) [5], the International Conference on Machine Learning workshop on Learning from Imbalanced Data Sets (ICML '03) [2], and the Association for Computing Machinery Special Interest Group on Knowledge Discovery and Data Mining Explorations (ACM SIGKDD Explorations) (SIGKDD '04) [6].

In spite of the growing amount of attention devoted to the imbalanced learning problem and the high activity of advancement in this field, remaining knowledgeable of all current developments can be an overwhelming task. Fig. 1 shows an estimation of the number of publications on the imbalanced learning problem over the past decade based on the Institute of Electrical and Electronics Engineers (IEEE) and Association for Computing Machinery (ACM) databases. As can be seen, the activity of publications in this field is growing at an explosive rate. Due to the relatively young age of this field and because of its rapid expansion, consistent assessments of past and current works in the field in addition to projections for future research are essential for long-term development. In this paper, we seek to provide a survey of the current understanding of the imbalanced learning problem and the state-of-the-art solutions created to address this problem. Furthermore, in order to stimulate future research in this field, we also highlight the major opportunities and challenges for learning from imbalanced data.

In particular, we first describe the nature of the imbalanced learning problem in Section 2, which provides the foundation for our review of imbalanced learning solutions. In Section 3, we provide a critical review of the innovative research developments targeting the imbalanced learning



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Learning from Imbalanced Data Sets

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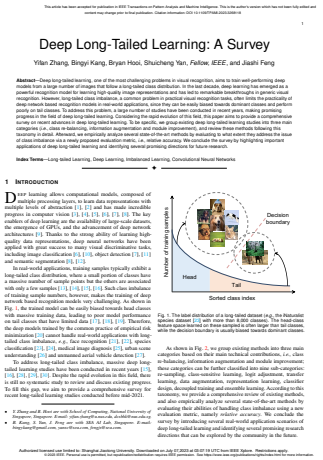


Deep Long-Tailed Learning: A Survey

Yifan Zhang, Bingyi Kang, Bryan Hooi, Shuicheng Yan, Fellow, IEEE, and Jiashi Feng

Abstract—Deep long-tailed learning, one of the most challenging problems in visual recognition, aims to train well-performing deep models from a large number of images that follow a long-tailed class distribution. In the last decade, deep learning has emerged as a powerful recognition model for learning high-quality image representations and has led to remarkable breakthroughs in generic visual recognition. However, long-tailed class imbalance, a common problem in practical visual recognition tasks, often limits the practicality of deep-network based recognition models in real-world applications, since they can be easily biased towards dominant classes and perform poorly on tail classes. To address this problem, a large number of studies have been conducted in recent years, making promising progress in the field. In this paper, we provide a comprehensive survey on deep long-tailed learning. Specifically, we first formalize the problem and review existing surveys on recent advances in deep long-tailed learning. To be specific, we group existing deep long-tailed learning studies into three main categories (i.e., class re-balancing, information augmentation and module improvement), and review these methods following this taxonomy in detail. Afterward, we empirically analyze several state-of-the-art methods by evaluating to what extent they address the issue of class imbalance via a newly proposed evaluation metric, i.e., relative accuracy. We conclude the survey by highlighting important applications of deep long-tailed learning and identifying several promising directions for future research.

Index Terms—Long-tailed Learning, Deep Learning, Imbalanced Learning, Convolutional Neural Networks.

1 Introduction

Deep learning allows computational models, composed of multiple processing layers, to learn data representations with multiple levels of abstraction [1], [2] and has made incredible progress in computer vision [3], [4], [5], [6], [7], [8], [9]. The key enablers of deep learning are the availability of large-scale datasets, powerful hardware, and the flexibility of various neural network architectures [10]. Thanks to the strong ability of learning high-quality data representations, deep neural networks have been applied with great success to many visual discriminative tasks, including image classification [6], [8], object detection [7], [11] and semantic segmentation [9], [12].

In real-world applications, training samples typically exhibit a long-tailed class distribution, where a small portion of classes have a massive number of sample points but the others are associated with only a few samples [13], [14], [15], [16]. Such class imbalance of training sample matchers, however, makes the training of deep network based recognition models very challenging. As shown in Fig. 1, the trained model can be easily biased towards head classes with massive training data, leading to poor model performance on tail classes that have limited data [17], [18], [19]. Therefore, the deep models trained by the common practice of empirical risk minimization [20] cannot handle real-world applications with long-tailed class imbalance, e.g., face recognition [21], [22], species classification [14], [23], medical image diagnosis [24], urban scene understanding [25] and unmanned aerial vehicle detection [27].

To address long-tailed class imbalance, massive deep long-tailed learning studies have been conducted in recent years [13], [16], [18], [28], [29], [30]. Despite the rapid evolution in this field, there is still no systematic study to review and discuss existing progress. To fill this gap, we aim to provide a comprehensive survey for recent long-tailed learning studies conducted before mid-2021.

Fig. 1. The label distribution of a long-tailed dataset (e.g., the iNaturalist species dataset [26] with more than 8,000 classes). The head-class samples (e.g., cat, dog) are abundant and dominate the model training, while the decision boundary is usually biased towards dominant classes.

As shown in Fig. 2, we group existing methods into three main categories based on their main technical contributions, i.e., class re-balancing, information augmentation and module improvement. Specifically, class re-balancing includes logit adjustment, meta-learning, class-sensitive learning, logit adjustment, transfer learning, data augmentation, representation learning, classifier design, decoupled training and ensemble learning. According to this taxonomy, we provide a comprehensive review of existing methods, and also empirically analyze several state-of-the-art methods by evaluating their abilities of handling class imbalance using a new evaluation metric, namely *relative accuracy*. We conclude the survey by introducing several real-world application scenarios of deep long-tailed learning and identifying several promising research directions that can be explored by the community in the future.

[1] Karakoulas et al. Optimizing Classifers for Imbalanced Training Sets. NIPS 1998.

[2] He et al. Learning from Imbalanced Data. TKDE 2009.

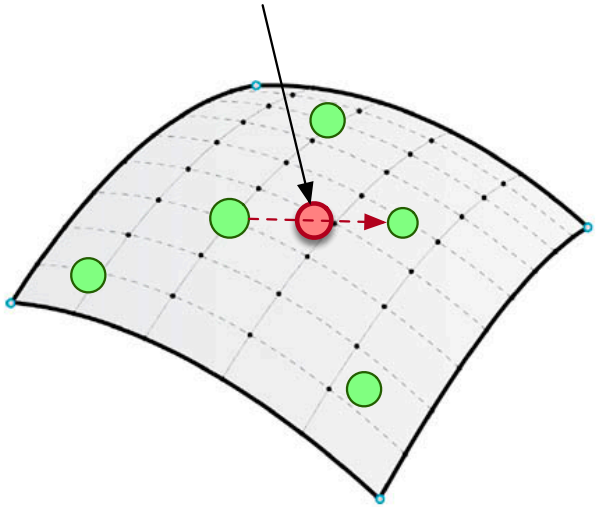
[3] Fernández et al. Learning from Imbalanced Data Sets. Springer, 2018.

[4] Zhang et al. Deep Long-tailed Learning: A Survey. TPAMI 2023.

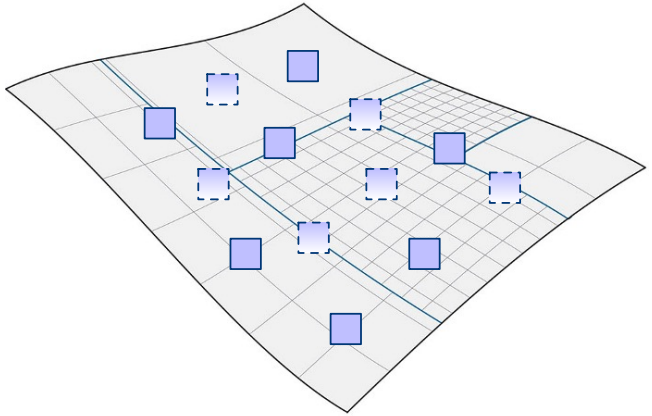
SMOTE: Synthetic Minority Over-sampling Technique

Motivation: Replication of the minority class does not cause its decision boundary to spread into the majority class region (but overfitting).

Interpolation on minority manifold



Under-sampling in the majority class



The main idea of SMOTE: augmentation for minority class by interpolation instead of over-sampling with replacement.

Interpolation is limited by the samples. Thus, SMOTE also always runs with the under-sampling for majority class.

Increase minority diversity and decrease majority diversity

Chawla, Nitesh V., et al. "SMOTE: Synthetic Minority Over-Sampling Technique." *JAIR 2002*.

Retrospection-II: Threshold-Moving Method

Threshold-Moving: adjust the prediction in a post-hoc manner.

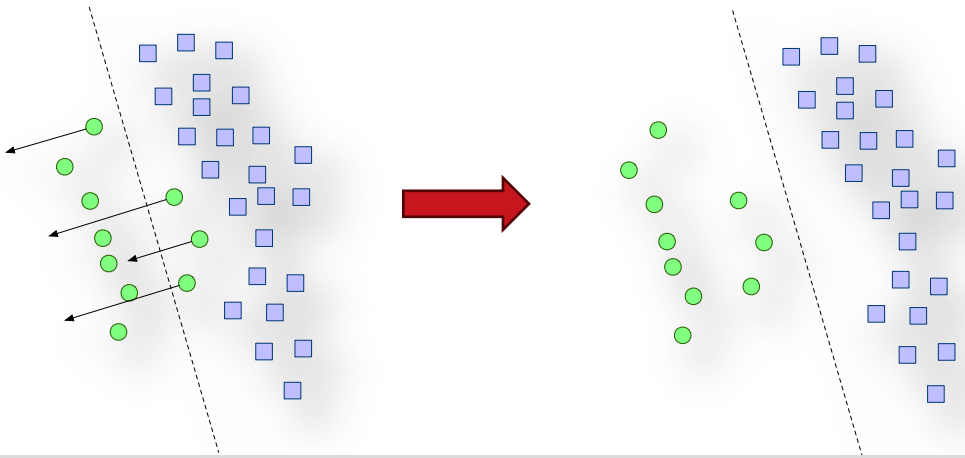
Motivation: The over-confident prediction for majority or the low-confident prediction for minority can be calibrated after training.

THE THRESHOLD-MOVING ALGORITHM

Training phase:
1. Let S be the original training set.
2. Train a neural network from S.

Test phase:
1. Generate real-value outputs with the trained neural network.
2. For every output, multiply it with the sum of the costs of misclassifying the corresponding class to other classes.
3. Return the class with the biggest output.

Sampling methods might not always show promise in multi-class imbalance learning, but threshold-moving way does.



Moving function

$$\hat{p}_k = \frac{p_k * \sum_{k'=1}^{K} C[k][k']}{\eta}$$

where p_k is the probabilistic prediction, $C[k][k']$ is the cost mis-predicted from class k to k', and η is renormalization parameter.

Let $p_k = \frac{e^{z_k}}{\sum_{k'}^{K} e^{z_{k'}}}$ denote the class prediction. If we set $\sum_{k'=1}^{K} C[k][k'] = e^{-\tau \log \pi_k}$ where π_k is the class prior and τ is the temperature, the threshold-moving method recovers the popular **logit adjustment** method for long-tailed learning.

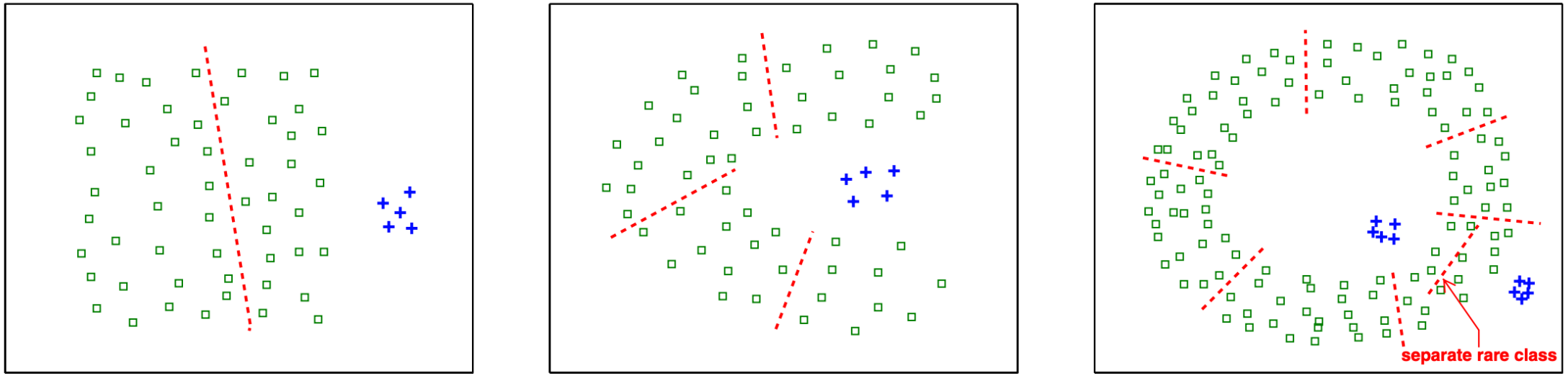
Majority classes have the smaller cost than minority classes, e.g., $e^{-\tau \log \pi_k}$ is monotonously decreasing.

Zhou, Z. H., & Liu, X. Y. Training Cost-Sensitive Neural Networks with Methods Addressing the Class Imbalance Problem. *TKDE, 2005*.

COG: Local Decomposition for Rare Class Analysis

Intuition: Quantity imbalance limits the learning pace of minority over majority. We can adjust the quantities by decomposition.

How to properly decompose the majority classes (or including minority classes) into subclasses to balance the training?



Phase I: local clustering

for class $i = 1$ to c // *"c" represents #classes*

  clusterLabel(i) = Clustering$(\mathcal{D}(i), \boldsymbol{K}(i))$;

  $\mathcal{D}(i)^* =$ changeLabel$(\mathcal{D}(i)$, clusterLabel$(i))$;

end for

Phase II: over-sampling (for COG-OS only)

for class $j = 1$ to c

  $\mathcal{D}(j)^{**} =$ replicate$(\mathcal{D}(j)^*, \boldsymbol{r}(j))$

end for

$\mathcal{D}^{**} = \bigcup_{j=1}^{c}(\mathcal{D}(j)^{**})$;

Phase III: training

$\mathbb{M} =$ train$(\mathcal{D}^{**}, \mathbb{L})$;

Phase IV: predicting

$\boldsymbol{p}' =$ predict$(\mathcal{T}, \mathbb{M})$;

$\boldsymbol{p} =$ convertLabel$(\boldsymbol{p}')$;

Wu. J. J. et al. COG: Local Decomposition for Rare Class Analysis. *DMKD, 2010*.

On Statistical Consistency of Binary Classification with Balanced Accuracy

Motivation: The early ERM theory is developed for the instance-wise evaluation, but cannot guarantee the consistency for balanced measure.

$$\text{Accuracy} = \mathrm{E}_{p(x,y)}[h(x) = y] \quad \Rightarrow \quad \text{Balanced Accuracy} = \frac{\sum_{k\in\{-1,1\}} \mathrm{E}_{p(x|y=k)}[h(x)=k]}{2}$$

If we consider the balanced accuracy, how to modify the algorithm to satisfy the statistical consistency?

