

A Survey of Mix-based Data Augmentation: Taxonomy, Methods, Applications, and Explainability

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Abstract—Data augmentation (DA) is indispensable in modern machine learning and deep neural networks. The basic idea of DA is to construct new training data to improve the model’s generalization by adding slightly disturbed versions of existing data or synthesizing new data. In this work, we review a small but essential subset of DA – Mix-based Data Augmentation (MixDA) that generates novel samples by mixing multiple examples. Unlike conventional DA approaches based on a single-sample operation or requiring domain knowledge, MixDA is more general in creating a broad spectrum of new data and has received increasing attention in the community. We begin with proposing a new taxonomy classifying MixDA into, Mixup-based, Cutmix-based, and hybrid approaches according to a hierarchical view of the data mix. Various MixDA techniques are then comprehensively reviewed in a more fine-grained way. Owing to its generalization, MixDA has penetrated a variety of applications which are also completely reviewed in this work. We also examine why MixDA works from different aspects of improving model performance, generalization, and calibration while explaining the model behavior based on the properties of MixDA. Finally, we recapitulate the critical findings and fundamental challenges of current MixDA studies, and outline the potential directions for future works. Different from previous related works that summarize the DA approaches in a specific domain (e.g., images or natural language processing) or only review a part of MixDA studies, we are the first to provide a systematical survey of MixDA in terms of its taxonomy, methodology, applications, and explainability. This work can serve as a roadmap to MixDA techniques and application reviews while providing promising directions for researchers interested in this exciting area. A curated list of reviewed methods can be found at <https://github.com/ChengtaiCao/Awesome-Mix>.

Index Terms—Data augmentation, Mix Strategies, Image Data, Generalization.

1 INTRODUCTION

Deep Learning (DL) has a transformative impact on diverse areas [1] thanks to its ability to learn expressive representation. As the problems to be solved have become more and more challenging, the network structure becomes more sophisticated with more layers. However, deep neural networks (DNNs) are notorious for the fact that they are data-hungry with millions, even billions of parameters (e.g., Bert [2]), making them prone to overfitting.

Many innovations have been dedicated to making DNNs more data-efficient through the use of improved network architectures. For example, convolutional neural networks (CNNs) undergo an increasingly advanced evolutionary process from AlexNet [3] to ResNet [4]. Besides, a variety of regularization approaches have been proposed to improve DNNs’ generalization, such as weight decay [5], dropout [6], stochastic depth [7], and batch normalization [8]. Dropout randomly zeros out some activations during training to simulate more network architecture subsets and

prevent co-adaptation of neurons. Batch normalization normalizes the activations by subtracting the batch mean from each activation and dividing by the batch standard deviation.

Data augmentation (DA), which refers to increasing the number of and the diversity of training data without explicitly collecting new examples, is usually a remedy to reduce overfitting. DA methods try to enlarge limited data and extract additional information, which, combined with advanced network architectures and existing regularization techniques, can enhance the overall model performance. For example, adding random noise into samples, as a simple DA method, can generate numerous new training samples to benefit model robustness. When dealing with image data, label-invariant data transformation such as random-cropping, horizontal-flipping, and changing the intensity of RGB channels [3] can improve performance and boost the robustness of translation, reflection, and illumination. As another example, a model trained with random erasing [9] or Cutout [10] shows improved regularization. In natural language processing (NLP) applications, synonym replacement, random insertion, random swap, and random deletion [11] are prevailing methods to augment language data. Finally, generative models such as variational auto-encoders (VAE) [12] and generative adversarial networks (GANs) [13] that can generate any number of fake but realistic samples are also widely used for data augmentation.

In this survey, we focus on a burgeoning area of data augmentation – Mix-based Data Augmentation (MixDA), which has aroused considerable research in recent years. Different from traditional DA methods operating on a single instance, MixDA creates virtual training data by combining multiple examples and

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generating a great deal of training data without domain knowledge. For example, Mixup [14] linearly interpolates input-output pairs from two randomly sampled training examples in the holistic perspective. Cutmix [15] cuts a patch from one image (source image) and then pastes it onto the corresponding region of the other image (target image) from the locality point of view. Later, a plethora of improved versions of MixDA following Mixup and Cutmix have been proposed through the different lenses that are also the bases of the taxonomy of this review, such as flexible mix ratio, saliency guidance, and improved divergence. Due to its generality, MixDA has been successfully applied to diverse tasks, including semi-supervised learning, generative models, graph learning, and NLP. Besides, some theoretical investigations are also proposed to interpret MixDA from different perspectives. Therefore, it is time for a comprehensive survey of the foundations, methods, applications, and explainability of MixDA. To illuminate the follow-up study, we present our findings of current MixDA and its challenges in addition to some promising future avenues.

Related Surveys. Here we clearly state the differences between our survey and related works. First, the papers reviewing data augmentation [16], [17], [18], [19] are related to our work. However, these reviews focus on a particular field of applying various data augmentation techniques. For example, Feng et al. [16] focus on the DA approaches in text data processing. Similarly, there are also several surveys reviewing the DA methods in other domains, including image recognition [17], time series learning [18], and graph-structure data learning [19]. Although there is a slight overlap between these works and our work, we focus exclusively on a special DA method, MixDA, which can be exploited in a wide range of domains (cf. Section 4 for details).

Another line of similar work is the surveys on model regularization [20], [21], [22], [23] which overview the regularization techniques for different purposes, such as learning with noise label [21], improving the performance of GANs [22], and generalizing to out-of-distribution data [23]. Our work is orthogonal to these reviews as we pay attention to the works investigating the methodology of combining multiple examples and leveraging MixDA to improve the performance of different tasks, although some MixDA methods have a regularization effect [24], [25], [26].

The most similar works to ours are [27] and [28]. The former reviews the methods for *image mix* and *image deletion* while the latter reviews both mix augmentation and *other* augmentation strategies. They only summarize a part of mix-based data augmentation methods and have other focal points: (1) [27] reviews some deleting-based data augmentation such as Random Erasing [9] and Hide-and-Seek [29]; (2) [27] reviews some cut-based data augmentation such as Patch Gaussian [30] that adds Gaussian noise to randomly selected region of the input image and Cutout [10] that masks/erase a region of the input image with 0 pixel value. However, this work dedicates full attention to mix-based data augmentation, and most importantly, we also provide a thorough review of the MixDA application which has not been covered in previous work.

To the best of our knowledge, this survey is the first work comprehensively reviewing MixDA techniques and summarizing its wide spectrum of applications. In particular, we review more than 70 MixDA methods (Section 3) and more than 10 MixDA applications (Section 4). It is anticipated that this survey can serve as a MixDA technique roadmap for researchers in this exciting area.

Organization. This survey is structured as follows. The over-

all picture of DA and MixDA is depicted in Section 2 where we also provide a new taxonomy of MixDA. In Section 3, we systematically review existing methods and discuss their pros and cons. Section 4 investigates the important applications of MixDA, followed by an explainability analysis of MixDA in Section 5. Moreover, the critical findings and challenges are presented in Section 6, which also outlines the potential research directions. Finally, we conclude this work in Section 7.

2 PRELIMINARY

2.1 Data Augmentation

The quantity and diversity of training data have a crucial impact on the performance of the learned models. To fully take advantage of machine learning approaches, a lot of data augmentation methods have been proposed to increase the size, variety, and quality of training examples via covering unexplored input space while maintaining correct labels. Except for the differences in inherent augmentation methods and applicable fields [16], [17], [18], [19], data augmentation can be categorized into two classes: (1) single-sample data augmentation (SsDA) and (2) mix-based data augmentation (MixDA). There are three main substantial differences between SsDA and MixDA. First, MixDA creates new training data by combining multiple training samples, while SsDA only considers single examples. Second, data feature transformation in SsDA is usually label-invariant, i.e., newly generated data has the same target. In contrast, the label combination strategy should be carefully designed in MixDA to align with the feature mix process. Third, compared with SsDA, most MixDA techniques are domain-agnostic and, therefore, can be applied to a wide range of fields.

Formally, SsDA approaches generate new instances $(\tilde{\mathbf{x}}_i, \tilde{\mathbf{y}}_i)$ for each training sample $(\mathbf{x}_i, \mathbf{y}_i)$ based on itself while maintaining its label:

$$\begin{aligned}\tilde{\mathbf{x}}_i &= \mathcal{A}_{\theta}(\mathbf{x}_i), \\ \tilde{\mathbf{y}}_i &= \mathbf{y}_i,\end{aligned}\tag{1}$$

where \mathcal{A}_{θ} specifies a specific feature transformation operation (e.g., rotation, flipping, and cropping) with parameters θ (e.g., rotation angles).

On the contrary, MixDA constructs synthetic data by mingling multiple training examples that can be formulated as:

$$\begin{aligned}\tilde{\mathbf{x}}_i &= \mathcal{A}_{\theta}(\mathbf{x}_i, \mathbf{x}_j), \\ \tilde{\mathbf{y}}_i &= \mathcal{A}_{\phi}(\mathbf{y}_i, \mathbf{y}_j),\end{aligned}\tag{2}$$

where \mathcal{A}_{ϕ} denotes the label combination scheme parameterized by ϕ . Note that Equation (2) only mixes two training examples for simplicity. However, blending more samples is a straightforward extension. For better comprehension, Table 1 summarizes the notation frequently used in this work.

2.2 Taxonomy of MixDA

In this work, we provide the first taxonomy of MixDA methods. In particular, we classify existing studies into three groups: (1) the methods that mix training examples from a global perspective represented by the pioneering work Mixup [14]; (2) the approaches that construct new data through the lens of the locality represented by Cutmix [15]; and (3) other techniques based on the principle of mixing but cannot be simply grouped into the above two categories, e.g., mixing with data reconstruction and integrating multiple MixDA solutions.