Theorem 3. *Let D be a probability distribution on $\mathcal{X}\times\{\pm1\}$ satisfying Assumption A. Let $\widehat{p}_S$ denote any estimator of $p = \mathbf{P}(y=1)$ satisfying $\widehat{p}_S \in (0,1)$ and $\widehat{p}_S \xrightarrow{P} p$. Let $\widehat{\eta}_S : \mathcal{X}\to[0,1]$ denote any class probability estimator satisfying $\mathbf{E}_x\left[|\widehat{\eta}_S(x) - \eta(x)|^r\right] \xrightarrow{P} 0$ for some $r \geq 1$, and let $h_S(x) = \boxed{\mathrm{sign}(\widehat{\eta}_S(x) - \widehat{p}_S).}$ Then*

$$\mathrm{regret}_D^{\mathrm{AM}}[h_S] \xrightarrow{P} 0\,.$$

Algorithm 1 Plug-in with Empirical Threshold

1: **Input:** $S = ((x_1,y_1),\ldots,(x_n,y_n)) \in (\mathcal{X}\times\{\pm1\})^n$
2: **Select:** (a) Proper (composite) loss $\ell : \{\pm1\}\times\bar{\mathbb{R}}\to\bar{\mathbb{R}}_+$, with link function $\psi : [0,1]\to\bar{\mathbb{R}}$; (b) RKHS $\mathcal{F}_K$ with positive definite kernel $K : \mathcal{X}\times\mathcal{X}\to\mathbb{R}$; (c) regularization parameter $\lambda_n > 0$
3: $f_S \in \mathrm{argmin}_{f\in\mathcal{F}_K}\left\{\frac{1}{n}\sum_{i=1}^n \ell(y_i, f(x_i)) + \lambda_n\|f\|_K^2\right\}$
4: $\widehat{\eta}_S = \psi^{-1}\circ f_S$
5: $\widehat{p}_S =$ (as in Eq. (2))
6: **Output:** Classifier $h_S(x) = \mathrm{sign}(\widehat{\eta}_S(x) - \widehat{p}_S)$

Menon, Aditya, et al. "On the Statistical Consistency of Algorithms for Binary Classification under Class Imbalance." *ICML 2013.*

Summary

Summary of imbalanced learning in the early years

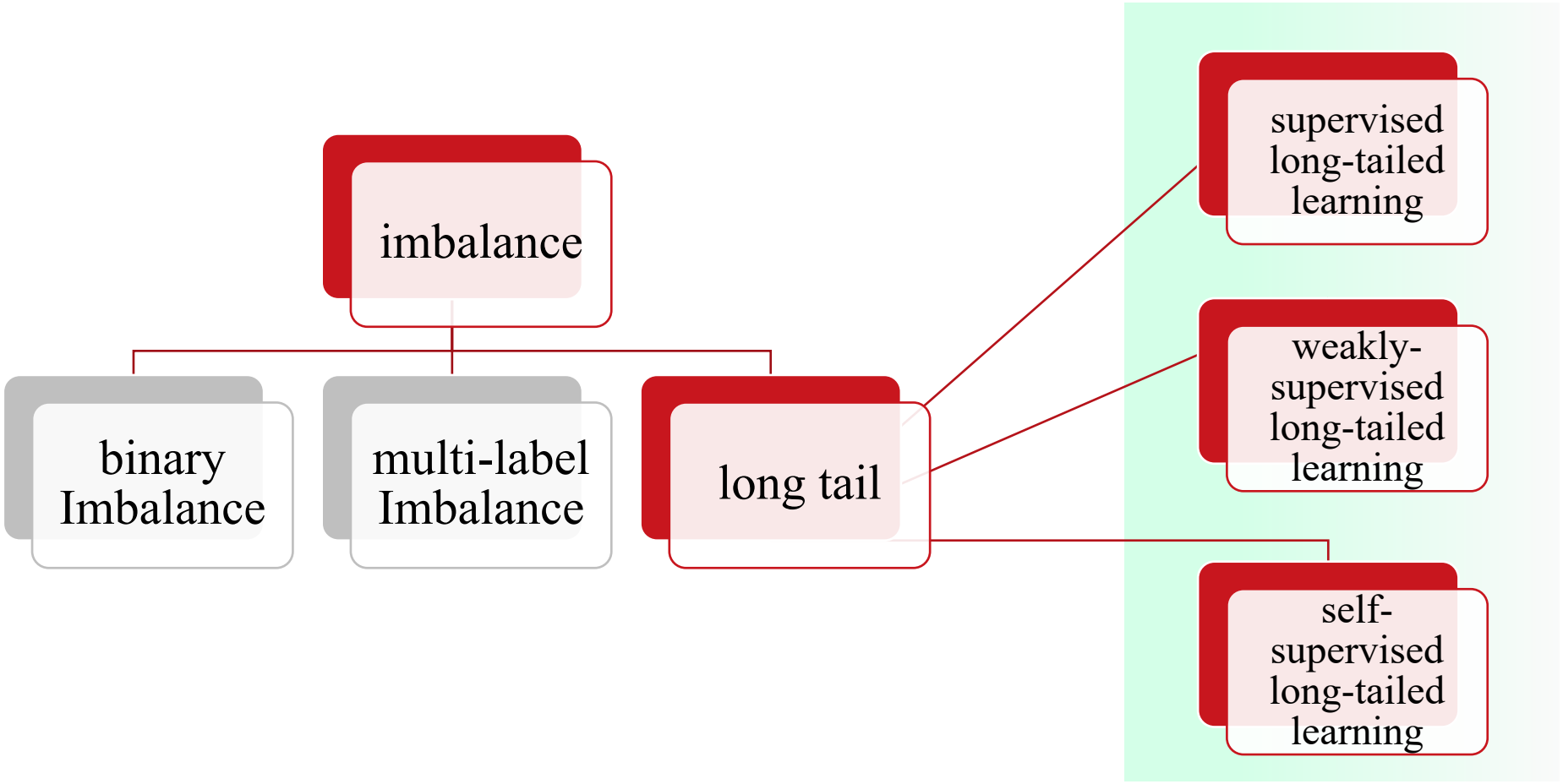
Imbalanced Learning

- **Re-Sampling** → Control sample quantity from the input augmentation perspective
- **Loss Adjustment** → Adjust penalty preference from the loss perspective.
- **Re-Labeling** → Control learning complexity from the label manipulation perspective
- **Statistical Consistency** → The statistically-consistent loss family for imbalanced binary classification

What is the new of this topic in the recent years?

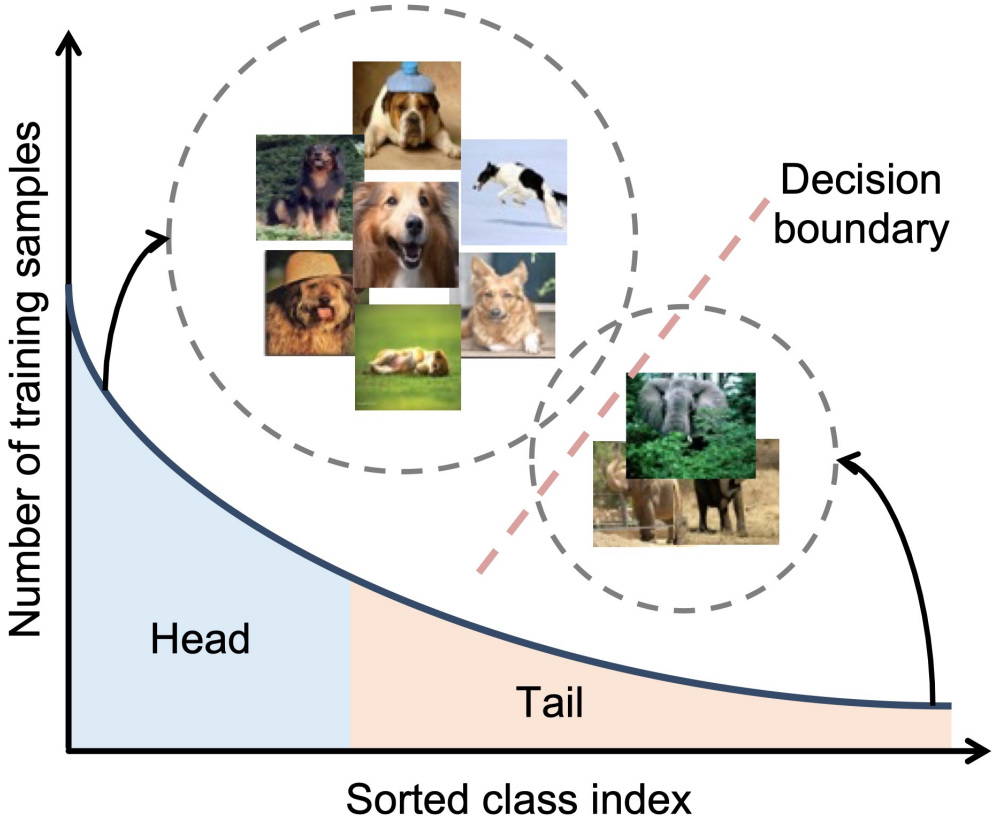
The Following Part in This Tutorial

The recent advances of imbalance learning powered by deep learning



Supervised Long-tailed Learning

It has been contributed with very broad explorations

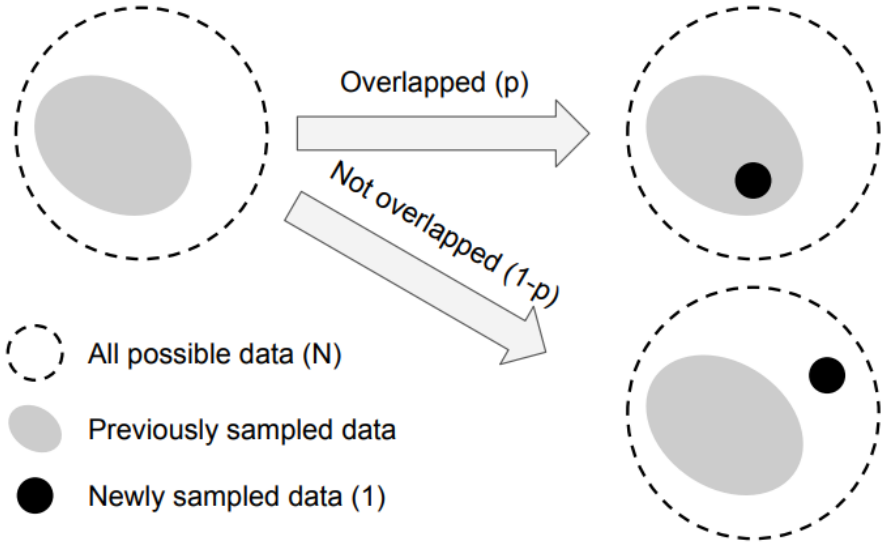


Method	Year	Class Re-balancing			Augmentation		Module Improvement				Target Aspect
		Re-sampling	CSL	LA	TL	Aug	RL	CD	DT	Ensemble	
LMLE [89]	2016						✓				feature
HFL [90]	2016						✓				feature
Focal loss [54]	2017		✓								objective
Range loss [21]	2017						✓				feature
CRL [50]	2017						✓				feature
MetaModelNet [91]	2017				✓						
DSTL [92]	2018				✓						
DCL [93]	2019	✓									sample
Meta-Weight-Net [94]	2019		✓								objective
LDAM [18]	2019		✓								objective
CB [16]	2019		✓								objective
UML [95]	2019		✓								feature
FTL [96]	2019				✓	✓					feature
Unequal-training [48]	2019						✓				feature
OLTR [15]	2019						✓				feature
Balanced Meta-Softmax [97]	2020	✓	✓								sample, objective
Decoupling [32]	2020	✓	✓				✓	✓	✓		feature, classifier
LST [98]	2020	✓			✓						sample
Domain adaptation [28]	2020		✓								objective
Equalization loss (ESQL) [19]	2020		✓								objective
DBM [22]	2020		✓								objective
Distribution-balanced loss [37]	2020		✓								objective
UNO-IC [99]	2020			✓							prediction
De-confound-TDE [45]	2020			✓				✓			prediction
M2m [100]	2020				✓	✓					sample
LEAP [49]	2020				✓	✓	✓				feature
OFA [101]	2020				✓	✓			✓		feature
SSP [102]	2020				✓		✓				feature
LFME [103]	2020				✓					✓	sample, model
IEM [104]	2020						✓				feature
Deep-RTC [105]	2020							✓			classifier
SimCal [34]	2020								✓	✓	sample, model
BBN [44]	2020									✓	sample, model
BAGS [56]	2020									✓	sample, model
VideoLT [38]	2021	✓									sample
LOCE [33]	2021	✓	✓								sample, objective
DARS [26]	2021	✓	✓		✓						sample, objective
CReST [106]	2021	✓			✓						sample
GIST [107]	2021	✓			✓			✓			classifier
FASA [58]	2021	✓				✓					feature
Equalization loss v2 [108]	2021		✓								objective
Seesaw loss [109]	2021		✓								objective
ACSL [110]	2021		✓								objective
IB [111]	2021		✓								objective
PML [51]	2021		✓								objective
VS [112]	2021		✓								objective
LADE [31]	2021		✓	✓							objective, prediction
RoBal [113]	2021		✓	✓				✓			objective, prediction
DisAlign [29]	2021		✓	✓					✓		objective, classifier
MiSLAS [114]	2021		✓			✓			✓		objective, feature, classifier
Logit adjustment [14]	2021			✓							prediction
Conceptual 12M [115]	2021				✓						
DiVE [116]	2021				✓						
MosaicOS [117]	2021				✓						
RSG [118]	2021				✓	✓					feature
SSD [119]	2021				✓				✓		
RIDE [17]	2021				✓					✓	model
MetaSAug [120]	2021					✓					sample
PaCo [121]	2021						✓				feature
DRO-LT [122]	2021						✓				feature
Unsupervised discovery [35]	2021						✓				feature
Hybrid [123]	2021						✓				feature
KCL [13]	2021						✓		✓		feature
DT2 [61]	2021								✓		feature, classifier
LTML [46]	2021									✓	sample, model
ACE [124]	2021									✓	sample, model
ResLT [125]	2021									✓	sample, model
SADE [30]	2021									✓	objective, model

[1] Zhang et al. "Deep Long-Tailed Learning: A Survey" TPAMI 2023.

loss re-weighting by effective number

- **Intuition:** Non-overlapping sample number, instead of the vanilla quantity number, playing the role of imbalance



- **Effective Number:** The effective number of examples is the expected volume of samples.

$$E_n = (1-\beta^n)/(1-\beta)$$

$$\text{where } \beta = (N-1)/N$$

$$\lim_{\beta \to 1} E_n = n$$

- **Class-Balanced Loss:** Training from imbalanced data by introducing a weighting factor that is inversely proportional to the effective number of samples.

The class-balanced loss term can be applied to a wide range of deep networks and loss functions.

[1] Cui et al. "Class-Balanced Loss Based on Effective Number of Samples" CVPR 2019.