TABLE 1
Summary of the frequently used notations.

Notation	Description
X / Y	input/output random variables
x / y	data input/output
(\tilde{x}, \tilde{y})	the generated input-output pair
u	an unlabeled example
\hat{x}	batch reference representation
$\hat{y} / y_{\text{target}}$	predicted label / target label
\bar{x}_j / \bar{y}_j	input mean / output mean
λ	mix ratio
c	a class
$\lambda_c / \bar{\lambda}$	mix ratio for class c / ratio expectation
λ_x / λ_y	input mix ratio / output mix ratio
λ_s / λ_t	style ratio / content ratio
α	parameter of distribution
\mathcal{L}	loss function
M	matrix
f / f^*	model / optimal model
ω	parameter vector of the Gaussian classifier
P / p	probability distribution / probability
\hat{p}	the largest entry in the probability distribution
\hat{p}^c	probability for class c
\mathcal{P}	policy mapping module
\mathcal{F}	autoencoder
$\mathcal{G} / \mathcal{H}$	encoder / decoder
L / l	number of network layers / the l -th layer
d_w	
\mathcal{D}	discriminator
h	hidden representation
z	label embedding
\mathbb{I}	indicator function
μ / σ	mean / standard deviation
A_θ	feature transformation with parameter θ
A_ϕ	label combination parametrized by ϕ
W / H	image width / image height
w / h	patch width / patch height
$q \times q$	the number of grids
K	number of mixed examples
S	neighborhood region
\mathcal{V}	vicinity function
δ	perturbation
$\mathcal{X}_s / \mathcal{X}_t$	source domain / target domain
ρ	Dirac mass

The rationale behind our proposed taxonomy is as follows. Mixup and its variants usually develop a global mix scheme and apply it to all features. For example, Mixup draws a mix ratio from a Beta distribution, and each feature in the created example is a linear combination of the corresponding features of two sampled training examples, encouraging the model to understand data *globally*. In contrast, Cutmix and its adaptions intercept partial features from one instance and then paste them on another example, towards improved *localization* ability of the model. Furthermore, there exist a number of hybrid works that integrate multiple MixDA approaches or incorporate MixDA with other SsDA methods. For example, RandomMix [31] creates augmented data by the mix operation sampled from a set of MixDA methods for each mini-batch. Similarly, AugMix [32] constructs multiple versions for each sample by SsDA and then mixes them via MixDA.

3 METHODOLOGY

In this section, we review a wide variety of mix-based strategies which can be categorized into three groups: (1) Mixup [14] and its variants that mix multiple examples in the holistic perspective, (2) Cutmix [15] and its adaptions that combine multiple samples through the lens of locality, and (3) other MixDA methods such as

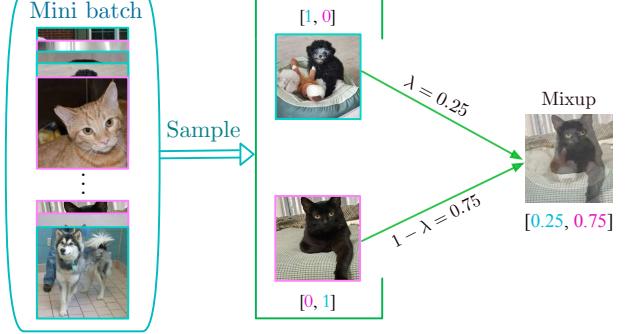


Fig. 1. The sketch of Mixup. Each pixel in the Mixup-ed images is the convex composite of corresponding pixels from two sampled images with a mix ratio $\lambda = 0.25$.

mixing wit itself, combining multiple mix-based approaches, and integrating MixDA with SsDA. Table 2 summarizes the commonly used benchmarks and corresponding tasks.

3.1 Mixup-based Methods

3.1.1 Mixup

Mixup [14] is the seminal work of MixDA which proposes a straightforward, data-independent, model-agnostic, effective, and efficient principle to construct new training samples. Mixup imposes an inductive bias on training distribution that linear interpolations of input pair will result in convex combinations of their outputs, extending the training data distribution. From a regularization point of view, Mixup forces the neural networks to behave linearly in-between training examples. In particular, the combination operation of Mixup is defined as:

$$\begin{aligned}\tilde{x} &= \lambda x_i + (1 - \lambda)x_j, \\ \tilde{y} &= \lambda y_i + (1 - \lambda)y_j,\end{aligned}\quad (3)$$

where (x_i, y_i) and (x_j, y_j) are two data points randomly sampled from the original training distribution, and (\tilde{x}, \tilde{y}) is the generated instance. The targets y_i and y_j are usually represented as one-hot vectors and $\lambda \in [0, 1]$ is a hyperparameter controlling the interpolation strength (*a.k.a.* mix ratio) which is usually sampled from a Beta distribution: $\lambda \sim \text{Beta}(\alpha, \alpha) - \alpha \in (0, \infty)$.

In practical implementation, Mixup takes advantage of a data loader to get one mini-batch with random shuffle and then synthesizes new training data using Equation (3) that only introduces a small computation overhead. A sketch of Mixup is shown in Figure 1 where each pixel in created images is the linear combination of corresponding pixels from two sample images with regard to mix ratio $\lambda = 0.25$.

In parallel with [14], Tokozume et al. present a Between-Class (BC) learning strategy [154] which composes synthetic sounds by mixing two origin samples and feeds the virtual data to the model. Unlike Mixup which explicitly blends the target pairs, BC learning encourages the model to output the mix ratio λ . Another distinction between Mixup and BC learning is that the latter takes the property of sound into account:

$$\begin{aligned}g &= \frac{1}{1 + 10^{\frac{G_i - G_j}{20}} \cdot \frac{1-\lambda}{\lambda}}, \\ \tilde{x} &= \frac{g x_i + (1-g)x_j}{\sqrt{g^2 + (1-g)^2}},\end{aligned}\quad (4)$$

TABLE 2
The commonly used MixDA benchmarks and learning tasks.

Benchmark	Task	Article
CIFAR [33]	Image Classification	[14], [15], [24], [25], [26], [32], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82]
	Robustness	[14], [43], [47], [51], [61], [65], [69], [70], [71], [83], [84], [85], [86], [87], [88], [89], [90], [91]
	Uncertainty & Calibration	[74], [86]
	Semi-Supervised	[44], [62], [71], [92], [93], [94], [95], [96], [97], [98]
	Federated Learning	[99], [100]
ImageNet [101]	Image Classification	[14], [15], [26], [32], [35], [37], [38], [39], [40], [41], [43], [44], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [57], [58], [59], [62], [63], [64], [65], [66], [67], [68], [70], [71], [72], [74], [75], [77], [79], [81], [82], [85], [102], [103], [104], [105]
	Robustness	[14], [46], [49], [52], [57], [71], [74], [89], [91], [105], [106]
	Uncertainty & Calibration	[52], [74], [86], [105], [106]
	Object Localization	[15], [49], [52], [95]
	Pascal VOC [107] Object Detection	[15], [46], [57], [58], [64], [66], [68], [70], [72], [102], [105], [108], [109], [110], [111], [112]
	Cityscapes [113] Object Detection	[108], [112]
	MS-COCO [114] Image Captioning	[15], [50], [54], [57], [66], [70], [102], [103], [105]
	ADE [115] Semantic Segmentation	[50], [103], [104]
	Image Classification	[25], [35], [36], [39], [44], [59], [61], [76], [80], [83], [117]
	Semi-Supervised	[96], [97]
MNIST [116]	Uncertainty & Calibration	[118]
	Federated Learning	[99], [100], [119]
	Robustness	[24], [32], [51], [62], [62], [68], [74], [85], [86], [91], [121], [122]
CIFAR-C & ImageNet-C [120]	Image Classification	[66]
	Semi-Supervised	[93], [97]
	Uncertainty & Calibration	[106]
	Robustness	[106]
STL [123]	Image Classification	[40], [43], [44], [61], [62], [69], [76], [77], [80], [83], [117]
	Semi-Supervised	[44], [92], [93], [95], [98]
	Robustness	[87], [89], [90]
SVHN [124]	Image Classification	[45], [110]
Caltech [125]	Image Classification	[66], [68], [84]
iNaturalist [126]	Unbalanced Image Classification	[15], [55], [57], [66], [68], [128]
CUB200-2011 [127]	Object Localization	[54], [68], [71], [129]
Stanford Cars [130]	Fine-Grained Image Classification	[128], [129]
FGVC-Aircraft [131]	Fine-Grained Image Classification	[66], [68], [71], [128], [129]
UCI [132]	Tabular Data Classification	[14], [54], [61]
	Semi-Supervised	[96]
ModelNet [133]	Point Cloud Classification	[35], [72]
MR [134]	Sentence Classification	[135], [136], [137]
	Uncertainty & Calibration	[106]
TREC [138]	Sentence Classification	[135], [136], [137], [139], [140], [141], [142]
	Uncertainty & Calibration	[106]
SST [143]	Sentence Classification	[135], [136], [137], [140], [141], [142]
	Robustness	[144]
Subj [145]	Sentence Classification	[135], [136], [137], [140], [142]
CoNLL [146]	Named Entity Recognition	[147], [148]
GLUE [149]	Natural Language Understanding	[139], [150], [151], [152]
Google Command [153]	Audio Classification	[14], [35], [49], [72]

where G_i and G_j are the sound pressure level [dB] of x_i and x_j , respectively, and in essence, $x_i : x_j = \lambda : (1 - \lambda)$. BC learning not only enlarges the diversity of training data but also regularizes the feature space by increasing the ratio of the between-class distance to the within-class variance (i.e., Fisher's criterion [155]). A version extended for image data is BC+ [37] which builds on the fact that CNNs take image data as waveforms, even though mixed images cannot be recognized by humans. SamplePairing [40] also bears some similarities with Mixup [14] except that it only mixes inputs with the feature mix ratio $\lambda_x = 0.5$ while not combining targets, i.e., constant label mix ratio $\lambda_y = 1$ for the output.