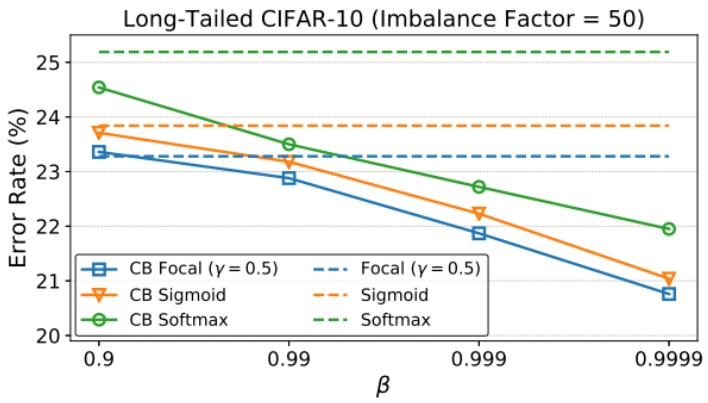
Supervised Long-tailed Learning

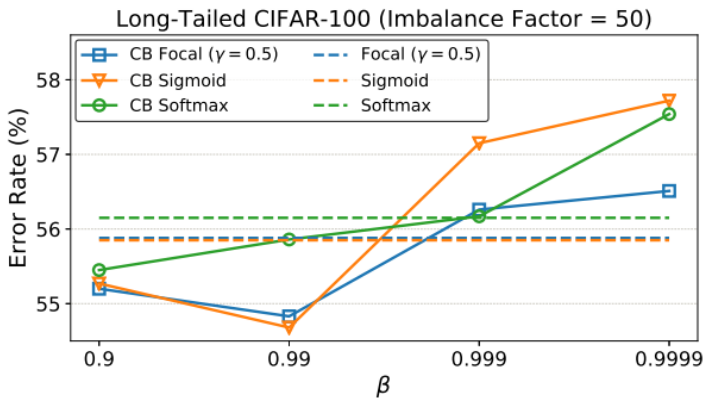
➢ **Class-Balanced Loss:** The class-balanced (CB) loss can be written as:

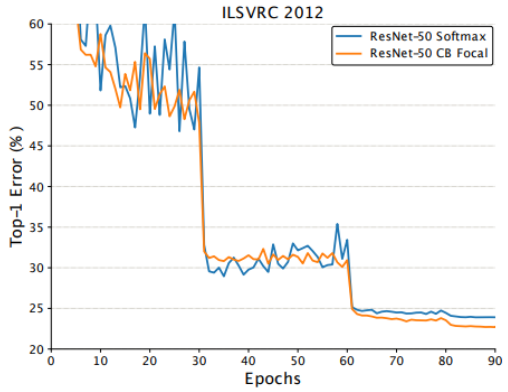
$$\mathrm{CB}(\mathbf{p}, y) = \frac{1}{E_{n_y}} \mathcal{L}(\mathbf{p}, y) = \frac{1-\beta}{1-\beta^{n_y}} \mathcal{L}(\mathbf{p}, y)$$

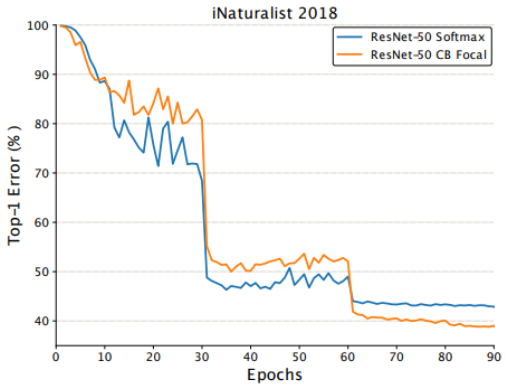
$$\mathrm{CB}_{\mathrm{softmax}}(\mathbf{z}, y) = -\frac{1-\beta}{1-\beta^{n_y}} \log\left(\frac{\exp(z_y)}{\sum_{j=1}^{C}\exp(z_j)}\right)$$

Class-Balanced loss can also combined with sigmoid cross-entropy loss, focal loss, etc.









Dataset Name	Long-Tailed CIFAR-10						Long-Tailed CIFAR-100					
Imbalance	200	100	50	20	10	1	200	100	50	20	10	1
Softmax	**34.32**	29.64	25.19	17.77	13.61	6.61	65.16	61.68	56.15	48.86	44.29	29.07
Sigmoid	34.51	**29.55**	23.84	**16.40**	**12.97**	**6.36**	64.39	**61.22**	55.85	48.57	44.73	**28.39**
Focal ($\gamma = 0.5$)	36.00	29.77	**23.28**	17.11	13.19	6.75	65.00	61.31	55.88	48.90	44.30	28.55
Focal ($\gamma = 1.0$)	34.71	29.62	23.29	17.24	13.34	6.60	**64.38**	61.59	**55.68**	**48.05**	**44.22**	28.85
Focal ($\gamma = 2.0$)	35.12	30.41	23.48	16.77	13.68	6.61	65.25	61.61	56.30	48.98	45.00	28.52
Class-Balanced	**31.11**	**25.43**	**20.73**	**15.64**	**12.51**	**6.36***	**63.77**	**60.40**	**54.68**	**47.41**	**42.01**	**28.39***
Loss Type	SM	Focal	Focal	SM	SGM	SGM	Focal	Focal	SGM	Focal	Focal	SGM
β	0.9999	0.9999	0.9999	0.9999	0.9999	-	0.9	0.9	0.99	0.99	0.999	-
γ	-	1.0	2.0	-	-	-	1.0	1.0	-	0.5	0.5	-

The proposed framework provides a non-parametric means of quantifying data overlap.

[1] Cui et al. "Class-Balanced Loss Based on Effective Number of Samples" CVPR 2019.

Class-wise margin calibration

- **Motivation:** Re-weighting and re-sampling often cause over-fitting. The authors propose to regularize the minority classes more strongly than the frequent classes to improve the generalization error of minority classes without sacrificing the model's ability to fit the frequent classes.

- **Class-distribution-aware margin trade-off:** Enforcing bigger margins can improve generalization, but may also hurt the margins of the frequent classes.

The generalization error is proportional to the following:

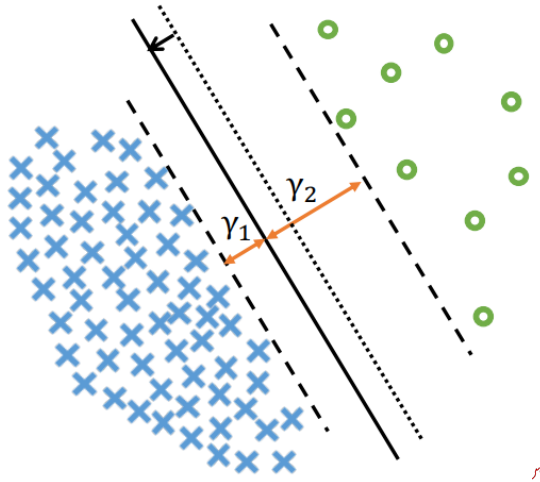
$$\frac{1}{\gamma_1\sqrt{n_1}} + \frac{1}{\gamma_2\sqrt{n_2}} \qquad \gamma_1 + \gamma_2 = \gamma$$

For multi-class classification tasks, the margin of a sample is defined as:

$$\gamma(x, y) = f(x)_y - \max_{j \neq y} f(x)_j$$

The margin of a class is defined as the minimum value of the spacing between all its samples:

$$\gamma_j = \min_{i \in S_j} \gamma(x_i, y_i) \qquad \gamma_j = \frac{C}{n_j^{1/4}}$$



[1] Cao et al. "Learning Imbalanced Datasets with Label-Distribution-Aware Margin Loss" NeurIPS 2019.

Supervised Long-tailed Learning

➢ **LDAM:** The authors define their loss function as:

$$\mathcal{L}_{\text{LDAM-HG}}((x,y);f) = \max(\max_{j\neq y}\{z_j\} - z_y + \Delta_y, 0)$$

$$\text{where } \Delta_j = \frac{C}{n_j^{1/4}} \text{ for } j \in \{1,\ldots,k\}$$

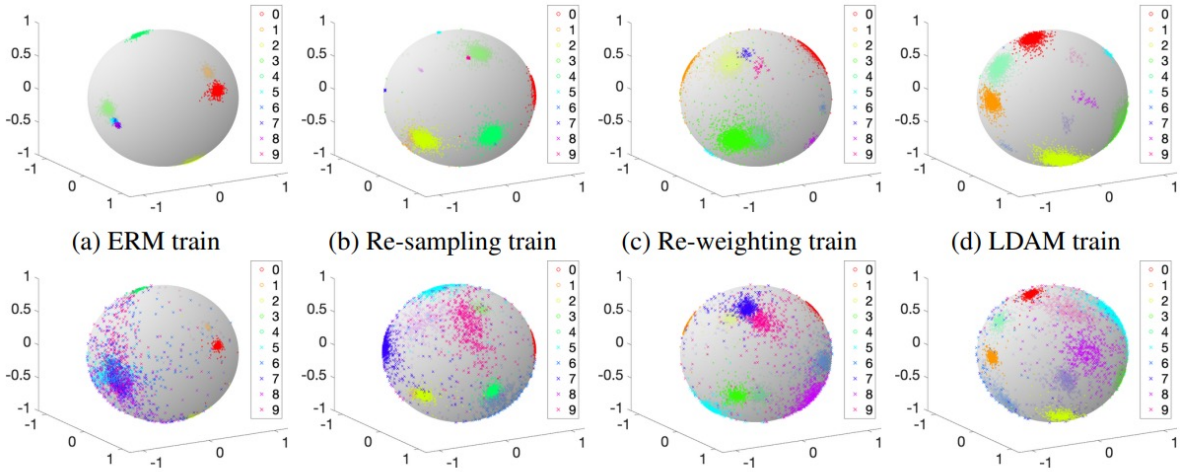
The smooth relaxation of the hinge loss is the following cross-entropy loss with enforced margins:

$$\mathcal{L}_{\text{LDAM}}((x,y);f) = -\log \frac{e^{z_y-\Delta_y}}{e^{z_y-\Delta_y} + \sum_{j\neq y} e^{z_j}}$$

$$\text{where } \Delta_j = \frac{C}{n_j^{1/4}} \text{ for } j \in \{1,\ldots,k\}$$

Approach	Error on positive reviews	Error on negative reviews	Mean Error
ERM	2.86	70.78	36.82
RS	7.12	45.88	26.50
RW	5.20	42.12	23.66
LDAM-DRW	4.91	30.77	17.84

Dataset	Imbalanced CIFAR-10				Imbalanced CIFAR-100			
Imbalance Type	long-tailed		step		long-tailed		step	
Imbalance Ratio	100	10	100	10	100	10	100	10
ERM	29.64	13.61	36.70	17.50	61.68	44.30	61.45	45.37
Focal [Lin et al., 2017]	29.62	13.34	36.09	16.36	61.59	44.22	61.43	46.54
LDAM	26.65	13.04	33.42	15.00	60.40	43.09	60.42	43.73
CB RS	29.45	13.21	38.14	15.41	66.56	44.94	66.23	46.92
CB RW [Cui et al., 2019]	27.63	13.46	38.06	16.20	66.01	42.88	78.69	47.52
CB Focal [Cui et al., 2019]	25.43	12.90	39.73	16.54	63.98	42.01	80.24	49.98
HG-DRS	27.16	14.03	29.93	14.85	-	-	-	-
LDAM-HG-DRS	24.42	12.72	24.53	12.82	-	-	-	-
M-DRW	24.94	13.57	27.67	13.17	59.49	43.78	58.91	44.72
LDAM-DRW	**22.97**	**11.84**	**23.08**	**12.19**	**57.96**	**41.29**	**54.64**	**40.54**



(a) ERM train (b) Re-sampling train (c) Re-weighting train (d) LDAM train

(e) ERM val (f) Re-sampling val (g) Re-weighting val (h) LDAM val

[1] Cao et al. "Learning Imbalanced Datasets with Label-Distribution-Aware Margin Loss" NeurIPS 2019.

Class-wise logit adjustment

- **Motivation:** Design a consistent loss function that allows for a relatively elastic margin in the logit for head and tail.

- **Balanced error:** Under class imbalance, to measure balanced error:

$$\mathrm{BER}(f) \doteq \frac{1}{L} \sum_{y \in [L]} \mathbb{P}_{x|y} \left(y \notin \mathrm{argmax}_{y' \in \mathcal{Y}} f_{y'}(x) \right)$$

Under Bayes-optimal prediction, if $\mathbb{P}^{\mathrm{bal}}(y \mid x) \propto \mathbb{P}(y \mid x) / \mathbb{P}(y)$

Then

$$\mathrm{argmax}_{y \in [L]} \mathbb{P}^{\mathrm{bal}}(y \mid x) = \mathrm{argmax}_{y \in [L]} \exp(s_y^*(x)) / \mathbb{P}(y) = \mathrm{argmax}_{y \in [L]} s_y^*(x) - \ln \mathbb{P}(y)$$

[1] Menon et al. ”Long-tailed Learning via Logit Adjustment" ICLR 2021.

Supervised Long-tailed Learning

➢ **The logit adjusted softmax cross-entropy**

$$\ell(y, f(x)) = -\log \frac{e^{f_y(x)+\tau\cdot\log\pi_y}}{\sum_{y'\in[L]} e^{f_{y'}(x)+\tau\cdot\log\pi_{y'}}} = \log\left[1+\sum_{y'\neq y}\left(\frac{\pi_{y'}}{\pi_y}\right)^{\tau}\cdot e^{(f_{y'}(x)-f_y(x))}\right]$$

$$\boxed{w_1^\top\Phi(x)/\pi_1 < w_2^\top\Phi(x)/\pi_2 \;\underset{\not\Leftarrow}{\not\Rightarrow}\; \exp(w_1^\top\Phi(x))/\pi_1 < \exp(w_2^\top\Phi(x))/\pi_2.}$$

➢ **Post-hoc logit adjustment**

$$\mathrm{argmax}_{y\in[L]}\exp(w_y^\top\Phi(x))/\pi_y^\tau = \mathrm{argmax}_{y\in[L]} f_y(x) - \tau\cdot\log\pi_y$$

[1] Menon et al. ”Long-tailed Learning via Logit Adjustment" ICLR 2021.

Supervised Long-tailed Learning

➢ **An remarkable point on the statistical consistency of long-tailed multi-class classification**

$$\ell(y, f(x)) = \alpha_y \cdot \log\left[1 + \sum\nolimits_{y' \neq y} e^{\Delta_{yy'}} \cdot e^{(f_{y'}(x) - f_y(x))}\right]$$

Theorem 1. *For any $\delta \in \mathbb{R}_+^L$, the pairwise loss in (11) is Fisher consistent with weights and margins*

$$\alpha_y = \delta_y / \mathbb{P}(y) \qquad \Delta_{yy'} = \log\left(\delta_{y'} / \delta_y\right).$$

Letting $\delta_y = \pi_y$, we immediately deduce that the logit-adjusted loss of (10) is consistent, *provided* our π_y is a consistent estimate of $\mathbb{P}(y)$. Similarly, $\delta_y = 1$ recovers the classic result that the balanced loss is consistent. While Theorem 1 only provides a sufficient condition in multi-class setting, one can provide a necessary and sufficient condition that rules out other choices of Δ in the binary case.

[1] Menon et al. ”Long-tailed Learning via Logit Adjustment" ICLR 2021.

Supervised Long-tailed Learning

Dynamic adjustment based on a fine-grained generalization bound

Proposition 3 (Data-Dependent Bound for the VS Loss). *Given the function set $\mathcal{F}$ and the VS loss L_{VS}, for any $\delta \in (0,1)$, with probability at least $1-\delta$ over the training set $\mathcal{S}$, the following generalization bound holds for all $f \in \mathcal{F}$:*

$$\mathcal{R}^L_{bal}(f) \precsim \Phi(L_{VS}, \delta) + \frac{\hat{\mathfrak{C}}_{\mathcal{S}}(\mathcal{F})}{C\pi_C} \sum_{y=1}^{C} \alpha_y \tilde{\beta}_y \sqrt{\pi_y} \left[1 - softmax\left(\beta_y B_y(f) + \Delta_y\right)\right].$$

$$L_{\mathrm{VS}}(f(\boldsymbol{x}), y) = -\alpha_y \log\left(\frac{e^{\beta_y f(\boldsymbol{x})_y + \Delta_y}}{\sum_{y'} e^{\beta_{y'} f(\boldsymbol{x})_{y'} + \Delta_{y'}}}\right).$$

Algorithm 1: Principled Learning Algorithm induced by the Theoretical Insights

Require: Training set $\mathcal{S} = \{(x_i, y_i)\}_{i=1}^N$ and a model f parameterized by Θ.

```
Initialize the model parameters Θ randomly.
for t = 1, 2, ··· , T do
    B ← SampleMiniBatch(S, m)                          ▷ A mini-batch of m samples
    if t < T_0 then
        Set α = 1, β_y, Δ_y                            ▷ Adjust logits during the initial phase
    else
        Set α_y ∝ π_y^{-ν}, β_y = 1, Δ_y, ν > 0        ▷ TLA and ADRW
    end if
    L(f, B) ← (1/m) Σ_{(x,y)∈B} L_VS(f(x), y)          ▷ Calculate the loss
    Θ ← Θ − η∇_Θ L(f, B)                               ▷ One SGD step
    Optional: anneal the learning rate η.              ▷ Required when t = T_0
end for
```

[1] Wang et al. "A Unified Generalization Analysis of Re-Weighting and Logit-Adjustment for Imbalanced Learning" NeurIPS 2023.

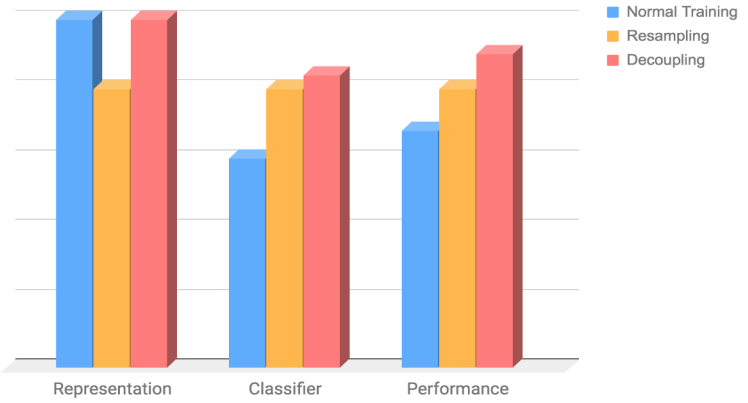
Supervised Long-tailed Learning

Both representation and classifier matter

➢ **Motivation:** Representation and classifier are in the different learning pace, and can be treated differently during training.

➢ **The problem behind long-tail:**

Classification performance =
Representation Quality + Classifier Quality



➢ **Ways of learning classifiers:**

Classifier Re-training (cRT)

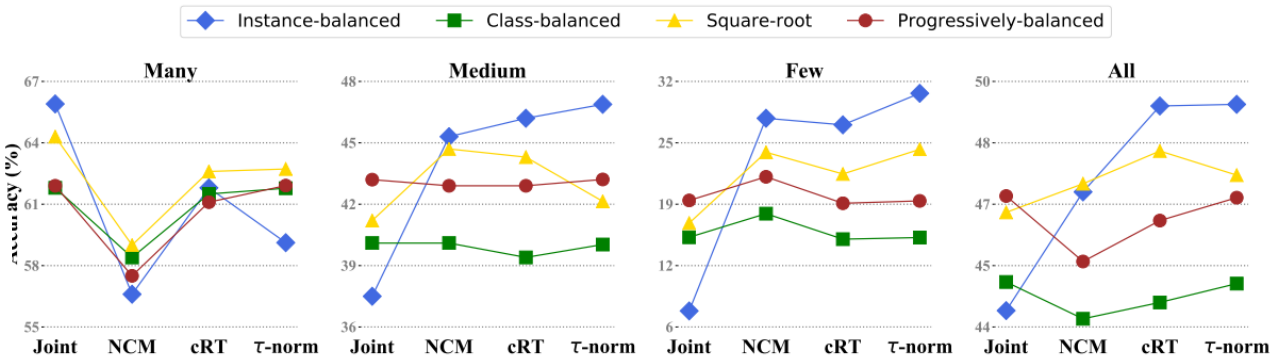
Nearest Class Mean classifier (NCM)

τ -normalized classifier (τ -normalized)

$$\widetilde{w_i} = \frac{w_i}{||w_i||^\tau}$$

Learnable weight scaling (LWS)

$$\widetilde{w_i} = f_i * w_i, \text{ where } f_i = \frac{1}{||w_i||^\tau}$$



[1] Kang et al. " Decoupling Representation and Classifier for Long-Tailed Recognition " ICLR 2020.

Supervised Long-tailed Learning

The special constant classifier geometry

- **Motivation:** In the training on an imbalanced dataset, the classifier vectors of minor classes will be merged, termed as minority collapse, which breaks up the ETF structure and deteriorates the performance on test data.

- **Simplex Equiangular Tight Frame:**

$$\mathbf{M} = \sqrt{\frac{K}{K-1}}\mathbf{U}\left(\mathbf{I}_K - \frac{1}{K}\mathbf{1}_K\mathbf{1}_K^T\right)$$

$$\mathbf{m}_i^T\mathbf{m}_j = \frac{K}{K-1}\delta_{i,j} - \frac{1}{K-1}, \forall i,j \in [1,K]$$

- **ETF Classifier:**

$$\min_{\mathbf{H}} \quad \frac{1}{N}\sum_{k=1}^{K}\sum_{i=1}^{n_k}\mathcal{L}_{CE}(\mathbf{h}_{k,i}, \mathbf{W}^*)$$

$$\mathbf{w}_k^{*T}\mathbf{w}_{k'}^* = E_W\left(\frac{K}{K-1}\delta_{k,k'} - \frac{1}{K-1}\right), \forall k,k' \in [1,K]$$

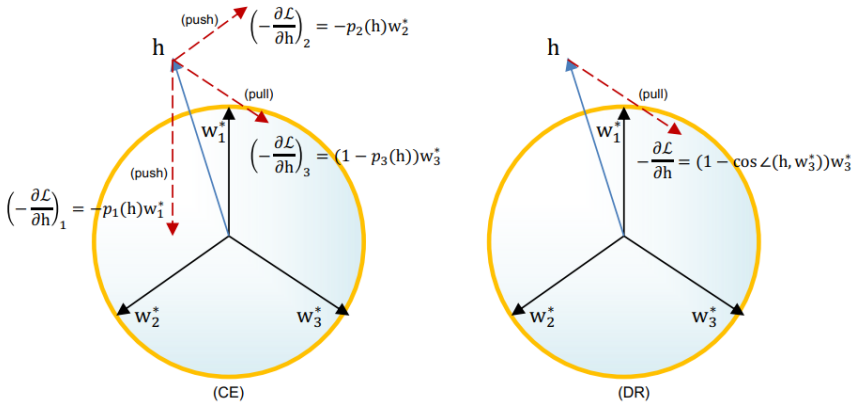
[1] Yang et al. "Inducing Neural Collapse in Imbalanced Learning: Do We Really Need a Learnable Classifier at the End of Deep Neural Network?" NeurIPS 2022.

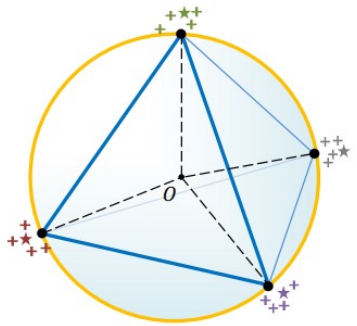
Supervised Long-tailed Learning

➢ **Dot-Regression Loss:**

Squared loss function:

$$\mathcal{L}_{DR}(\mathbf{h}, \mathbf{W}^*) = \frac{1}{2\sqrt{E_W E_H}} \left(\mathbf{w}_c^{*T} \mathbf{h} - \sqrt{E_W E_H} \right)^2 \qquad \frac{\partial \mathcal{L}_{DR}}{\partial \mathbf{h}} = -\left(1 - \cos \angle(\mathbf{h}, \mathbf{w}_c^*)\right) \mathbf{w}_c^*$$





Epoch	Methods	Acc. (%)
90	Learnable Classifier + CE	34.6
	ETF Classifier + DR	41.8
120	Learnable Classifier + CE	41.9
	ETF Classifier + DR	43.2
150	Learnable Classifier + CE	42.5
	ETF Classifier + DR	43.8
180	Learnable Classifier + CE	44.3
	ETF Classifier + DR	44.7

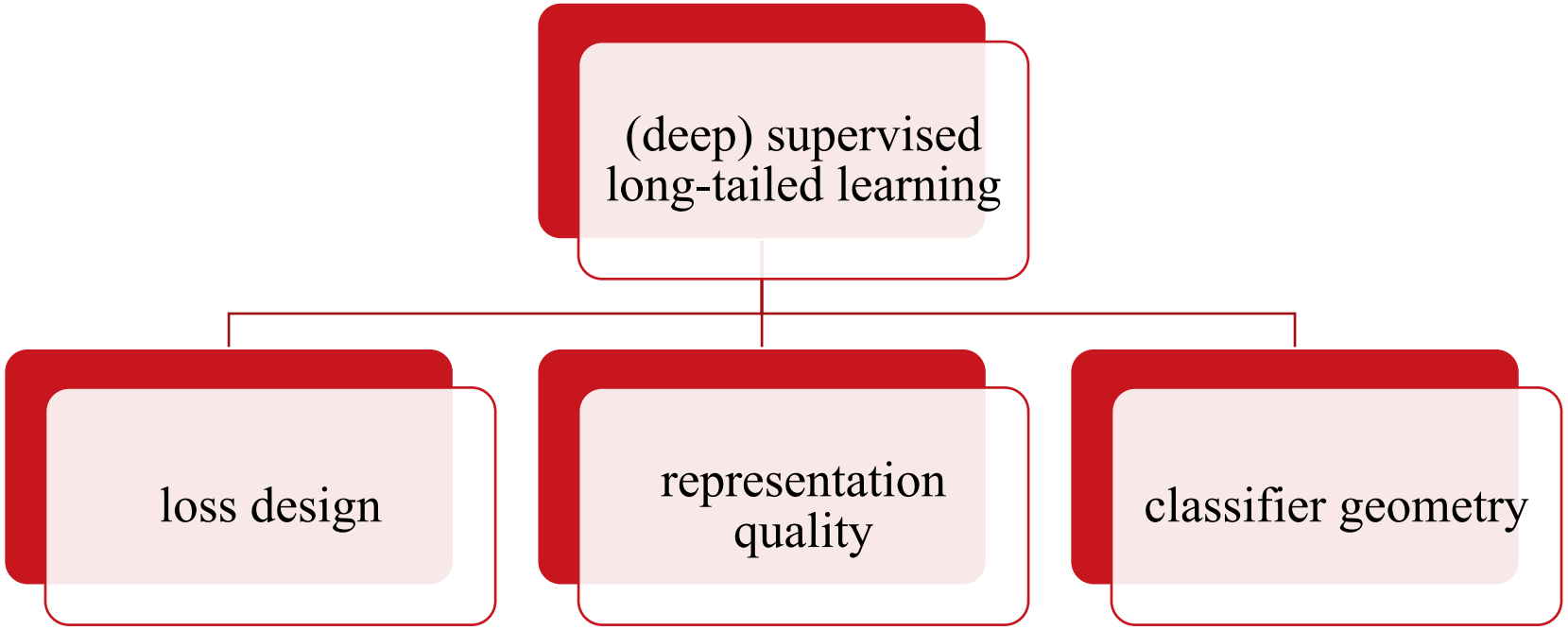
Backbone	Methods	Acc. (%)
ResNet-34	Learnable Classifier + CE	82.2
	ETF Classifier + DR	83.0
ResNet-50	Learnable Classifier + CE	85.5
	ETF Classifier + DR	86.1
ResNet-101	Learnable Classifier + CE	86.2
	ETF Classifier + DR	87.0

Methods	CIFAR-10 [17]			CIFAR-100 [17]			SVHN [25]			STL-10 [3]		
	0.005	0.01	0.02	0.005	0.01	0.02	0.005	0.01	0.02	0.005	0.01	0.02
ResNet												
Learnable Classifier + CE	67.3	72.8	78.6	38.7	43.0	48.1	40.5	40.9	49.3	33.1	37.9	38.8
ETF Classifier + DR	71.9	76.5	81.0	40.9	45.3	50.4	42.8	45.7	49.8	33.5	37.2	37.9
Improvements	**+4.6**	**+3.7**	**+2.4**	**+2.2**	**+2.3**	**+2.3**	**+2.3**	**+4.8**	**+0.5**	**+0.4**	-0.7	-0.9
DenseNet												
Learnable Classifier + CE	71.1	77.7	84.1	40.3	43.8	49.8	39.7	40.5	46.4	38.5	41.2	44.9
ETF Classifier + DR	72.9	78.5	83.4	40.1	44.0	49.7	40.5	44.8	48.4	39.5	42.9	46.3
Improvements	**+1.8**	**+0.8**	-0.7	-0.2	**+0.2**	-0.1	**+0.8**	**+4.3**	**+2.0**	**+1.0**	**+1.7**	**+1.4**

[1] Yang et al. "Inducing Neural Collapse in Imbalanced Learning: Do We Really Need a Learnable Classifier at the End of Deep Neural Network?" NeurIPS 2022.

Supervised Long-tailed Learning

Summary: supervised long-tailed learning in the context of deep learning, should take more factors (loss, representation etc.) into account to improve the performance of imbalanced learning.



Weakly-Supervised Long-tailed Learning

Weak supervision

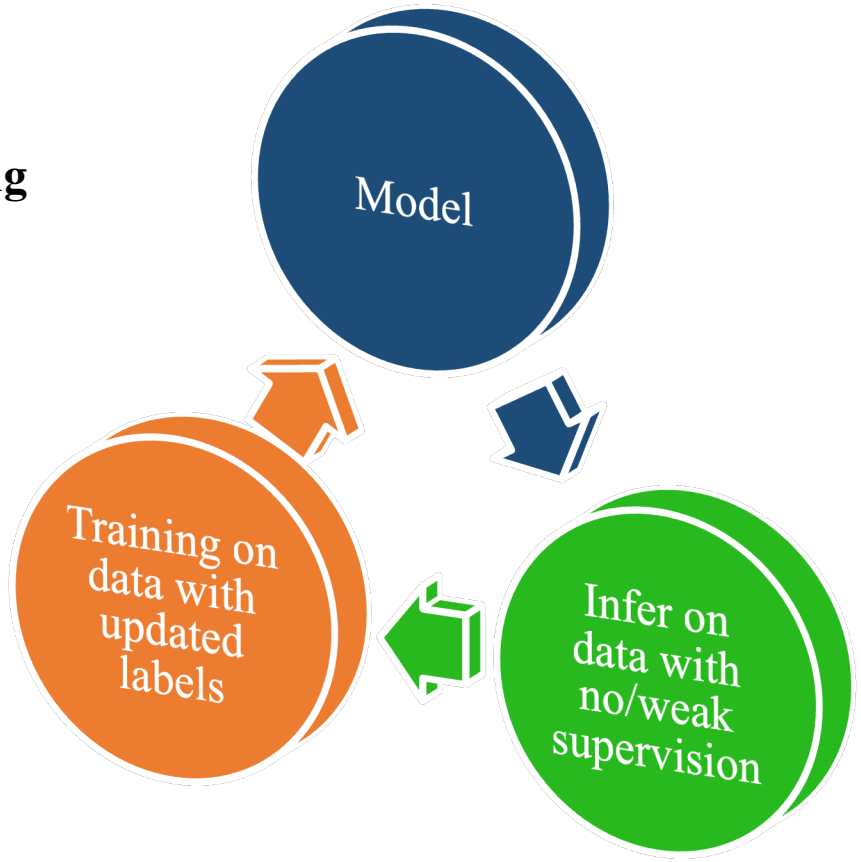
- Incomplete supervision: **semi-supervised learning**
- Inexact supervision: **partial label learning**, **multi-instance learning**
- Inaccurate supervision: **label-noise learning**

Target: *low labeling cost* but *high accuracy*.