3.1.2 Mixing in Embedding Space

Word2Vec [156] has revealed that the linearity calculation of words (e.g., king - man + woman \approx queen) is a desirable property for embedding space. Therefore, linearly combining samples in embedding space to create augmented data is a natural choice.

Manifold Mixup [43] linearly mixes the intermediate hidden representations of two inputs to make the most of feature space. Similar to Mixup [14], the same linear composite of the corresponding output pair is constructed as the new supervision signal, smoothing the decision boundaries in different levels of embedding space and reducing the intra-cluster distance. More specifically, consider a deep neural network with L hidden layers (including the input layer), Manifold Mixup first stochastically

chooses one layer and mixes the embeddings from two sampled examples. The combined result then proceeds to the output layer. Due to the extra randomness in layer selection for mix, the loss function in Manifold Mixup has an additional expectation term for optional layers, compared with Mixup. Venkataramanan et al. interpret Mixup from the deformation perspective and then propose AlignMixup [52] to further spatially align two sampled embeddings, allowing consistent interpolation in the feature space. To further smooth the decision boundaries and improve model robustness, Noisy Feature Mixup (NFM) [91] injects noise when conducting convex combinations of input-output pairs in both input space and embedding space, which is verified to obtain a favorable trade-off between performance on clean data and robustness with respect to various kinds of data attack.

Linear interpolation in embedding space directly tackles the decision boundary problem and provides enhanced diversity compared to only mixing in data space, resulting in more various augmented data and better regularisation effects.

3.1.3 Adaptive Mix Strategy

Mixup is equivalent to imposing “local linearity” constraints on the outside of the data manifold (“out-of-manifold regularization” [39]). However, the mix ratio λ obtained by a blind sample process may be sub-optimal. An original example in the data manifold endowed with a soft label may conflict with its actual one. This phenomenon is also called “manifold intrusion”.

To adaptively generate a mix ratio, AdaMixUp [39] is proposed in which an auxiliary network automatically determines a flexible combination scheme. It also designs a novel objective function to resist “manifold intrusion”. Mai et al. [157] apply the meta-learning paradigm [44] to *learn to mix*, which also aims to resolve the underfitting issue caused by “manifold intrusion”. Instead of a predefined distribution for mix policy, the introduced MetaMixUp [157] dynamically determines the combination strategy in a data-adaptive way. To be specific, MetaMixUp is a two-level framework in which a *meta* model explores a new interpolation scheme that is used to guide the *main* model. AutoMix [68] decomposes mix training as two sub-tasks – the mixed data generation with a Mix Block and the mix classification – and unifies both in an end-to-end framework to optimize combination policy directly.

An unexpected phenomenon of Mixup training is that when learning an ensemble model, calibration will be undermined [86] due to a trade-off between accuracy and calibration. Similar to “manifold intrusion”, the reason behind this trade-off is the soft target in mix training introduces an under-confidence issue which would be further aggravated with ensembles. To deal with this issue, motivated by the fact that some classes are more difficult to identify than other categories, CAMixup [86], instead of a policy from a Beta distribution, adjusts the mix ratio λ_c of class c with $|c|$ samples based on its confidence $\text{Conf}(c)$ and accuracy $\text{Acc}(c)$, and only applies Mixup on hard classes:

$$\begin{aligned} \text{Conf}(c) &= \frac{1}{|c|} \sum_{\mathbf{x}_i \in c} \hat{p}_i^c, \\ \text{Acc}(c) &= \frac{1}{|c|} \sum_{\mathbf{x}_i \in c} \mathbb{I}(\hat{\mathbf{y}}_i = c), \\ \lambda_c &= \begin{cases} 0 & \text{Acc}(c) > \text{Conf}(c) \\ \lambda & \text{Acc}(c) \leq \text{Conf}(c) \end{cases}, \end{aligned} \quad (5)$$

where \hat{p}_i^c is the prediction probability of i -th sample for class c . $\hat{\mathbf{y}}_i$ is the predicted label and \mathbb{I} is the indicator function. Mixup is not applied to the under-confident class c ($\text{Acc}(c) > \text{Conf}(c)$) while being used to synthesize new data for the over-confident class ($\text{Acc}(c) \leq \text{Conf}(c)$) to decrease model confidence. Note that confidence and accuracy are calculated on a validation dataset at the end of each training epoch. In other words, the mix ratio λ_c is dynamically updated after each training epoch.

Linearity in Mixup constrains the diversity of augmented examples and leads to the “manifold intrusion” issue due to its simplicity, jeopardizing the regularization effect. Nonlinear Mixup [135] is proposed to synthesize the input-output pairs adaptively. Unlike Mixup allocates the same mix ratio to each dimension of input, for the input $\mathbf{x}_i \in \mathbb{R}^{W \times H}$, the input mix strategy of Nonlinear Mixup is a *matrix* $\mathbf{M} \in \mathbb{R}^{W \times H}$, where each value of \mathbf{M} is independently sampled from the Beta distribution $\text{Beta}(\alpha, \alpha)$:

$$\tilde{\mathbf{x}} = \mathbf{M} \odot \mathbf{x}_i + (1 - \mathbf{M}) \odot \mathbf{x}_j, \quad (6)$$

where \odot is the element-wise multiplication (i.e., Hadamard product). Note that Nonlinear Mixup is different from Cutmix (will be detailed in the next sub-section) since the combination matrix of Cutmix [15] is binary. When mixing target pair, Nonlinear Mixup projects one-hot label vector as a k -dimensional representation $\mathbf{z} \in \mathbb{R}^k$ by label embedding [158] and Gram-Schmidt process [159]. The resulting matrix with c rows (number of categories) and k columns (dimension of label embedding) is then used to model targets. The combined instance $\tilde{\mathbf{x}}$ passes a Policy Mapping module \mathcal{P} , enabling the label assignment of mixed $\tilde{\mathbf{x}}$ is based on the synthetic input:

$$\begin{aligned} \Phi &= \mathcal{P}(\tilde{\mathbf{x}}), \\ \tilde{\mathbf{z}} &= \Phi \odot \mathbf{z}_i + (1 - \Phi) \odot \mathbf{z}_j, \end{aligned} \quad (7)$$

where Φ has the same dimension as the label embedding, i.e., a k -dimensional vector.

Adversarial Mixing Policy (AMP) [136] constructs new examples with perturbed mix policy by a “rand-max-min” pipeline in which (1) a random mix ratio λ is used to interpolate input-output pairs to create new data; (2) a slight adversarial perturbation is imposed to the λ to regenerate the mixed feature without changing the mixed target, but introducing non-linearity to the model; and (3) the model is trained with the adjusted data by minimizing the loss function.

Liu et al. identify an over-smoothing problem in Mixup [71] originated in the aimless mix ratio and present a decoupled Mixup loss to obtain a good trade-off between discrimination and smoothness. Similarly, to adapt Mixup in the class-imbalanced scenario where the model expected to move the decision boundary towards the majority, Remix [84] is proposed to disentangle the combination coefficient of inputs (λ_x) and output (λ_y) to balance the generalization of minority and majority classes. The combination manipulation for input in Remix is the same as in Mixup. However, for target combination, Remix sets a higher weight on the minority class to favor the label to the minority class:

$$\lambda_y = \begin{cases} 0 & N_i/N_j \geq \kappa \text{ and } \lambda < \tau \\ 1 & N_i/N_j \leq 1/\kappa \text{ and } 1 - \lambda < \tau \\ \lambda & \text{otherwise} \end{cases}, \quad (8)$$

where N_i and N_j are the number of examples in class i and class j . κ and τ are two hyperparameters that control the magnitude that the minority classes dominate the label mix ratio λ_y .

In total, a flexible combination strategy can eschew the “manifold intrusion” problem and the resulting under-confidence and over-smoothing issues, thus maximizing the effectiveness of MixDA.

3.1.4 Sample Selection

When the samples to be mixed are very dissimilar (i.e., distant samples), Mixup could synthesize out-of-distribution samples, harming the model’s performance.

In the context of semi-supervised named entity recognition (NER), Local Additivity based Data Augmentation (LADA) [147] generates new examples by combining closed samples. LADA has two variants: Intra-LADA and Inter-LADA. The former obtains some new sentences by exchanging the words in a single sentence and conducts interpolations among these, while the latter combines different sentences to construct new data. Besides, a weighted mixture of the random sample and k -nearest neighbors (kNNs) sample is proposed to balance the noise and regularization. Experimental evaluations demonstrate that augmented data benefits both entity learning and context learning. There also are some other approaches that share a similar motivation, such as loss decayed with the distance between input (e.g., Local Mixup [83]), choosing similar inputs for combination (e.g., Pani [56]), interpolating in hyperbolic [160] space (e.g., HypMix [161]), local-emphasized and global-constrained sub-tasks (e.g., SAMix [66]), and generative models (e.g., GenLabel [162]). Similar to HypMix, a distance-aware method called DMix [141] adaptively chooses instances based on the dissimilarity/diversity between the latent representations of examples in the hyperbolic space.

In the context of self-supervised learning [163], Zhang et al. put forward M-Mix [73] to adaptively construct a succession of hard negatives, which can dynamically select multiple examples to mix and assign different weights based on similarity measurement or a learnable function.

For the supervised neural machine translation (NMT) task, Continuous Semantic Augmentation (CSANMT) [164] generates augmented data for each sample within a semantic adjacency region to cover sufficiently divergent synonymous representations. More specifically, an encoder is trained to assign each training sample a semantic neighborhood in the hidden space in which each tangent points are semantically equivalent via tangential contrast. A Mixed Gaussian Recurrent Chain (MGRC) procedure is proposed to select a group of representations from the semantic neighborhood, and each of them is incorporated into the continuous hidden space.

The regression problem differs from the classification task since interpolation in continual target space may lead to arbitrarily incorrect labels. To handle this issue, Hwang et al. present Reg-Mixup [165] that learns a policy to determine which examples to be mixed based on the distance metric using reinforcement learning.

Overall, mixing with appropriate sample selection schemes could synthesize more plausible virtual data, minimizing the adverse effects of out-of-distribution data.

3.1.5 Saliency & Style For Guidance

Saliency information underlying the data (e.g., object in the image) is informative and manifests regularity [166], [167], which,

therefore, can be exploited to guide the Mixup.

A supervised interpolation policy termed SuperMix [53] is introduced to exploit the semantics of inputs for generating new training instances. SuperMix has two additional loss functions – one is used to smooth the mask matrices, and the other encourages the sparsity of masks. With the help of teacher-student consistency training and the awareness of object boundaries, Superpixel-mix [112] synthesizes new examples by mingling superpixels between inputs to improve segmentation performance. StyleMix [65] further discerns the content features from the style characteristics when mixing two input images to improve the variety of synthetic examples. Specifically, let \mathcal{G} and \mathcal{H} denote the pre-trained style encoder and style decoder, respectively. The four obtained features are:

$$\begin{aligned} \mathbf{f}_{ii} &= \mathcal{G}(\mathbf{x}_i), \\ \mathbf{f}_{jj} &= \mathcal{G}(\mathbf{x}_j), \\ \mathbf{f}_{ij} &= \text{AdaIN}(\mathbf{f}_{ii}, \mathbf{f}_{jj}), \\ \mathbf{f}_{ji} &= \text{AdaIN}(\mathbf{f}_{jj}, \mathbf{f}_{ii}), \end{aligned} \quad (9)$$

where AdaIN [168] adaptively normalizes instances with the mean μ and the standard deviation σ :

$$\text{AdaIN}(\mathbf{f}_{ii}, \mathbf{f}_{jj}) = \sigma(\mathbf{f}_{jj})(\frac{\mathbf{f}_{ii} - \mu(\mathbf{f}_{ii})}{\sigma(\mathbf{f}_{ii})}) + \mu(\mathbf{f}_{jj}). \quad (10)$$

The mixed image is then generated by interpolating the four features:

$$\begin{aligned} \tilde{\mathbf{x}} = \mathcal{H}(t\mathbf{f}_{ii} + (1 - \lambda_t - \lambda_s + t)\mathbf{f}_{jj} \\ + (\lambda_t - t)\mathbf{f}_{ij} + (\lambda_s - t)\mathbf{f}_{ji}), \end{aligned} \quad (11)$$

where λ_t and λ_s are the content ratio and style ratio stochastically drawn from the Beta distribution. Hyperparameter t is defined as $\max(0, \lambda_t + \lambda_s - 1) \leq t \leq \min(\lambda_t, \lambda_s)$ and the combined target of mixed image is:

$$\begin{aligned} \mathbf{y}_c &= \lambda_t \mathbf{y}_i + (1 - \lambda_t) \mathbf{y}_j, \\ \mathbf{y}_s &= \lambda_s \mathbf{y}_i + (1 - \lambda_s) \mathbf{y}_j, \\ \tilde{\mathbf{y}} &= \lambda \mathbf{y}_c + (1 - \lambda) \mathbf{y}_s. \end{aligned} \quad (12)$$

Inspired by the observation that the visual domain is associated with the image style (e.g., abstract painting vs. landscape), Mixstyle [169] probabilistically combines instance-level feature statistics of training data. Due to the modular nature of CNN, style information is modeled in the bottom layers where the proposed style-mixing operation takes place. Combining styles of the training data may implicitly synthesize a new domain, therefore enhancing the domain diversity and further the generalization of the model. Specifically, MixStyle follows the paradigm of mini-batch training, i.e., shuffling and mingling are conducted along the batch dimension:

$$\begin{aligned} \gamma_{\text{mix}} &= \lambda \sigma(\mathbf{x}) + (1 - \lambda) \sigma(\hat{\mathbf{x}}), \\ \beta_{\text{mix}} &= \lambda \mu(\mathbf{x}) + (1 - \lambda) \mu(\hat{\mathbf{x}}), \\ \text{MixStyle}(\tilde{\mathbf{x}}) &= \gamma_{\text{mix}} \frac{\mathbf{x} - \mu(\mathbf{x})}{\sigma(\mathbf{x})} + \beta_{\text{mix}}, \end{aligned} \quad (13)$$

where $\hat{\mathbf{x}}$ is a batch reference representation obtained by shuffling and sampling from two different domains (domain labels are known). The mean vector $\mu(\cdot)$ and standard deviation vectors $\sigma(\cdot)$ are calculated across the spatial dimension within each channel of each instance, similar to Batch Normalization [8].

Some works [168], [170] have demonstrated that positional moments (i.e., mean μ and standard deviation σ) and instance moments can approximately represent shape and style information which are usually discarded to accelerate and stabilize training. However, Moment Exchange (MoEx) [72] takes advantage of this instructive information to generate new samples. To be specific, MoEx switches the moments of an example with those of the other:

$$\mathbf{h}_i^{(j)} = \sigma_j \frac{\mathbf{h}_i - \mu_i}{\sigma_i} + \mu_j, \quad (14)$$

where $\mathbf{h}_i^{(j)}$ is the resulted feature for i -input's hidden representation \mathbf{h}_i mixed with j -input hidden representation \mathbf{h}_j . This combined feature then passes through the network to calculate loss with labels \mathbf{y}_i and \mathbf{y}_j .

For natural language understanding tasks, Park et al. put forward a combination scheme [171] to calibrate a pre-trained language model based on the saliency map [172] and the Area Under the Margin (AUM) statistic [173]. Training data is first divided into two groups – a set of samples that are easy to distinguish and a batch of ambiguous samples that are difficult to learn by computing the AUM of each instance. Then a Mixup process is executed to blend these two sets based on the saliency map proxied by the gradient norm, reconciling the learning complexity and hence sample confidence for model calibration. Similarly, explainable artificial intelligence (XAI) [140] explicitly extracts the weight of manipulated words and calculates the mixed label based on the importance. Besides, to circumvent the intense computation in saliency detectors, TokenMixup [81] leverages the attention map to guide the token-level data augmentation by optimally matching sample pairs, achieving $\times 15$ speed-up. SciMix [98] is proposed to generate new samples with many characteristics not from their semantic parents by teaching a StyleGAN [174] generator to replace a global semantic content from other samples into image backgrounds.

In general, saliency and style information can be exploited to deduce a content-aware combination policy, guiding the mix process for more reasonable augmented data.

3.1.6 Diversity in Mixup

There are some constraints in Mixup that limit the diversity of Mixup-ed data, such as only linear interpolating input-output pairs in the same single batch and only blending 2 examples.

BatchMixup [150] breaks the “same batch” rule by interpolating across all mini-batch, enlarging the space of Mixup-ed examples. K -Mixup [61] produces more augmented data through perturbing K instances in the direction of other K samples by interpolating under the Wasserstein metric [175]. Further to interpolate an arbitrary number of samples, MultiMix [70] assigns one vector from a Dirichlet distribution to each sample and implements the mix operation in the last layer of the network. Besides, a dense interpolation and a spatial loss term are integrated for sequence data. For label combination, self-distillation [176] is applied. Instead of single output in Mixup, MixMo [62] is presented with multi-input multi-output sub-modules for combining multiple samples. To be specific, inputs are passed through shared encoding layers and then mingled. The mixed representations are fed to multiple output blocks corresponding to multiple labels. Besides, a parametric weight function is designed to balance the contribution of multiple cross-entropy loss. Jeong et al. present a novel K -image mixing paradigm [177], which is based on the

stick-breaking process under Dirichlet prior. To further enlarge the space of augmented data, Hendrycks et al. present PixMix [51] to combine origin training data with structurally complex images, which include fractals from DeviantArt¹ and feature visualizations OpenAI Microscope².

In total, expanding the range of samples to mix and combining more examples when taking convex interpolation both benefit the variety of constructed data.

3.1.7 Miscellaneous Mixup Methods

In addition to the methods described above, there are some other approaches to improve Mixup from other perspectives.

To obtain better *robustness*, a guided interpolation framework (GIF) [90] is developed to leverage the meta information from the previous epochs for interpolation guidance. Compared with the conventional Mixup, GIF generates a higher proportion of attackable data (i.e., $\lambda = 0.5$). Besides, GIF tranquilizes the linear behavior in-between classes, which benefits standard training but is not favorable to adversarial training for robustness, encouraging the model to predict invariably in a cluster.

Through the lens of the *exploration-exploitation* dilemma in reinforcement learning, Mixup constantly explores the data space. To achieve a pleasurable trade-off between exploration and exploitation, Mixup Without hesitation (MWh) proposed in [54] divides a set of mini-batch examples from into 3 parts: (1) the standard Mixup, (2) the combination of Mixup and basic data augmentation, and (3) a damped Mixup.

Mixup has been proved to be equivalent to discovering Euclidean *barycenters* to boost the performance of the classifier from the barycenter perspective [59]. Besides, motivated by the connection between cross-entropy loss and Kullback–Leibler (KL) divergence, AutoMix [59] constructs barycenter samples with a generative model where OptTransMix, instead of the Euclidean metric, utilizes Wasserstein distance to define the mix policy with the optimal transport-based transformation technique [178].