Pseudo Labeling

- Generate more precise annotations for weakly supervised data

Transfer weakly-supervised learning → supervised learning

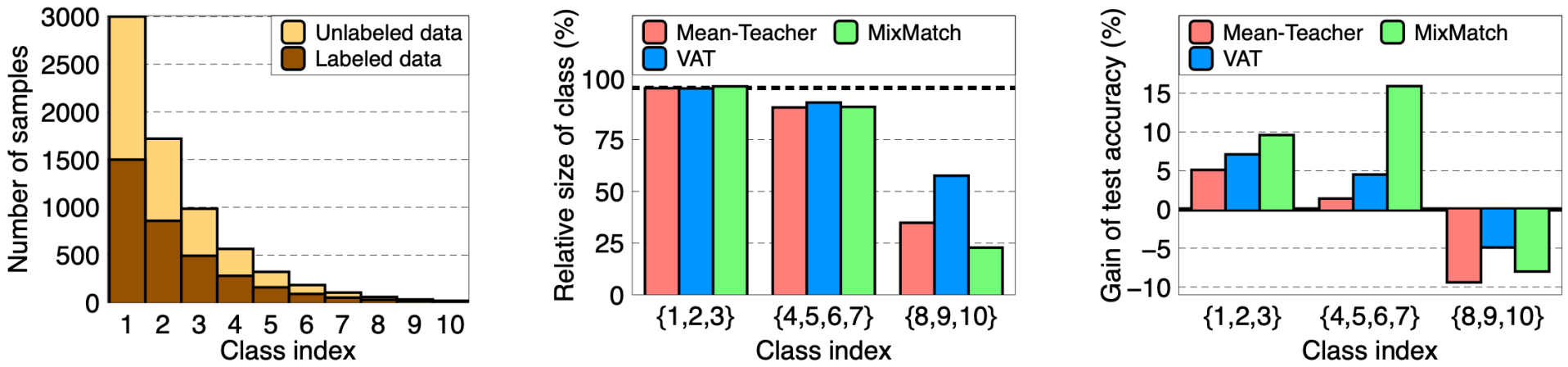


Pseudo Labeling

Zhou, Z. H. (2018). A brief introduction to weakly supervised learning. *National science review*, *5*(1), 44-53.

When long-tailed distribution meets weak supervision

- Positive feedback property of pseudo-labeling: head get better and more



(a) Imbalanced class distribution (b) Bias of pseudo-labels (c) Accuracy gain from SSL

[1]

- Distributional corrections need to go deeper into training and pseudo-labeling

[1]Kim, J., Hur, Y., Park, S., et al. Distribution aligning refinery of pseudo-label for imbalanced semi-supervised learning. *NeurIPS*. 2020.

Long-tailed Semi-Supervised Learning

- Motivation: Label propagation on unlabeled data biased toward the majority classes.
- Main idea: Refine the original, biased pseudo-labels so that their distribution can match the true class distribution of unlabeled data, while constrain the refined pseudo-labels to be close from the original ones.
- Formulation: An optimization problem for constructing refined pseudo-labels: minimizing the distortion from the original pseudo-labels, while matching the true class distribution.

$$\text{minimize} \quad \sum_{m=1}^{M} w_m D_{KL}(\hat{y}_m \,||\, \hat{y}_m^{\texttt{unlabeled}})$$

$$\text{subject to} \quad \sum_{m=1}^{M} \hat{y}_m(k) = M_k,\ \forall k,\ \sum_{k=1}^{K} \hat{y}_m(k) = 1,\ \forall m,\ \hat{y}_m(k) \in [0,1],\ \forall m,k$$

Algorithm 1 `DualCoordinateAscent`: Coordinate ascent algorithm for dual of (1)

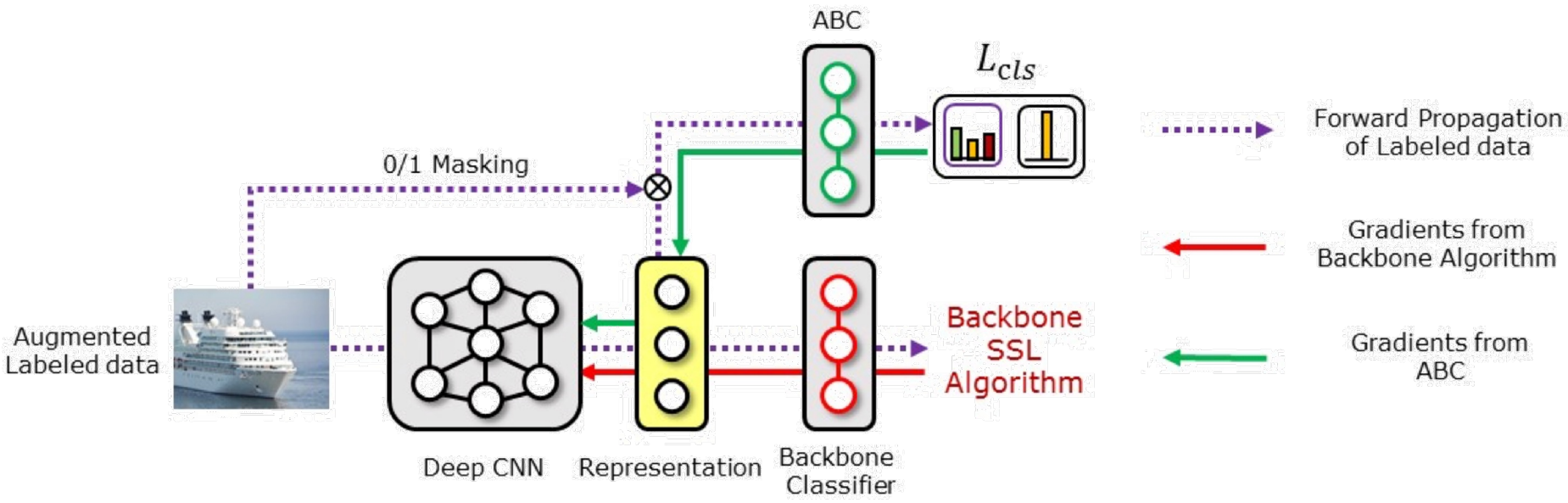
Require: $\{\hat{y}_m^{\texttt{unlabeled}}\}_{m=1}^M, \{w_m\}_{m=1}^M, \{M_k\}_{k=1}^K, T$
Ensure: The unique solution of (1)

$\hat{y}_m^0 \leftarrow y_m^{\texttt{unlabeled}},\ \alpha_m^0 \leftarrow 1,\ \beta_k^0 \leftarrow 1, \quad \forall m,k$
for $t = 1$ **to** T **do**
  if t is odd or $t = T$ **then**
    $\beta_k^t \leftarrow \beta_k^{t-1}, \quad \alpha_m^t \leftarrow \left(\sum_{k=1}^K \hat{y}_m^0(k)(\beta_k^{t-1})^{\frac{1}{w_m}}\right)^{-1}, \quad \forall m,k,$
  else
    $\alpha_m^t \leftarrow \alpha_m^{t-1}, \quad \beta_k^t \leftarrow \texttt{Solve}_{Z\geq 0}\left(\sum_{m=1}^M \hat{y}_m^0(k)\alpha_m^{t-1} Z^{\frac{1}{w_m}} - M_k\right), \quad \forall m,k$
  end if
end for
$\hat{y}_m^{\texttt{out}}(k) \leftarrow \hat{y}_m^0(k)\alpha_m^T(\beta_k^T)^{\frac{1}{w_m}}, \quad \forall m,k$

Kim, J., Hur, Y., Park, S., et al. Distribution aligning refinery of pseudo-label for imbalanced semi-supervised learning. *NeurIPS*, 2020.

ABC: Auxiliary Balanced Classifier [1]

- Motivation: high-quality representations can be learned even the classifier is biased [2].
- Train an Auxiliary Balanced Classifier (ABC) by resampling a balanced subset while using the high-quality representations learned from all data.



[1] Lee, H., Shin, S., & Kim, H.. Abc: Auxiliary balanced classifier for class-imbalanced semi-supervised learning. *NeurIPS*. 2021.
[2] Kang, B., Xie, S., Rohrbach, M., et al. Decoupling Representation and Classifier for Long-Tailed Recognition. *ICLR*. 2020.

Long-tailed Partial Label Learning

- Dataset $\mathcal{X} = \{(x_i, y_i, S_i): i \in (1, 2, 3, \dots, N)\}$, where any x_i is associated with a candidate label set S_i and its ground truth $y_i \in S_i$ is invisible.

Parker: Morning, Flash.
Thompson: Good morning, Parker.

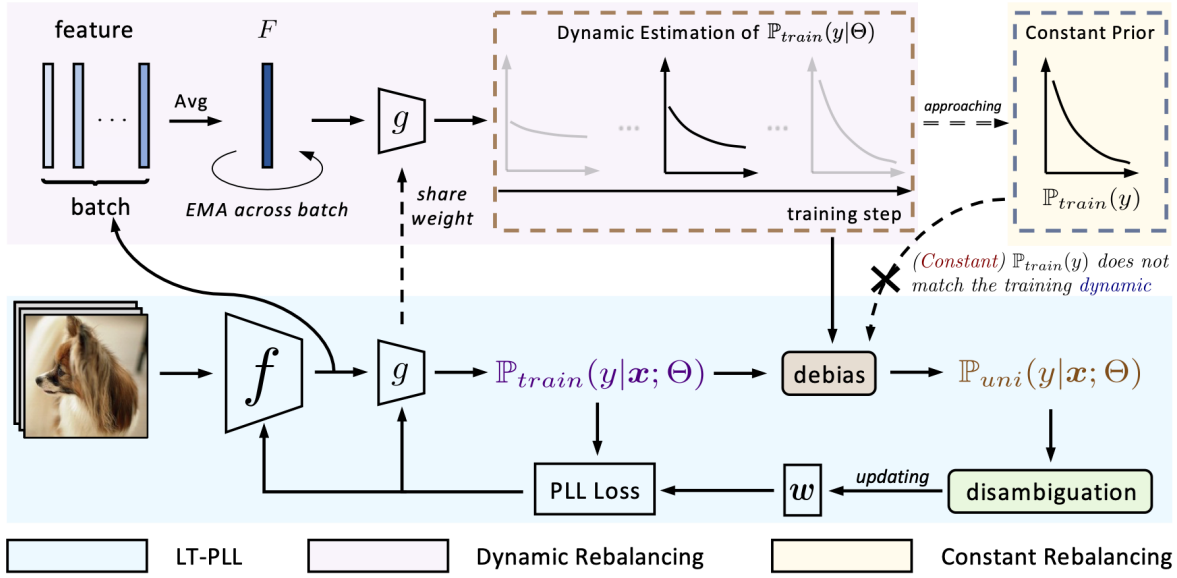
The History of LeBron James and Stephen Curry's Rivalrous Friendship

Annotator 1: Korat
Annotator 2: Russian Blue

- The sample number of L classes in descending order
  - $N_1 \geq N_2 \geq \cdots \geq N_L$, Imbalance ratio $\gamma = \frac{N_1}{N_L} \gg 1$
- Main challenges:
  - Tail samples cannot be correctly recognized even in training
  - No available class prior

RECORDS: Rebalancing for dynamic bias

- Observation: even after applying an oracle class distribution prior in the training, existing long-tailed techniques underperform in LT-PLL and even fail in some cases.
  - Existing long-tailed techniques: leverage a constant class distribution prior to rebalance the training and does not consider the dynamic of label disambiguation.
- A dynamic rebalancing mechanism friendly to the training dynamic



Constant Rebalancing

$$z^y_{uni}(\boldsymbol{x}) = z^y(\boldsymbol{x}) - \log \mathbb{P}_{train}(y|\Theta) = z^y(\boldsymbol{x}) - \log \mathrm{softmax}(g^y(F;\boldsymbol{W})).$$

Match the training dynamic

Dynamic Rebalancing

$$z^y_{uni}(\boldsymbol{x}) = z^y(\boldsymbol{x}) - \log \mathbb{P}_{train}(y|\Theta) = z^y(\boldsymbol{x}) - \log \mathrm{softmax}(g^y(F;\boldsymbol{W})).$$

Hong, F., Yao, J., Zhou, Z., Zhang, Y., & Wang, Y. Long-Tailed Partial Label Learning via Dynamic Rebalancing. *ICLR*. 2023.

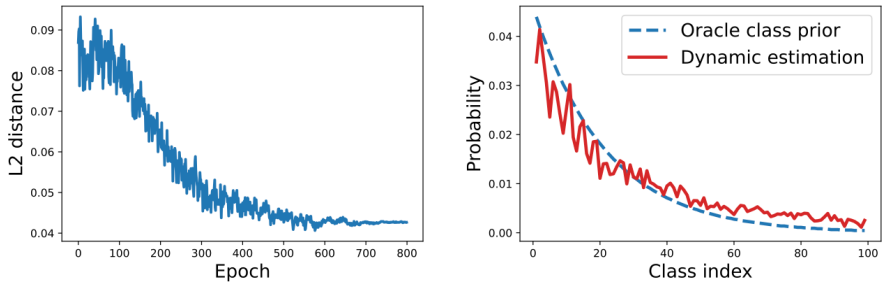
RECORDS: Rebalancing for dynamic bias

➢ Theory: alongside the label disambiguation, the dynamic estimation can progressively approach to the oracle class distribution.