RegMixup [74] trains the model on data distribution which combines the origin data and the Mixup vicinal approximation to the data distribution instead of using any of them as the exclusive training objective as in standard empirical risk minimization or original Mixup. This *additional Mixup regularization term* to the standard loss function provides improved accuracy and uncertainty estimation when evaluating models under out-of-distribution data and numerous covariate shifts, where Mixup tends to obtain high-entropy models and, therefore, cannot separate in-distribution instances from out-distribution ones well.

3.2 Cutmix-based Methods

3.2.1 Cutmix

Inspired by Cutout [10] and Random Erasing [9] operations that respectively randomly mask/cut out a region (e.g., a rectangle) of input images and replace the pixels of the selected area with random values, Yun et al. design the Cutmix [15] scheme which replaces a region of one image with the corresponding patch of the other sample and blends their ground targets proportionally to the area of the combined examples. Compared with Cutout and Random Erasing, each pixel of the Cutmix-ed image is informative, therefore accelerating the training process. Besides,

1. <https://www.deviantart.com>

2. <https://openai.com/blog/microscope>

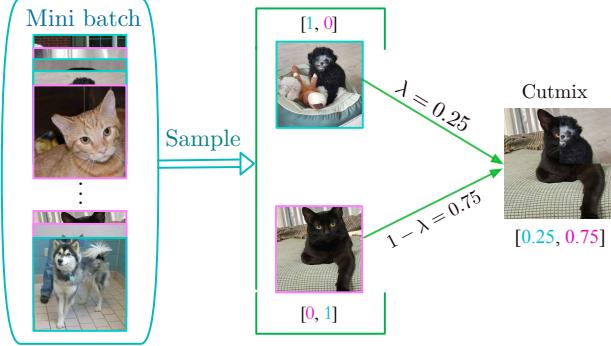


Fig. 2. An example of Cutmix with mix ratio $\lambda = 0.25$, where 1/4 area of the dog image (upper right) is cut and pasted onto the corresponding location of the cat (upper right).

the pixels from the other image upgrade the localization ability of the model by encouraging the model to identify the object from a partial perspective. Specifically, Cutmix constructs new training samples by:

$$\begin{aligned}\tilde{\mathbf{x}} &= \mathbf{M} \odot \mathbf{x}_i + (1 - \mathbf{M}) \odot \mathbf{x}_j, \\ \tilde{\mathbf{y}} &= \lambda \mathbf{y}_i + (1 - \lambda) \mathbf{y}_j,\end{aligned}\quad (15)$$

where \mathbf{M} is a binary mask indicating the cut-and-paste area of the images. Similar to Mixup [14], the mix ratio λ is drawn from a Beta distribution. To obtain the binary mask \mathbf{M} , Cutmix generates a bounding box by uniformly sampling a rectangle with height $\sqrt{\lambda}H$ and width $\sqrt{\lambda}W$, where H and W are the height and width of whole images. The binary matrix is determined by setting the element within the bounding box as 1 and 0 otherwise. A sketch of Cutmix is shown in Figure 2 where the upper right 1/4 (i.e., $\lambda = 0.25$) patch of the dog image is cut and then pasted onto the corresponding region of the cat image.

In parallel with [15], work [45] expands the space of mixed examples and investigates a dozen cut-and-paste policies. Taking *Vertical Concat* as an example, it vertically integrates the top λ part of image \mathbf{x}_i with the bottom $1 - \lambda$ region of image \mathbf{x}_j . Not limited to only combining two instances, random image cropping and patching (RICAP) blends four images [41]. RICAP draws two parameters a and b from the uniform distribution: $a \sim \text{Unif}(0, W), b \sim \text{Unif}(0, H)$ and the cropping sizes w_i, h_i for i -th image is automatically obtained via $w_1 = w_3 = a, w_2 = w_4 = W - a, h_1 = h_2 = b$, and $h_3 = h_4 = H - b$. For i -th image, the coordinate of the upper left corner $[m_i, n_i]$ of the cropped areas is decided by $m_i \sim \text{Unif}(0, W - w_i)$ and $n_i \sim \text{Unif}(0, H - h_i)$. Similar to Cutmix, the mingled target is defined as mixing their one-hot vector with the ratio λ proportional to their areas in the generated image:

$$\begin{aligned}\lambda_i &= \frac{w_i h_i}{WH}, \\ \tilde{\mathbf{y}} &= \sum_{i=1}^4 \lambda_i \mathbf{y}_i.\end{aligned}\quad (16)$$

3.2.2 Integration with Saliency Information

Cutmix may be problematic since it aimlessly cuts a patch from a source image and pastes it onto the other image while the Cutmix-ed label is proportional to the patch area. It is evident that if the cut-and-paste patch is uninformative for the source image, Cutmix would not improve performance but introduces noise to the target

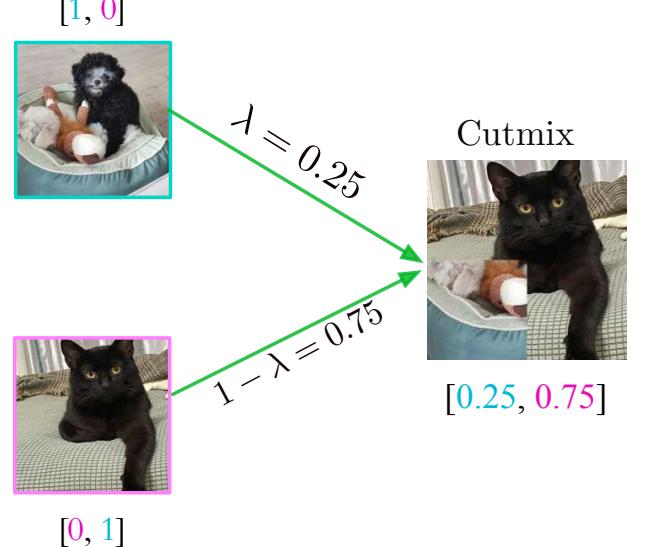


Fig. 3. Illustration of why Cutmix is problematic when the cut-and-paste patch does not contain any information about the dog. However, based on the label combination policy, the probability of the dog in the generated target is non-zero (0.25), misleading the learning model.

image, leading to unstable training due to the biased constructed target. An example is shown in Figure 3 in which the mix ratio $\lambda = 0.25$ and the cut patch is on the bottom left which does not contain any information about the dog, however, the probability value for the dog in the constructed label is 0.25, enforcing model to assign softmax score 0.25 to the dog which is undesirable.

To overcome the aforesaid issue, Walawalkar et al. [42] put forward Attentive Cutmix which selects the most illustrative regions based on the feature attention map and cuts the most representative parts. Besides, FocusMix [60] adopts proper sample approaches to cut-and-paste the instructive regions. Motivated by Vision Transformers (ViTs) [103], TransMix [105] is introduced to mix targets of input pair based on the attention maps learned with ViTs and assign larger values for input images with greater attention. However, directly applying Cutmix on ViTs [103] may lead to a token fluctuation phenomenon, i.e., the contributions of input tokens swing as forward propagation, resulting in a different mix ratio in the output tokens. To handle this issue, token-label alignment [179] is used to track the correspondence between the original tokens and the mixed tokens to keep the label for each token by reusing the computed attention at each layer.

SaliencyMix [46] prefers to cut the indicative regions of the source image with the help of the saliency detector and paste it into the target image. Four accepted saliency detection algorithms [180], [181], [182], [183] are evaluated and VSFs [180] performs best on both benchmarks. To explore the effect of the combination strategy, five possible schemes (source to target) are investigated: (i) *Salient to Corresponding*, (ii) *Salient to Salient*, (iii) *Salient to Non-Salient*, (iv) *Non-Salient to Salient*, and (v) *Non-Salient to Non-Salient* in which *(Non-)Salient* denotes the (non-)salient regions and *Corresponding* indicates the same location. Experiment evaluations show that scheme {iii} performs best since it can generate a variety of mixed examples compared with scheme {i} and contains more saliency information compared to schemes {ii, iv, v}.

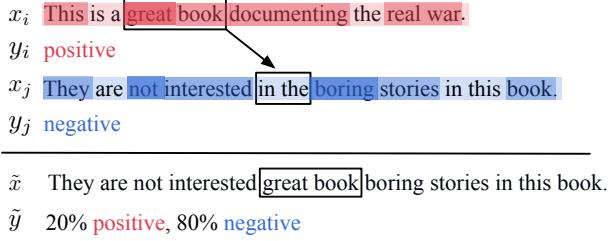


Fig. 4. Illustration of SSMix in NLP. The most 20% (λ) irrelevant tokens in the j -th sentence are replaced with the most 20% related tokens in the i -th sentence.

Similar to *Salient to Non-Salient* strategy in SaliencyMix, Kim et al. put forward Puzzle Mix [47] which joint hunts for (1) the optimal mask and (2) the optimal transport [175] by taking advantage of the saliency information and the underlying statistics of images. Besides, Puzzle Mix adapts the fast adversarial training method from [184] and randomly includes adversarial perturbation for better robustness. There are two main differences between SaliencyMix and Puzzle Mix: (1) the determination of the Non-Salient region in Puzzle Mix is formalized as an optimization problem rather than stochastically selecting non-informative regions in SaliencyMix, and (2) the saliency information in Puzzle Mix is the ℓ_2 norm of the gradient values across input channels rather than based on some detection models in SaliencyMix.