Proposition 1. *Let* $\eta = \sup_{(\boldsymbol{x},y)\in\mathcal{X}\times\mathcal{Y}, y_j\in\mathcal{Y}, y_j\neq y} \mathbb{P}_{S|(\boldsymbol{x},y)}(y_j \in S)$ *denote the ambiguity degree,* d_H *be the Natarajan dimension of the hypothesis space* H*,* $\tilde{h} = h_{\tilde{\Theta}}$ *be the optimal classifier on the basis of the label disambiguation, where* $\tilde{\Theta} = \arg\min_{\Theta} R^{\mathcal{D}_{train}}(\Theta)$*. If the small ambiguity degree condition (Cour et al., 2011a; Liu & Dietterich, 2014)) satisfies, namely,* $\eta \in [0, 1)$*, then for* $\forall\delta > 0$*, the* L_2 *distance between* $\mathbb{P}_{train}(y)$ *and* $\mathbb{P}_{train}(y|\tilde{\Theta})$ *given* $\tilde{h}$ *is bounded as*

$$L_2\left(\tilde{h}\right) < \frac{4}{(\ln 2 - \ln(1+\eta))N}(d_H(\ln 2N + 2\ln C) - \ln\delta + \ln 2)$$

with probability at least $1-\delta$*, where* N *is the sample number and* C *is the category number.*



(a) L_2 distance during training (b) Estimated class distribution

	CIFAR-10-LT						CIFAR-100-LT						PASCAL VOC
Imbalance ratio ρ	50			100			50			100			
Ambiguity q	0.3	0.5	0.7	0.3	0.5	0.7	0.03	0.05	0.07	0.03	0.05	0.07	
LW	71.31	39.69	25.23	66.08	41.2	26.59	37.34	31.59	30.6	33.78	30.69	27.91	20.73
CAVL	57.77	41.68	21.32	54.28	39.47	20.67	23.01	21.29	14.23	31.65	28.77	13.65	18.33
PRODEN	74.22	56.25	45.11	65.72	49.23	42.26	43.02	40.15	39.1	38.66	36.23	35.52	24.47
CORR	77.53	58.35	45.66	69.12	50.96	42.87	45.95	42.83	41.72	41.79	38.47	36.96	26.72
SoLar	83.88	76.55	54.61	75.38	70.63	53.15	47.93	46.85	45.1	42.51	41.71	39.15	56.49
LW+RECORDS	77.22	59.88	43.98	72.2	59.87	43.63	38.16	33.6	31.53	35.33	31.55	28.8	55.19
CAVL+RECORDS	68.93	63.59	44.61	66.65	59.62	41.88	46.13	41.93	34.01	41.33	35.79	31.29	55.03
PRODEN+RECORDS	81.23	78.82	68.03	73.92	66.21	55.73	48.12	46.01	44.19	42.98	41.03	40.25	54.78
CORR+RECORDS	**84.25**	**82.5**	**71.24**	**79.79**	**74.07**	**62.25**	**52.08**	**50.58**	**47.91**	**46.57**	**45.22**	**44.73**	**58.45**

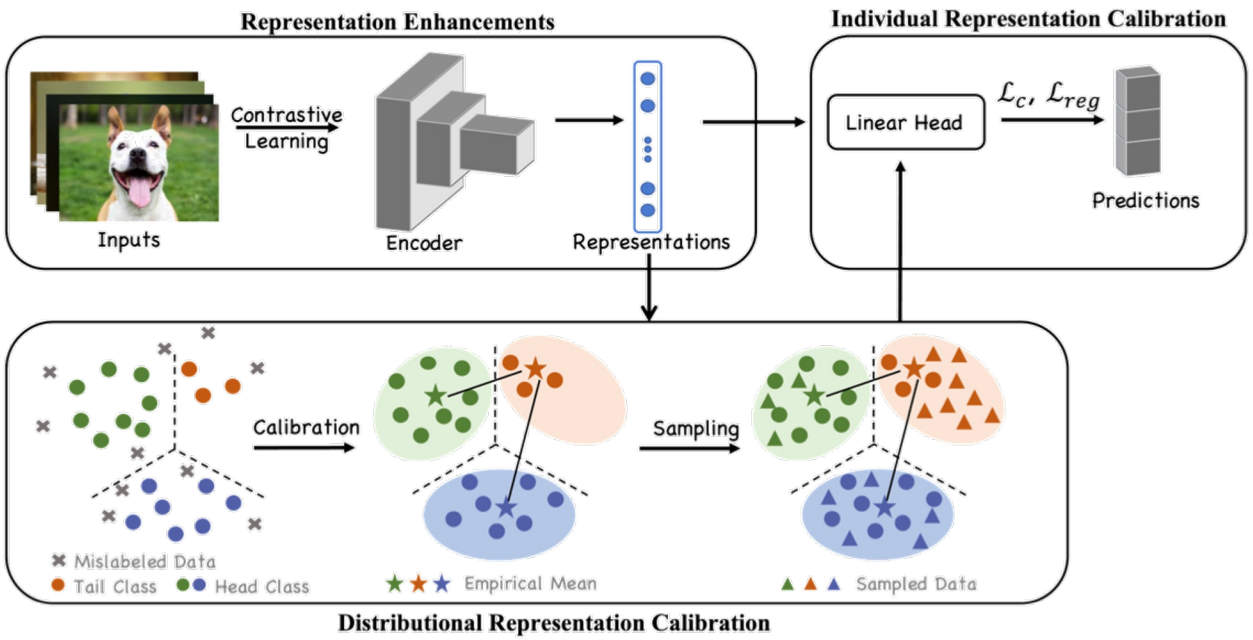
Hong, F., Yao, J., Zhou, Z., Zhang, Y., & Wang, Y. Long-Tailed Partial Label Learning via Dynamic Rebalancing. *ICLR*. 2023.

RCAL: Representation Calibration

- Motivation: The representations of unsupervised contrastive learning are not influenced by corrupted labels and thus naturally robust.

- Main spirit: Decoupling the imbalance from the noise labels with the help of self-supervised representation learning methods.

- Based upon the achieved representations, the calibration can be performed. Distributional representation calibration estimate the robust feature distribution considering data imbalance and perform balanced sampling. Individual representation calibration constrain the distance between supervised training representations and pre-training representations.



Zhang, M., Zhao, X., Yao, J., et al. When Noisy Labels Meet Long Tail Dilemmas: A Representation Calibration Method. *ICCV. 2023.*

RCAL: Representation Calibration

Algorithm 1 Algorithm of the proposed method RCAL

Require: the training dataset $\tilde{\mathcal{S}} = \{(\boldsymbol{x}_i, \tilde{y}_i\})_{i=1}^n$, regularization strength β, scalar temperature τ, confidence weight γ, the pre-training epochs T_p, max epochs T_m.

for $t = 1, ..., T_p$ **do**
  Pre-train the encoder network f with MoCo [20].
end for
Extract deep representations of instances with $\boldsymbol{z} = f(\boldsymbol{x})$.
for $c = 1, ..., K$ **do**
  Perform the LOF algorithm for the c-th class and obtain preserved examples $\tilde{\mathcal{S}}'_c$.
  Build the multivariate Gaussian distribution $\mathcal{N}(f(\boldsymbol{x})|\hat{\boldsymbol{\mu}}_c, \hat{\boldsymbol{\Sigma}}_c)$ for c-th class using $\tilde{\mathcal{S}}'_c$.
end for
Calibrate the multivariate Gaussian distributions of tail classes with the statistics of head classes.
Sample data points from achieved multivariate Gaussian distributions of all classes.
for $t = T_p + 1, ..., T_m$ **do**
  Add distance constraints between learned representations and representations brought by contrastive learning.
  Adopt the mixup technology to original examples.
  Train the encoder f and the linear head h simultaneously on the training dataset and sample data points with the training loss in Eq. (2).
end for
return The robust classifier $h(f(\boldsymbol{x}))$ for testing.

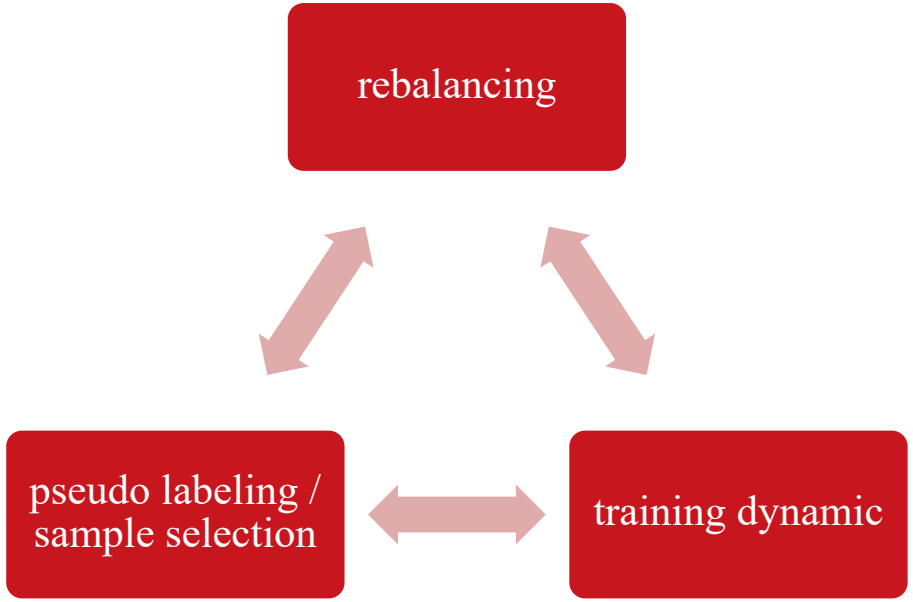
Dataset	Imbalance Ratio	10					100				
	Noise Rate	0.1	0.2	0.3	0.4	0.5	0.1	0.2	0.3	0.4	0.5
CIFAR-10	ERM	80.41	75.61	71.94	70.13	63.25	64.41	62.17	52.94	48.11	38.71
	ERM-DRW	81.72	77.61	71.94	70.13	63.25	66.74	62.17	52.94	48.11	38.71
	LDAM	84.59	82.37	77.48	71.41	60.30	71.46	66.26	58.34	46.64	36.66
	LDAM-DRW	85.94	83.73	80.20	74.87	67.93	76.58	72.28	66.68	57.51	43.23
	CRT	80.22	76.15	74.17	70.05	64.15	61.54	59.52	54.05	50.12	36.73
	NCM	82.33	74.73	74.76	68.43	64.82	68.09	66.25	60.91	55.47	42.61
	MiSLAS	87.58	85.21	83.39	76.16	72.46	75.62	71.48	67.90	62.04	54.54
	Co-teaching	80.30	78.54	68.71	57.10	46.77	55.58	50.29	38.01	30.75	22.85
	CDR	81.68	78.09	73.86	68.12	62.24	60.47	55.34	46.32	42.51	32.44
	Sel-CL+	86.47	85.11	84.41	80.35	77.27	72.31	71.02	65.70	61.37	56.21
	HAR-DRW	84.09	82.43	80.41	77.43	67.39	70.81	67.88	48.59	54.23	42.80
	RoLT	85.68	85.43	83.50	80.92	78.96	73.02	71.20	66.53	57.86	48.98
	RoLT-DRW	86.24	85.49	84.11	81.99	80.05	76.22	74.92	71.08	63.61	55.06
	RCAL (Ours)	88.09	86.46	84.58	83.43	80.80	78.60	75.81	72.76	69.78	65.05

Dataset	CIFAR-10				CIFAR-100			
Imbalance Ratio	10		100		10		100	
Noise Rate	0.2	0.4	0.2	0.4	0.2	0.4	0.2	0.4
RCAL	**86.46**	**83.43**	**75.81**	**69.78**	**54.85**	**48.91**	**39.85**	**33.36**
RCAL w/o Mixup	84.08	79.27	72.47	64.83	51.22	45.53	36.78	30.85
RCAL w/o Mixup, REG	83.23	78.12	67.49	58.27	48.74	42.15	34 31	27.14
RCAL w/o Mixup, REG, DC	80.40	74.37	64.02	54.61	47.01	40.85	32.27	25.42
RCAL w/o Mixup, REG, DC, CL	75.61	70.13	62.17	48.11	43.27	32.94	26.21	17.91

Zhang, M., Zhao, X., Yao, J., et al. When Noisy Labels Meet Long Tail Dilemmas: A Representation Calibration Method. *ICCV*. 2023.

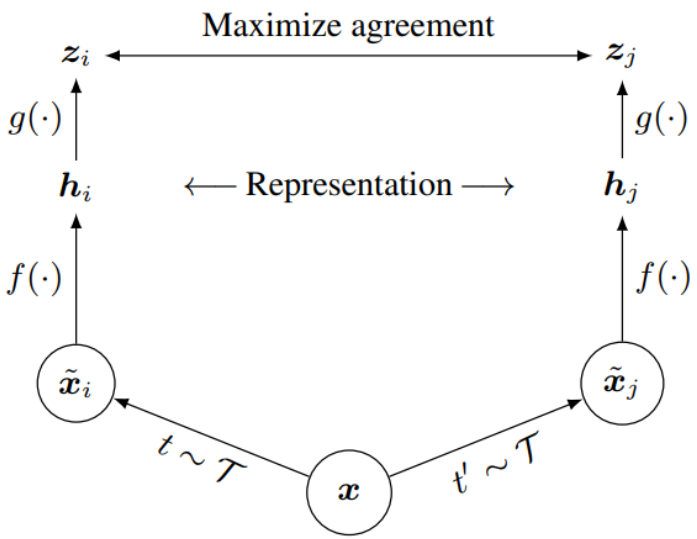
Summary

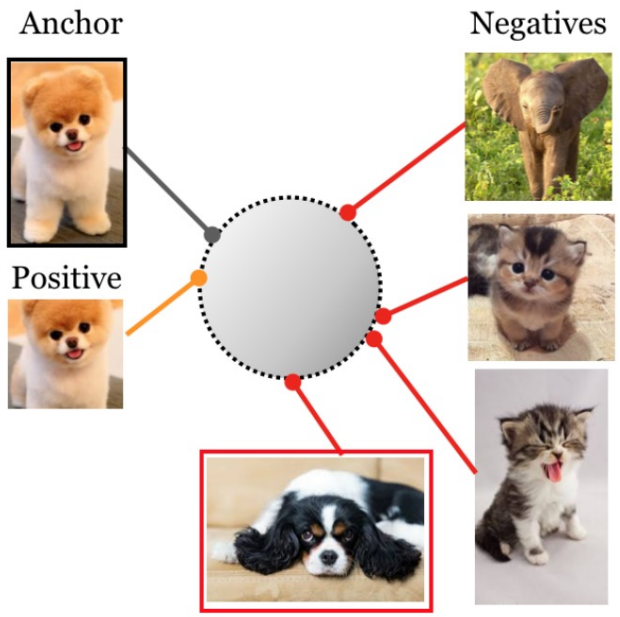
- Weak Supervision can exacerbate the long-tail effect, impairing the performance of minority classes.
- It is critical to construct a friendly mechanism to decouple *pseudo labeling / sample selection* and *rebalancing*.



Self-supervised learning

- The idea of contrastive learning: push augmented views of the same image closer, and embeddings to random pairs of images far apart

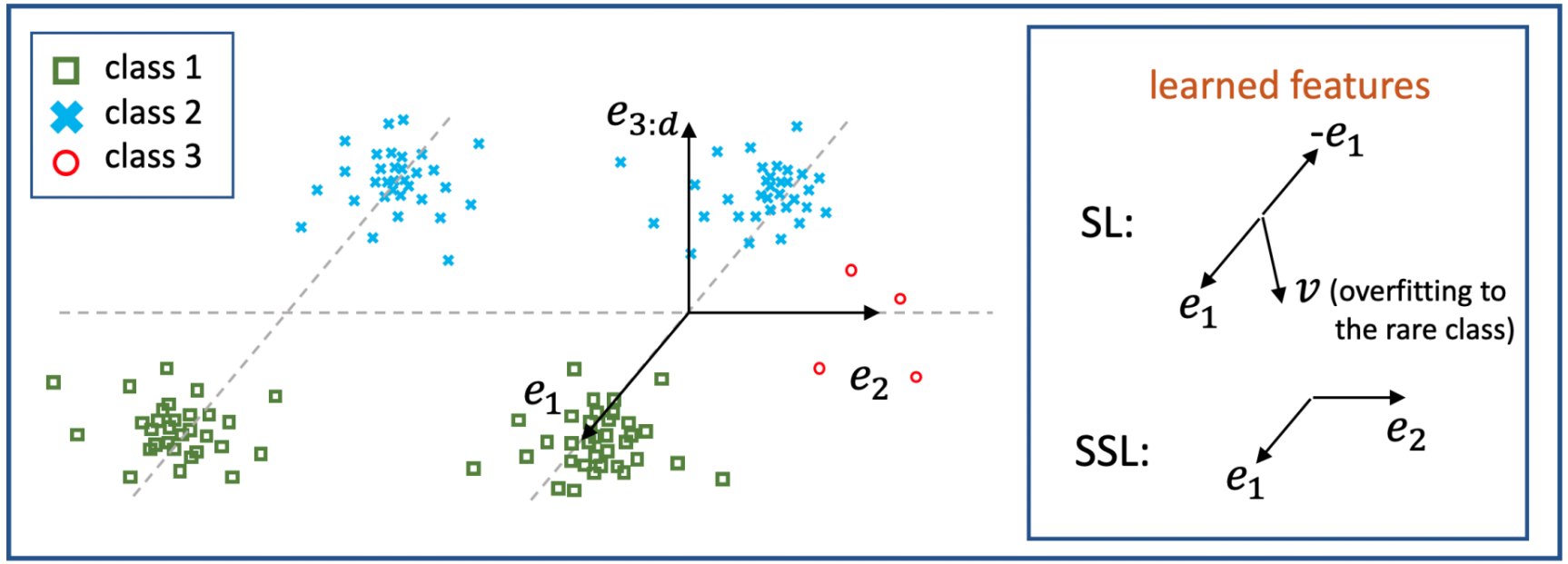




[1] Chen et al. "A simple framework for contrastive learning of visual representations." ICML 2020.
[2] Khosla et al. "Supervised contrastive learning." NeurIPS 2020.