In order to utilize saliency information when mixing two sentences, SSMix [139] produces a new instance while maintaining the locality of the original input through span-based combination and selecting the tokens most related to the prediction based on the magnitude of a gradient. In addition, inspired by [185], a loss-level mix is presented as:

$$\begin{aligned} \mathcal{L}_i &\leftarrow \text{CrossEntropy}(f(\tilde{\mathbf{x}}), \mathbf{y}_i), \\ \mathcal{L}_j &\leftarrow \text{CrossEntropy}(f(\tilde{\mathbf{x}}), \mathbf{y}_j), \\ \mathcal{L} &= \lambda \mathcal{L}_i + (1 - \lambda) \mathcal{L}_j, \end{aligned} \quad (17)$$

where $\mathcal{L}_{i(j)}$ is the loss with respect to label $\mathbf{y}_{i(j)}$ and \mathcal{L} is the mixed loss function. Figure 4 illustrates the idea of SSMix, where the most 20% (λ) irrelevant tokens in the j -th sentence are replaced with the most 20% related tokens in i -th sentence. Semantically Proportional Mixing (SnapMix) [129] calculates the underlying composition of generated images via class activation map (CAM) [186] to reduce label noise in fine-grained data. For the fine-grained recognition tasks, Li et al. propose Attribute Mix [128] to take advantage of semantic information from the input pair at the attribute level. To avoid object information missing and inappropriate mixed label, ResizeMix [58] directly shrinks one image into a small patch and pastes it on a location of the other input stochastically.

In general, saliency information is crucial for the Cutmix-based method due to its locality and the label combination scheme. An aimless cut-and-paste process would introduce noise into construct features and bias into generated targets. With the help of the saliency detector or surrogate (e.g., ℓ_2 norm of the gradient), the benefits of the model from training on Cutmix-ed data could be maximized.

3.2.3 Improved Divergence

Despite the advances, saliency-guided methods may harm the diversity of augmented data since only some specific regions with

rich information are selected.

To get a better trade-off between *plausibility* and *diversity*, Saliency Grafting [48] is designed to synthesize diverse and reasonable examples. Instead of choosing the most informative patch, Saliency Grafting scales and truncates the saliency map to increase the number of options and diversity. Besides, a Bernoulli distribution is used to sample these candidate regions. To guarantee the rationality of virtual input-output pairs, saliency is also utilized to guide the target combination. Similarly, Co-Mixup [49] generates mixed data by maximizing the saliency measure of each mixed sample and the supermodular [187] diversity among the augmented data. Representative Cutmix-based adaptions are summarized in Table 3, where the saliency methods and generated images with their saliency map are instantiated.

To integrate with the accumulated knowledge from the previous iteration, RecursiveMix [50] proposes a recursive mix policy that leverages the historical *Input-Prediction-Output* triplets. Specifically, RecursiveMix makes use of mixed input-output pairs from the last iteration to generate new synthetic examples, increasing data diversity and encouraging the model to learn from multi-scale and multi-space views. Furthermore, a consistency loss for matching spatial semantics between newly generated samples and the last historical inputs is designed to learn scale-invariant and space-invariant representation.

At the moment, there is no approach to achieving a perfect trade-off between plausibility and diversity or dynamically determining the weight of the two factors of augmented data. Training with plausibility data could improve performance on in-distribution data and increasing the diversity of created data makes the learned model more robust to out-of-distribution data and adversarial attacks.

3.2.4 Border Smooth

Another problem of Cutmix is the “strong-edge” issue of the sudden pixel change around the bounding box (i.e., the rectangle’s border). For example, part of the object in the source images could be cut and then pasted on the region of the target image where the object locates.

To solve this problem, the construction of mask M in SmoothMix [85] relies on some properties such as width, height, and spread. More specifically, M is defined as the combination of its center point coordinates $[m, n]$ and spread ζ in the image space, where m and n are randomly sampled from a uniform distribution with the range of width W and H . ζ denotes the area of the cut patch, and the smoothing region is also from a uniform distribution. Take the circle mask as an example:

$$\begin{aligned} m &\sim \text{Unif}(0, W), n \sim \text{Unif}(0, H), \\ M_w &= e^{-\frac{(r-m)^2}{2\zeta^2}}, M_h = e^{-\frac{(s-n)^2}{2\zeta^2}}, \\ M &= M_w \otimes M_h, \end{aligned} \quad (18)$$

where \otimes is the outer product and r/s is the pixel in the width/height dimension. In this way, images \mathbf{x}_i and \mathbf{x}_j are mixed with a smooth transition owing to the border gradually diminishing outward.

Park et al. present a Hybrid version of Mixup and Cutmix (HMix) and a Gaussian Mixup (GMix) [26] scheme. HMix cuts and pastes two samples as Cutmix and then linearly interpolates two images in the area out of the cropped box of Cutmix. In contrast, GMix randomly selects a point and then blends two instances gradually. It uses the Gaussian distribution to relax

TABLE 3
Summary of selected Cutmix-based Adoptions.

Method	Saliency Information	Generated Image	Saliency Map
SaliencyMix [46]	Saliency Detector		
Puzzle Mix [47]	ℓ_2 Norm of The Gradient		
ResizeMix [58]	All Source Image		
Saliency Grafting [48]	ℓ_2 Norm of The Gradient		

the Cutmix box condition to a continuous transition, preventing the rectangle cropping of Cutmix from generating implausible synthetic data.

The “strong-edge” problem limits the plausibility of the constructed data and, therefore, the effectiveness of Cutmix-based methods. A well-recognized solution for this issue is Smoothing borders.

3.2.5 Other Cutmix Techniques

Apart from the above mentioned approaches, there are some other methods to deal with different problems in Cutmix.

Similar to Manifold Mixup [43], PatchUp [69] carries out interpolation in *feature space* – selecting adjacent regions of feature maps for mixing two examples.

The benefit of Cutmix-based techniques on *transformer*-based methods [188] is limited since the transformer inherently has a global receptive field which forces the model to learn from a global perspective. To cope with this issue, Liu et al. put forward TokenMix [104] in which the mix of two images is token-level by dividing the input into multiple smaller sub-regions and assigning labels of combined images with CAM from a pre-trained teacher model. A similar work is ScoreMix [189] where the semantic information of images is based on learned self-attention.

GridMix [55] splits an image into $q \times q$ grids and then constructs instances by randomly selecting a local cell from one of the two inputs. The mixed label is determined by blending the label pair in proportion to the number of grids. Besides, an additional task predicting the label of each cell is integrated to

extract discriminative representations. One step further, PatchMix [57] presents a grid-level mix data augmentation method with a genetic search scheme to find the optimal patch mask. To exploit the spatial context information in remote sensing semantic segmentation data, ChessMix [190] combines transformed mini-patches in a chessboard-like grid to synthesize examples and assigns patches with more examples of the rarest classes the high weight to deal with the imbalance issue.

For *unbalanced* classification, Intra-Class Cutmix [191] boosts model performance by blending intra-class samples of minority classes to modify the decision boundary.

3.3 Beyond Mixup & Cutmix

Except for Mixup-based and Cutmix-based methods, there are some other techniques in the mix principle: such as mixing with itself, incorporating multiple MixDA approaches, and integrating with other DA methods.

Mixing with itself. DJMix [64], instead of blending two samples, combines each training example with its discretized one, i.e., mixing only one image essentially. Discretization is conducted by the Vector-Quantized Variational AutoEncoder [192] with encoder $\mathcal{G}(\cdot)$ in an unsupervised manner:

$$\tilde{\mathbf{x}} = \lambda \mathbf{x} + (1 - \lambda) \mathcal{G}(\mathbf{x}). \quad (19)$$

A Jensen–Shannon (JS) divergence based loss is introduced to map \mathbf{x} and $\tilde{\mathbf{x}}$ closely and obtain consistent representations. CutBlur [193] mixes two resolution versions of an image by cutting and pasting a high-resolution patch to the corresponding low-resolution image area and vice versa. It enforces the model to

learn not only “how” but also “where” to super-resolve an image and understand the degree of high resolution instead of simply applying super-resolution to all given pixels.

Incorporating multiple MixDA approaches. RandomMix [31] conducts random permutation for a batch of data to generate two times batch data and combine multiple mix policies – Mixup [14], Cutmix [15], ResizeMix [58], and Fmix [35]. Besides, AugRmixAT [67] simultaneously generated multiple different sets of augmented data for a single example by combining multiple MixDA [14], [15], [35], [58] and adversarial perturbation [194] to boost generalization and robustness.

Integrating with other DA methods. Through the lens of irregular superpixel decomposition, Hammoudi et al. propose SuperpixelGridMix [195] – a new style of data augmentation method that can be combined with mix-based approaches to form their variants. AugMix [32] presents a data augmentation pipeline with operations from AutoAugment [196]. AugMix consists of 3 sub-chains, each of which is a randomly selected conventional augmentation maneuver. The generated images are then combined by Mixup with a mix ratio drawn from a Dirichlet distribution $\text{Dirichlet}(\alpha, \alpha, \alpha)$. “skip connection” with Mixup is used to blend the images from sub-chains and the original image. Besides, a JS divergence based loss function is designed to get a consistent representation. StackMix [63] is an orthogonal work that takes input as the concatenation of two images and the target as the average of two one-hot vectors. It can be combined with mix-based methods. For example, Mixup with StackMix can generate new data based on 4 input in total, enlarging the space of augmented data, compared to the original Mixup that cannot benefit from blending more than 2 inputs [14]. Besides, no assumption is introduced to the model, decreasing the information loss when mixing data. Mixup and Cutmix also be used in CropMix [82] to generate a richer input data distribution.

4 MIXDA APPLICATIONS

In this section, we will review extensive applications of MixDA, such as semi-Supervised learning, generative model, contractive learning, and NLP. Representative applications and corresponding benchmarks are summarised in Table 4.