Self-Supervised Long-tailed Learning

Is self-supervised learning more robust to data imbalance?



- Supervised learning (SL) only extracts features that are useful for predicting labels (e_1)

- Self-supervised learning (SSL) learns task-irrelevant features regardless of the labels, which enables richer and more robust representation (e_1, e_2)

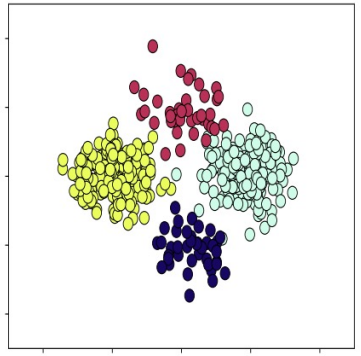
[1] Liu et al. "Self-supervised Learning is More Robust to Dataset Imbalance." ICLR 2021.

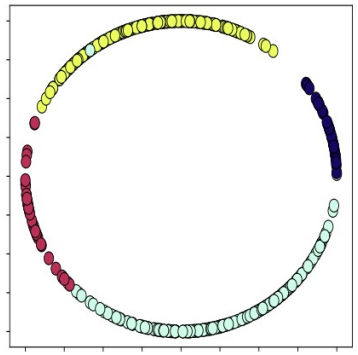
Self-supervised learning still suffers from data imbalance

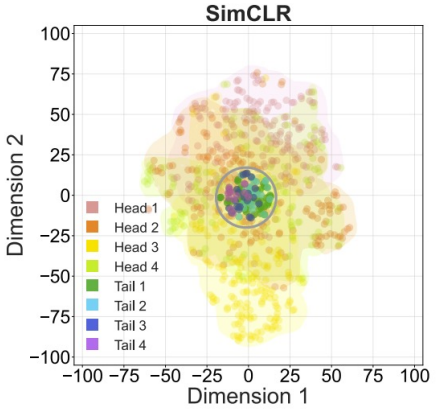
- Performance degeneration: Linear probing on imbalanced data $(\boldsymbol{D_i})$ and balanced data $(\boldsymbol{D_b})$ with same data amount

Dataset	Subset	*Many*	*Medium*	*Few*	All
CIFAR10	D_b	77.14 ± 4.64	74.25 ± 6.54	71.47 ± 7.55	74.57 ± 0.65
	D_i	76.07 ± 3.88	67.97 ± 5.84	54.21 ± 10.24	67.08 ± 2.15
CIFAR100	D_b	25.48 ± 1.74	25.16 ± 3.07	24.01 ± 1.23	24.89 ± 0.99
	D_i	30.72 ± 2.01	21.93 ± 2.61	15.99 ± 1.51	22.96 ± 0.43

- Representation learning disparity: head classes dominate the feature regime but tail classes passively collapse





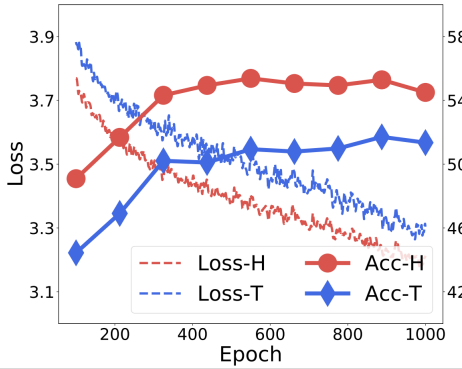


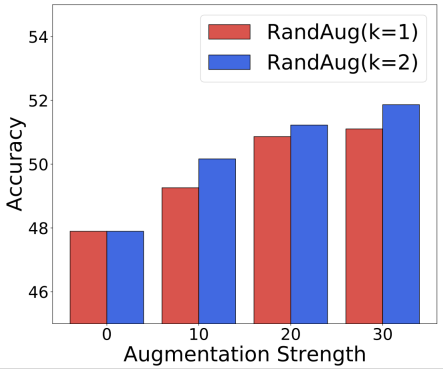
[1] Jiang et al. "Self-damaging contrastive learning." ICML 2021.
[2] Zhou et al. "Combating Representation Learning Disparity with Geometric Harmonization." NeurIPS 2023.

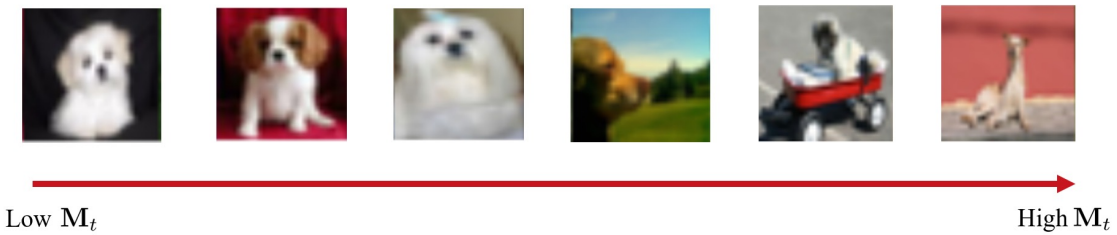
BCL: Boosted Contrastive Learning

- Motivation I: Memorization effect still holds under long-tailed distribution.
- Motivation II: Stronger information discrepancy motivates tail samples mining

- **Challenge:** how to **detect tail data** and how to construct the **desired information discrepancy**







- Motivated from the observation that *learning speed-based proxy* shows strong correlation with the memorization score[1], BCL extends the memorization estimation to *self-supervised learning*.

$$\mathcal{L}^m_{i,0} = \mathcal{L}_{i,0}, \quad \mathcal{L}^m_{i,t} = \beta \mathcal{L}^m_{i,t-1} + (1-\beta)\mathcal{L}_{i,t}$$

$$\mathbf{M}_{i,t} = \frac{1}{2}\left(\frac{\mathcal{L}^m_{i,t} - \bar{\mathcal{L}}^m_t}{\max\left\{\left|\mathcal{L}^m_{i,t} - \bar{\mathcal{L}}^m_t\right|\right\}_{i=0,\ldots,N}} + 1\right)$$

$$\Psi(x_i; \mathcal{A}, \mathbf{M}_i) = a_1(x_i) \circ \ldots \circ a_k(x_i),$$

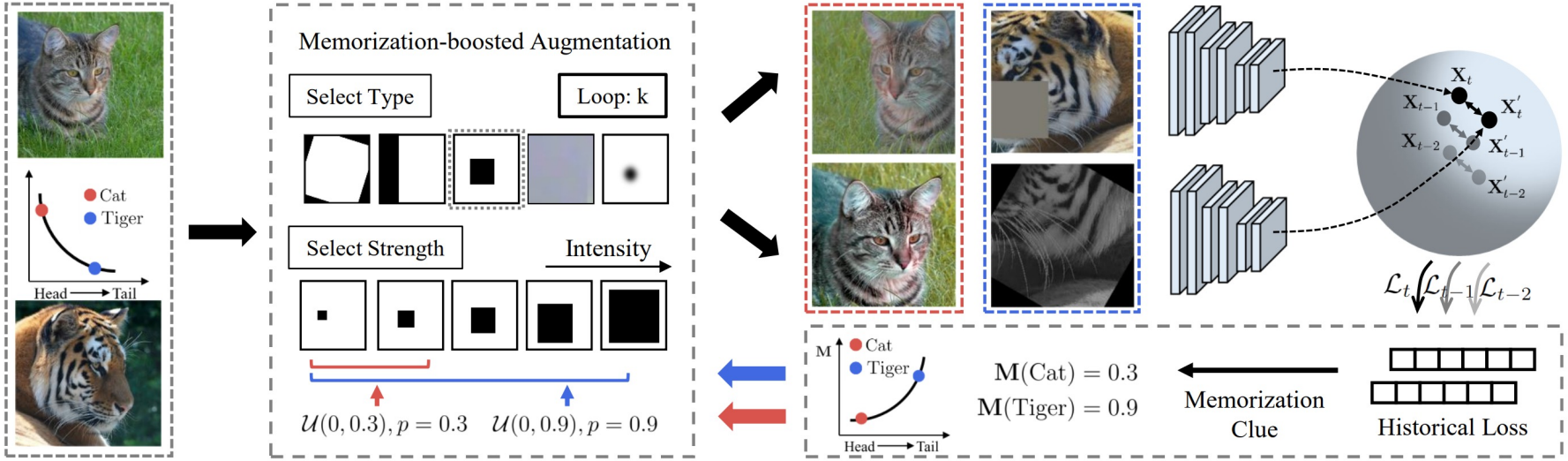
$$a_j(x_i) = \begin{cases} A_j(x_i; \mathbf{M}_i\zeta) & u \sim \mathcal{U}(0,1) \;\&\; u < \mathbf{M}_i \\ x_i & \text{otherwise} \end{cases}$$

$$\mathcal{L}_{\mathrm{BCL}} = \frac{1}{N}\sum_{i=1}^{N} -\log \frac{\exp\left(\frac{f(\Psi(x_i))^\top f(\Psi(x_i^+))}{\tau}\right)}{\sum_{x_i' \in X'} \exp\left(\frac{f(\Psi(x_i))^\top f(\Psi(x_i'))}{\tau}\right)}$$

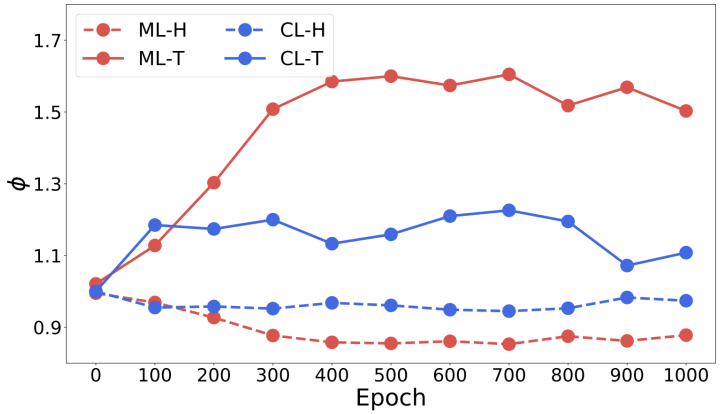
Adaptively assigns the appropriate augmentation strength for the individual sample according to the feedback from the memorization clues

[1] Jiang et al. “Characterizing structural regularities of labeled data in overparameterized models.” ICML 2021
[2] Zhou et al. “Contrastive learning with boosted memorization. " ICML 2022.

BCL: Boosted Contrastive Learning



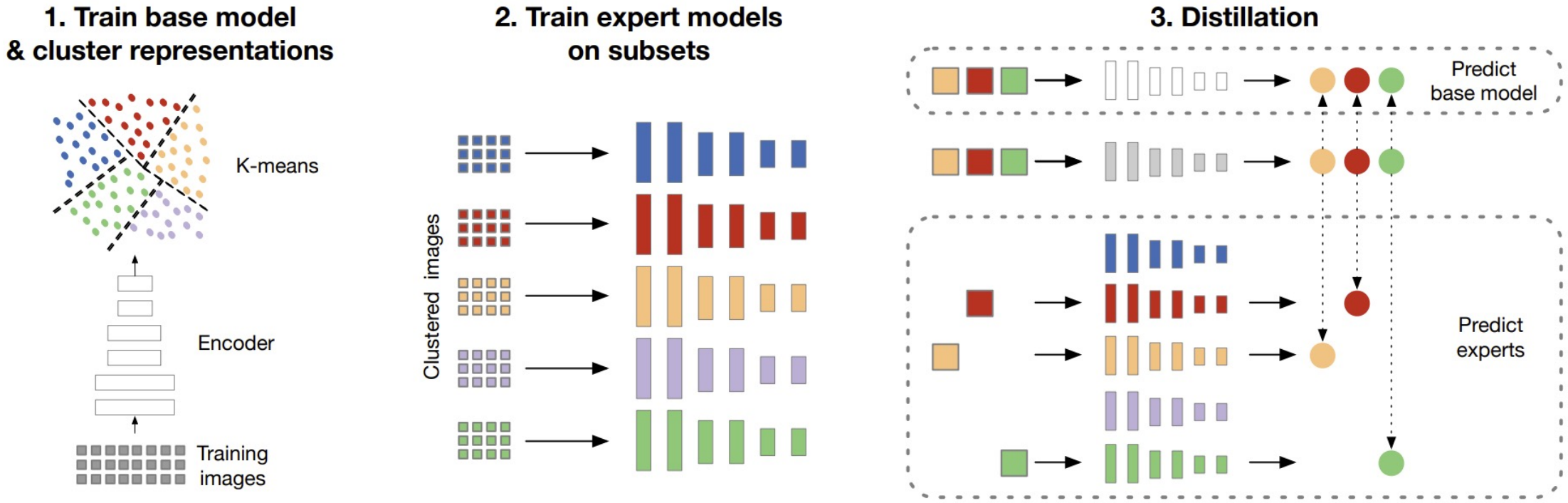
- Calculate memorization scores based on historical statistics to detect tail.
- Construct instance-wise augmentations to enhance representation learning.



[1] Zhou et al. “Contrastive learning with boosted memorization. " ICML 2022.

DnC: Divide and Contrast: Self-Supervised Learning from Uncurated Data

➢ **Motivation:** Conquer-and-Divide Training to isolate the negative effect on tail classes during training.

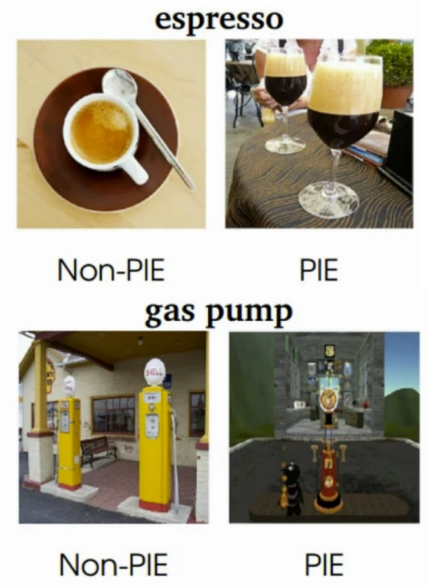


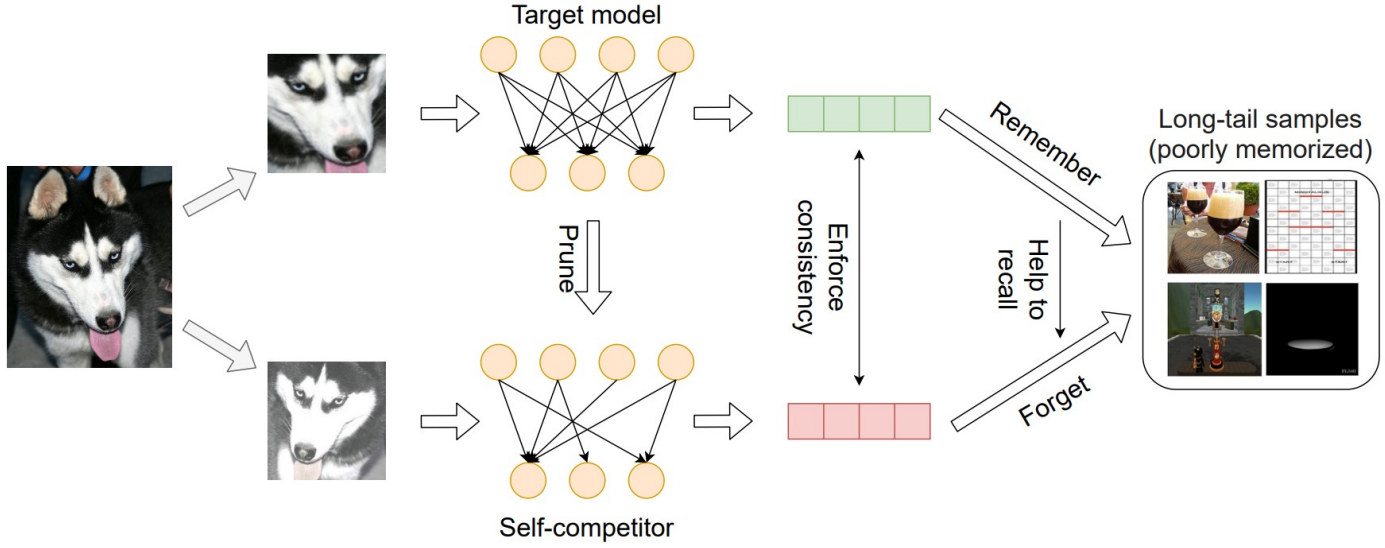
[1] Tian et al. "Divide and contrast: Self-supervised learning from uncurated data." ICCV 2021.

SDCLR: Self-damaging Contrastive Learning

- **Intuition:** The sensitivity of head and tail samples to the model pruning, are very different, which helps us to anchor and promote the training of tail samples.

- **Pruning identified exemplars (PIE)** systematically investigates the model output changes introduced by pruning and finds that certain examples are particularly sensitive to sparsity. They are high likely to be rare and atypical samples, which probably comes from tail classes.

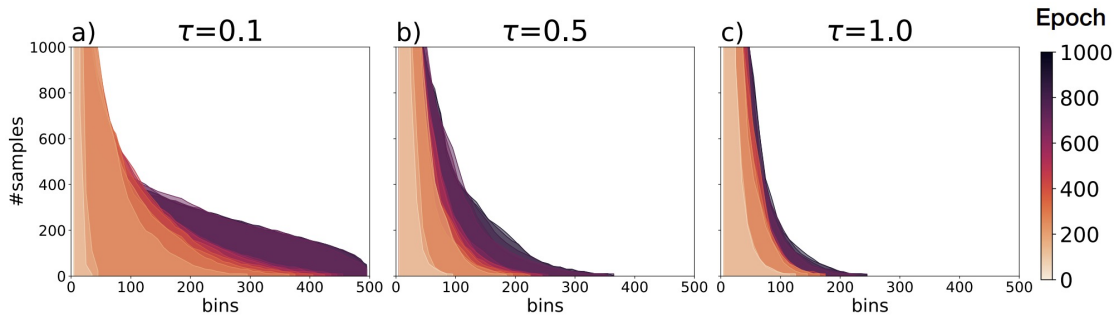




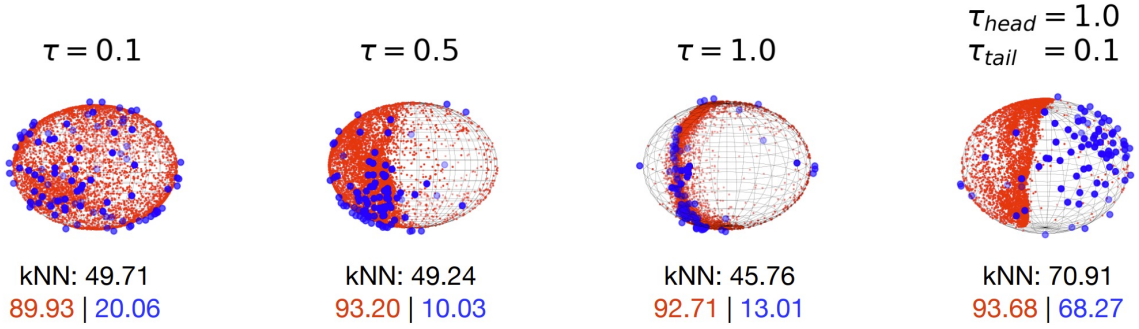
[1] Jiang et al. "Self-damaging contrastive learning." ICML 2021.

TS: Temperature Schedules for contrastive learning

- **Observation:** TS investigates the role of the temperature parameter τ in the contrastive loss, and find that a large τ emphasizes group-wise discrimination, whereas a small τ leads to a higher degree of instance discrimination.



Coverage of embedding space during training. For small τ the representations are more uniformly distributed.



Representations of a head and a tail class. Red: head class and blue: tail class. Small τ = 0.1 promotes uniformity, while large τ = 1.0 creates dense clusters. Tail classes benefit from instance discrimination.

- **Temperature Schedules (TS):** alternates between an upper τ and a lower τ bound at a fixed period length

$$\tau_{\cos}(t) = (\tau_+ - \tau_-) \times (1 + \cos(2\pi\, t/T))/2 + \tau_-$$

method	CIFAR-10-LT kNN@10	CIFAR-10-LT FS LP	CIFAR-10-LT LS LP	CIFAR-100-LT kNN@10	CIFAR-100-LT FS LP	CIFAR-100-LT LT LP	ImageNet-100-LT kNN@10	ImageNet-100-LT FS LP	ImageNet-100-LT LT LP
SimCLR	60.19	68.29	61.68	28.12	25.70	31.20	38.00	42.64	44.82
SDCLR	60.74	71.03	64.99	29.22	27.28	**34.23**	37.36	42.74	46.40
SimCLR + TS	**62.91**	**71.86**	**65.03**	**30.06**	**28.89**	33.28	**38.86**	**45.18**	**47.26**

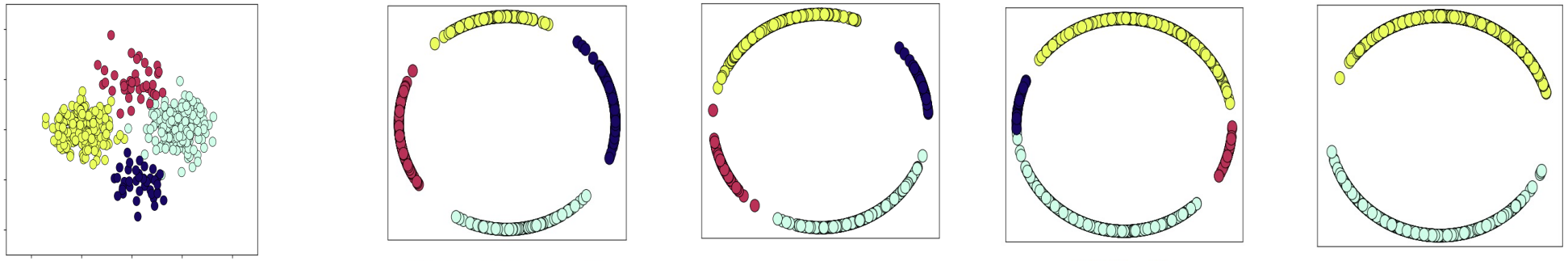
[1] Kukleva et al. "Temperature Schedules for self-supervised contrastive methods on long-tail data." ICLR 2023.

GH: Geometric Harmonization

- Why the conventional contrastive learning underperforms in self-supervised long-tailed context?

Conventional contrastive loss motivates *sample-level uniformity*, which is biased towards the head classes.

- Geometric Harmonization aims at achieves *category-level uniformity*, *i.e.*, equal allocation *w.r.t.* classes



(a) R=1(Balanced) (b) R=4 (c) R=16 (d) R=64

Contrastive learning causes severer representation learning disparity when enlarging the imbalance ratios.

- Challenges I: No guarantee for the desired category-level uniformity
- Challenges II: The latent true labels are not available, while the estimated labels are noisy

Geometric Uniform Structure

$$\mathbf{M}_i^\top \cdot \mathbf{M}_j = C, \ \ \forall i, j \in \{1, 2, \ldots, K\}, \ i \neq j,$$

Any two vectors in $\mathbf{M}$ have the same angle, namely, the unit space are equally partitioned by the vectors.

Surrogate Label Allocation

$$\min_{\hat{\mathbf{Q}}=[\hat{\boldsymbol{q}}_1,\ldots,\hat{\boldsymbol{q}}_N]} \mathcal{L}_{\mathrm{GH}} = -\frac{1}{|\mathcal{D}|} \sum_{\boldsymbol{x}_i \sim \mathcal{D}} \hat{\boldsymbol{q}}_i \log \boldsymbol{q}_i,$$

$$\text{s.t.} \ \ \hat{\mathbf{Q}} \cdot \mathbb{1}_N = N \cdot \boldsymbol{\pi}, \ \ \hat{\mathbf{Q}}^\top \cdot \mathbb{1}_K = \mathbb{1}_N,$$

Overall objective

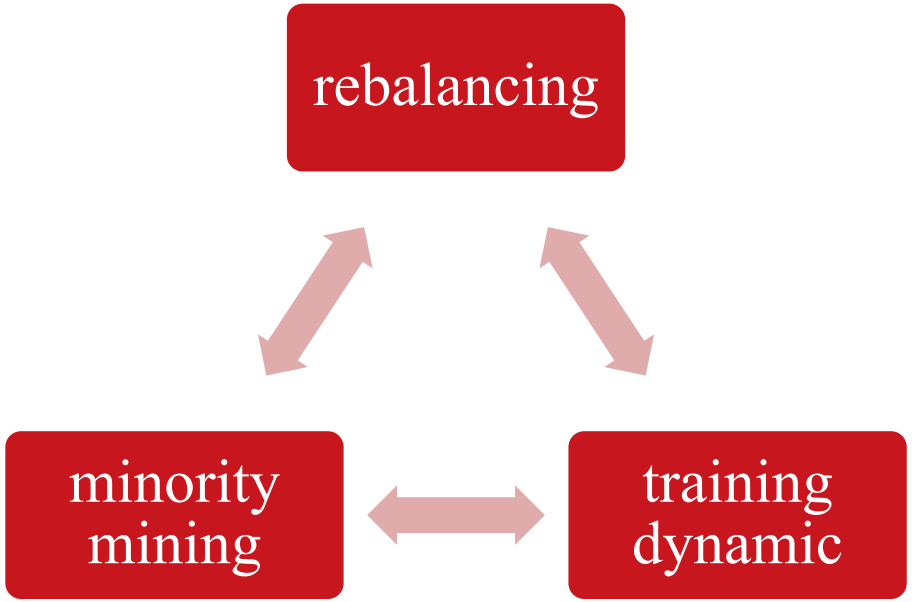
$$\min_{\theta, \hat{\mathbf{Q}}} \mathcal{L} = \mathcal{L}_{\mathrm{InfoNCE}} + w_{\mathrm{GH}} \mathcal{L}_{\mathrm{GH}},$$

[1] Zhou et al. "Combating Representation Learning Disparity with Geometric Harmonization." NeurIPS 2023.

Self-Supervised Long-tailed Learning

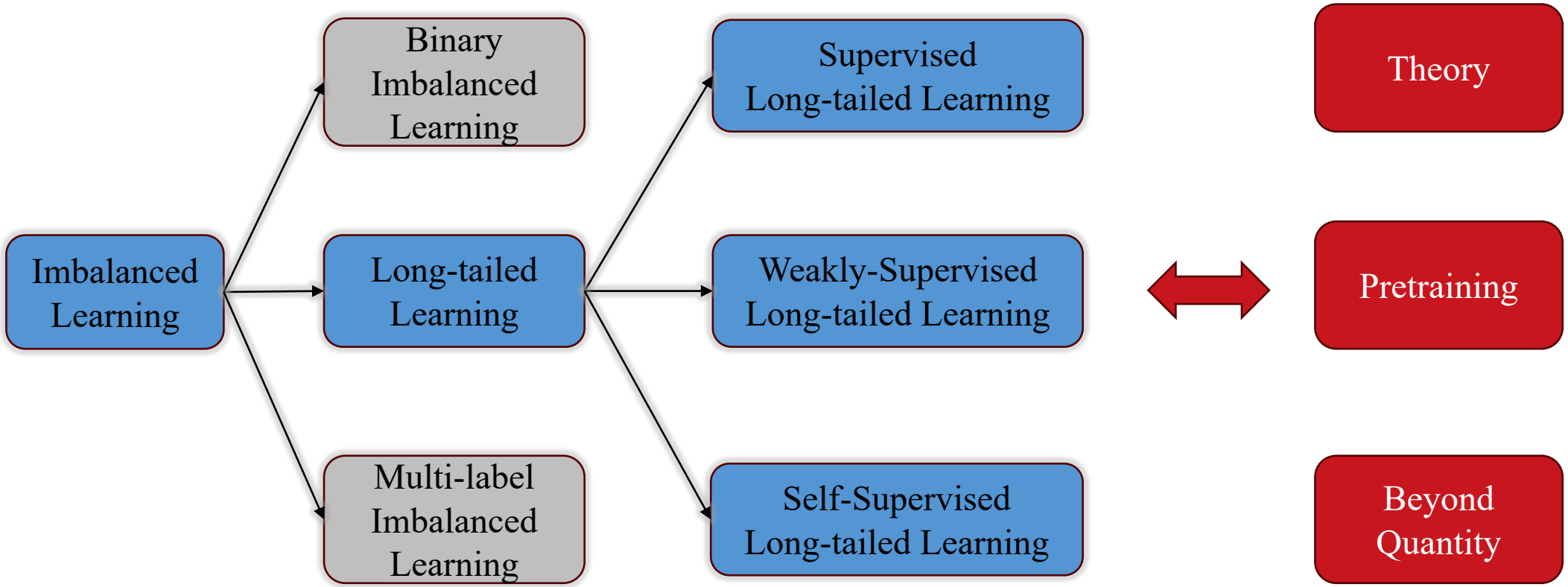
Summary

- Self-supervised learning is **more robust** to data imbalance **than the supervised counterpart**
- However, self-supervised learning still suffers from the long-tailed distribution, resulting in performance degeneration and **representation learning disparity**



Summary

Still require more efforts on this way



Thank you

Q & A

Tutorial website: https://tmlr-group.github.io/tutorials/aaai2024.html