4.1 Semi-Supervised Learning

Deep learning has been permeating various fields where unlabeled data is usually copious, but labeling data is prohibitive due to manpower and expertise knowledge. To handle this issue, semi-supervised Learning (SSL) [237] aims to improve the performance of the supervised model on small datasets by taking advantage of a large number of unlabeled data.

To integrate MixDA into SSL, Verma et al. put forward Interpolation Consistency Training (ICT) [92] by transiting the decision boundary to low-density regions of data distribution. Specifically, ICT forces the prediction of the interpolation of unlabeled samples to be consistent with the interpolation of the model prediction:

$$f(\lambda \mathbf{u}_1 + (1 - \lambda) \mathbf{u}_2) = \lambda f(\mathbf{u}_1) + (1 - \lambda) f(\mathbf{u}_2), \quad (20)$$

where \mathbf{u}_1 and \mathbf{u}_2 are sampled unlabeled examples, and $f(\mathbf{u}_1)$ and $f(\mathbf{u}_2)$ are the corresponding model predictions. In other words, ICT regards the prediction of an unlabeled instance as its target (i.e., “guessed” label). Similarly, Olsson et al. present ClassMix [108] which combines unlabelled data to construct new

TABLE 4
Benchmarks in different MixDA applications.

Application	Benchmark	Article
CL [163]	CIFAR [33]	[110], [111], [122] [197], [198]
		[66], [110], [111]
	ImageNet [101]	[122], [197], [197] [199], [200], [201]
		[202]
	FGVC-Aircraft [131]	[110], [201]
	Standford Cars [130]	[110], [203]
ML [204]	iNaturalist [126]	[201], [203]
	CUB200-2011 [127]	[205], [206]
	Standford Cars [130]	[205], [206]
	SOP [207]	[205], [206]
NLP [16]	AG News [208]	[144], [209]
	Yahoo! Answers [210]	[209], [211]
	IWSLT [212]	[213], [214]
	WMT [215]	[216], [217]
Graph [218]	Cora/Citeseer/Pubmed [219]	[220], [221], [222] [223], [224], [225]
	Cora-Full [226]	[220], [221]
	Coauthor [227], [227]	[220], [221], [222]
	IMDB/Reddit [228]	[222], [229]
Point Cloud [231]	BlogCatalog [230]	[223], [225]
	ModelNet40 [133]	[232], [233]
	ScanObjectNN [234]	[232]
	KITTI [235]	[236]

examples. The mixed image is generated by cutting half of one image and pasting it on top of the other, and its corresponding artificial target is computed based on the network’s semantic prediction.

Another independent work is MixMatch [93], which generates synthetic examples using a batch of labeled samples and another batch of unlabeled instances with “guessed” labels by interpolating both labeled data and unlabeled data. Besides, motivated by the success of entropy minimization [238], MixMatch applies a sharpening function to reduce the entropy of the label distribution. Different from ICT which can be regarded as a special case of MixMatch where only unlabeled is mixed, Mixup is utilized to both generate mixed labeled samples and mixed unlabeled examples in MixMatch. One step further, ReMixMatch [239] improves the semi-supervised learning performance of MixMatch by distribution alignment and augmentation anchoring. In particular, distribution alignment reduces the divergence between the prediction distribution of unlabeled examples and the distribution of ground-truth labels. Besides, the augmentation anchoring generates a weakly-augmented version and multiple strong-augmented versions of a single input and clusters the predictions of these strong-augmented examples around the output of the weakly-augmented sample. To avoid confirmation bias [176] (i.e., error accumulation) of self-training in MixMatch, DivideMix [94] rejects the sample’s label with high noise and regards it as unlabeled data to improve generalization. Specifically, DivideMix trains two individual gaussian mixture models (GMMs) to separate the training data into a label set (mostly clean) and an unlabeled collection (mostly noisy). These data will be used to train the main MixMatch network jointly. In addition, CowMix/CowOut is a combination of CowMask [95] and Mixup/Cutmix whose goal is to achieve consistency regularization in SSL.

A similar problem is positive and unlabeled learning (PUL) where there are only a small number of labeled positive examples with a large number of unlabeled instances. To solve this practical

problem, MixPUL [96] takes advantage of Mixup to transit the decision boundary towards data distribution regions with low density. To select more appropriate samples to mix, Li et al. present Partially Positive Mixup (P^3 Mix [97]). It aims to move the learned boundary along the direction of fully-supervised ones by mixing the marginal pseudo-negative instances that are partially positive and located between the two boundaries.

In total, in addition to blending between labeled instances as in supervised learning, MixDA enhances the performance of SSL by mixing between unlabeled data or between labeled samples with unlabeled examples.

4.2 Contrastive Learning

As a dominant methodology of self-supervised learning, contrastive learning (CL) models [163] try to cluster the embeddings of augmented versions (i.e., positive examples) around the same sample (i.e., anchor) and push away embeddings from different samples (i.e., negative samples).

A straightforward MixDA-based method is Mixup Contrast (MixCo) [199], which introduces *semi-positive* samples that are decoded from the mixture of positive and negative instances to learn fine-grained similarity between representations. Zhang et al. demonstrate that learning with contrastive loss benefits both representation learning and fine-tuning [110]. Correspondingly, Contrast-regularized tuning (Core-tuning) is proposed to fine-tune contrastive self-supervised learning models. Instead of simply integrating the contrastive loss term into the optimization of fine-tuning, a hard pair excavation scheme is applied to learn transferable features and smooth the decision boundary. In particular, Mixup is used to generate (1) *hard positive* pair by mixing the two hardest pairs and (2) *semi-hard negative* pair by blending a negative example and the anchor data. Similarly, Feature Transformation (FT) [201] constructs diversified negatives by making full use of (1) negative samples with their interpolations and (2) more positives via positive extrapolation to learn more view-invariant and powerful representations. Positive extrapolation mixes a positive sample and the anchor example to synthesize new transformed positive instances, and negative extrapolation combines multiple negative samples to obtain new negative data. To get more informative negative samples, a hard negative mixing strategy called MoCHi (mixing of contrastive hard negatives) [202] mixes (1) the existing hardest negative pair and (2) the hardest negative sample with the query itself in the feature space. Similarly, the background mixing [240] generates additional positives for each anchor and allows contrastive learning to leverage action semantics shared across video domains.

Following Single Instance Multi-view (SIM) paradigm, Siamese network [241] takes the augmented images of an example as input and conducts an element-wise maximum of features to compute the discriminative representation. Guo et al. present MixSiam [197], a mix-based algorithm that feeds the combinations of augmented images into the backbone and encourages the embeddings to be close to the original distinctive representation. In this way, MixSiam increases the diversity of the augmented sample and keeps predicted embeddings invariant. However, Siamese frameworks are prone to overfitting if the augmentation technique used to construct two views is not expressive enough. To deal with this problem, unsupervised image mixtures (Un-Mix) [198] entails the soft distance concept into the label space and make the model embrace the soft degree of similarity between image pairs

by interpolating in the input space. To be specific, Un-Mix first generates two views with a pre-defined transformation, followed by a mix operation such as Mixup and Cutmix. Finally, the mixed samples are fed into the two-branch framework to produce hidden representations. A different work is ScaleMix [200] which operates on views from a single example and outputs a single view to investigate the importance of asymmetry by explicitly differentiating the two encoders – one produces source embedding and the other generates target encoding.

Going beyond single instance multi-view learning, BSIM [109] takes the similarity of spurious-positive pairs (i.e., two randomly sampled instances and their mixture) into account for more even feature distribution, enhancing the discrimination capability of the model. Contrastive learning is, therefore, recast as learning a non-parametric classifier that assigns a virtual class to each sample in [111], which uses i -Mix to give a virtual label to each sample and conducts interpolation in both input space and virtual label space to regularize the contrastive representation learning.

MCL [242] designs a novel contrastive loss function to take advantage of the MixDA strategy. MCL aims to predict the mix coefficient regarded as the soft target in the loss function. Li et al. present CLIM [102] which finds local examples similar to a cluster center and utilizes a mix scheme to perform smoothing regularization to deduce powerful representation. Simple data mixing prior (SDMP) [122] considers the connections between source images and the generated counterparts and encodes the relationships into hidden space to model this prior. Besides, Similarity Mixup [203] virtually increases the batch size and operates on pair-wise scalar similarities. Many constructed hard negatives in Graph Contrastive Learning (GCL) are positive samples indeed, which will undermine the performance. To resolve this problem, ProGCL-Mix [243] is proposed to generate more hard negatives considering the probability of a negative being the true one.

Overall, MixDA is exploited to boost CL mainly in two manners: (1) generating various mixed examples (e.g., semi-hard negative pairs and semi-positive samples) to incorporate more fine-grained information for learning more discriminative representation; and (2) integrating MixDA in optimization as a prior to regularize CL.

4.3 Metric Learning

Metric learning (ML) [204] aims to quantify the similarity between examples and obtain an optimal task-specific distance metric such that the embeddings of the same or similar classes are close while those dissimilar ones are pushed far away. On the one hand, some works [244], [245] have demonstrated that producing new data points and training with metric learning loss can enhance generalization. However, these methods require additional generative networks for data augmentation, increasing the model size and training cost. On the other hand, the loss function of metric learning is based on two or more instances, sharing the same principle with MixDA approaches. Therefore, integrating mixed training into metric learning is preferred.

Embedding Expansion [205] synthesizes new data by mingling two or multiple feature representations. It also exploits negative pairs to learn the most discriminative feature. Similarly, Metric Mix (Metrix) [206] adapts Mixup and Manifold Mixup [43] into metric learning. It validates the effect of mixed samples with a novel metric called “utilization” and explores the regions of

the embedding space beyond the training classes to refine the representation.

4.4 Adversarial Training

Adversarial training [194] can significantly lift model robustness since it encourages the model to explore some unseen regions. This is achieved by perturbing a training data point in the direction of another instance while keeping its origin target as the training label, therefore potentially improving generalization.

Through the lens of optimization, Madry et al. formulate adversarial robustness as a min-max problem [246]:

$$f^* = \arg \min_{f \in \mathcal{F}} \int \max_{\delta \in \mathcal{S}} \mathcal{L}(f(\mathbf{x} + \delta), \mathbf{y}) dP_\psi(\mathbf{x}, \mathbf{y}), \quad (21)$$

where \mathcal{S} is the neighborhood region of each sample. $P_\psi(\mathbf{x}, \mathbf{y}) = \frac{1}{n} \sum_{i=1}^N \rho(\mathbf{x} = \mathbf{x}_i, \mathbf{y} = \mathbf{y}_i)$ in which $\rho(\mathbf{x} = \mathbf{x}_i, \mathbf{y} = \mathbf{y}_i)$ is a Dirac mass centered at $(\mathbf{x}_i, \mathbf{y}_i)$. It is deliberately designed to have visually imperceptible perturbations δ only. Adversarial training consists of two procedures: (1) generating adversarial examples and (2) training the model to assign the origin target to augmented data for improved robustness against unseen adversarial examples. The similarity between adversarial training and MixDA is formulated by reinterpreting Mixup as a kind of Directional Adversarial Training (DAT) [34]. Meanwhile, empirical risk minimization (ERM) is notorious as it can be easily fooled by adversarial examples [194], [247]. In contrast, MixDA can be regarded as a class of vicinal risk minimization (VRM) [14]. Besides, from the view of robust objectives [248] and the optimization dynamic for neural networks, adversarial training needs more training data to gain better generalization performance [249], [250], [251]. Thus, it would be natural to investigate the connection between MixDA and adversarial training deeply.

By investigating the mutual information between the function learned on the original data and the counterpart on the mixed data by a VAE, Harris et al. [35] demonstrate that MixDA approaches can be regarded as a form of adversarial training [247], therefore, enhancing robustness to attacks such as injecting uniform noise to create examples similar to those synthesized by Mixup. Moreover, MixDA methods are shown as a kind of directional adversarial training (DAT) [34], which perturbs one training sample based on the direction of the other instance as the same expected loss functions they have. In [25], the adversarial robustness gain of mix training is attributed to the approximate loss function, which acts as an upper bound of the adversarial loss with the L_2 attack. For robustness, minimizing the loss function with augmented instances is approximately equivalent to minimizing an upper bound of the adversarial loss, explaining why models trained with mixed data manifest robustness improvement for several adversarial attacks.

To increase training data, Interpolated Adversarial Training (IAT) [87] trains the model on the mixture of adversarial samples along with the combination of unperturbed instances based on Mixup and Manifold Mixup. In a similar way, a soft-labeled approach for improving adversarial generalization, Adversarial Vertex Mixup (AVMixup) [89], is presented to extend the training distribution via the interpolation between the raw input vector and the virtual vector (adversarial vertex) defined in the adversarial direction. Si et al. put forward Adversarial and Mixup Data Augmentation (AMDA) [144] to explore a much larger attack search space by linearly interpolating the representation pair to generate augmented data. The generated data are more diverse

and abundant than discrete text adversarial examples generated by general adversarial methods.

Taking advantage of Mixup, M-TLAT [121] designs a novel adversarial training algorithm called Targeted Labeling Adversarial Training (TLAT) to boost the robustness of image classifiers for 19 common corruptions and 5 adversarial attacks, without sacrificing the accuracy on clean samples. Specifically, M-TLAT interpolates the target labels of adversarial samples with the ground-truth labels:

$$\begin{aligned} \mathbf{x}_{\text{mtlat}} &= \tilde{\mathbf{x}} - \arg \max_{\delta \in \mathcal{S}} \{\mathcal{L}(\tilde{\mathbf{x}} + \delta \mathbf{y}_{\text{target}}, \tilde{\mathbf{y}})\}, \\ \mathbf{y}_{\text{mtlat}} &= (1 - \delta) * \tilde{\mathbf{y}} + \delta * \mathbf{y}_{\text{target}}, \end{aligned} \quad (22)$$

where $\tilde{\mathbf{x}}$ and $\tilde{\mathbf{y}}$ are the Mixup-ed input-output pair and $\mathbf{y}_{\text{target}}$ is the targeted label for adversarial attack. $\mathbf{x}_{\text{mtlat}}$ contains features from three different sources: two clean images specified by $\tilde{\mathbf{x}}$ and an adversarial perturbation targeting a specific class $\mathbf{y}_{\text{target}}$. Correspondingly, label $\mathbf{y}_{\text{mtlat}}$ embraces their supervised signals with the associated weights. They are jointly decided by the mix ratio λ and the perturbation δ . M-TLAT predicts the label corresponding to the three sources while outputting the weight of each source within the combined feature $\mathbf{x}_{\text{mtlat}}$. This scheme encourages the model to learn a subtle representation of mixed images.

Bunk et al. [78] combine Mixup and adversarial training by mining the space between samples using projected gradient descent. It utilizes back-propagation through the Mixup interpolation in the training stage to optimize for the matte and incongruous region. Besides, the effect of Mixup ratio optimization is also investigated to improve robustness. Similarly, MixACM [79] aligns activated channel maps (ACM) by transferring the robustness of a teacher to a student. Mixup-SSAT [252] mixes the adversarial and benign scenarios in an adversarial training manner to gain a trade-off between accuracy and adversarial training.

Above mentioned methods implicitly defend against adversarial attacks in the testing stage by directly classifying the test data in a vanilla model trained on mixed data. In contrast, an inference principle called Mixup Inference (MI) [88] exploit the induced global linearity in mix trained model. The basic idea is that breaking the locality via the globality of the model predictions would benefit the adversarial robustness. MI mingles one input with some other randomly chosen clean samples. They can be transformed into equivalent perturbations, destroying the locality of adversarial attacks and reducing their strength. Specifically, MI first samples a label \mathbf{y}_s and then samples K examples $\{\mathbf{x}_{s,k}\}_{k=1}^K$ from the sampled class. In the inference stage, Mixup is used to generate input $\tilde{\mathbf{x}}_{s,k} = \lambda \mathbf{x} + (1 - \lambda) \mathbf{x}_{s,k}$ and the final result is averaged on the output predictions of the K Mixup-ed examples:

$$f(\mathbf{x}) = f(\mathbf{x}) + \frac{1}{K} f(\tilde{\mathbf{x}}_{s,k}). \quad (23)$$

Empirical results in [88] demonstrate that applying MI can obtain more reliable predictions under different attack models.

4.5 Generative Models

Generative models, such as GANs [13], VAE [12], normalizing flows [253], and denoising diffusion probabilistic models [254], learn underlying probability distribution to understand data and generate new instances with new configurations of latent presentation. An autoencoder model $\mathcal{F}(\cdot)$ consists of an encoder module $\mathcal{G}(\cdot)$ and a decoder part $\mathcal{H}(\cdot)$, i.e., $\mathcal{F}(\cdot) = \mathcal{H}(\mathcal{G}(\cdot))$. An input \mathbf{x}

is encoded as a hidden embedding \mathbf{z} via an encoder \mathcal{G} and then reconstructed by a decoder \mathcal{H} . The optimization objective is to minimize the reconstruction:

$$\min_{\mathcal{F}} \mathbb{E}_{\mathbf{x} \sim P} \|\mathbf{x} - \mathcal{H}(\mathcal{G}(\mathbf{x}))\|_2. \quad (24)$$

Applying MixDA in the generative models is straightforward. For example, pseudo input is generated by Mixup and then leveraged to break the evidence lower bound (ELBO) value bottleneck by reducing the margin between ELBO and the data likelihood [80]. Another two direct applications of MixDA are adversarial autoencoder (AAE) [75] and VarMixup [77]. The former interpolates hidden features to construct a broad of latent representations. The latter linearly interpolates on the unfolded latent manifold where the linearity of training data points is preserved.

Berthelot et al. suggest that, in some cases, autoencoders can be “interpolable”, i.e., decoding the convex combination of the representations in the hidden space for two data points, the autoencoder can generate semantically mixed instances [76]. Accordingly, Adversarially Constrained Autoencoder Interpolation (ACAI) utilizes a critic network d to force interpolated data points to be “realistic”, and the training objective is to minimize:

$$\begin{aligned} \mathcal{L}_d = & \|d(\mathcal{H}(\lambda \mathcal{G}(\mathbf{x}_1) + (1 - \lambda) \mathcal{G}(\mathbf{x}_2)) - \lambda)\|^2 + \\ & \|d(\eta \mathbf{x} + (1 - \eta) \mathcal{F}(\mathbf{x}))\|^2, \end{aligned} \quad (25)$$

where η is a scalar hyperparameter. The first term aims to recover the mix ratio used for interpolation in latent space while the second term is a regularizer with two utilities: (1) it encourages the critic consistently to output 0 for non-interpolated inputs and (2) it enables the critic to obtain realistic data by interpolating in data space, i.e., \mathbf{x} and $\mathcal{F}(\mathbf{x})$, even when the autoencoder’s reconstructions are poor.

To improve the quality of reconstructed output, Larsen et al. combine it with an adversarial game [255]. In particular, a discriminator \mathcal{D} attempts to discern between real input and reconstructed output. In turn, the autoencoder is expected to generate “realistic” reconstructions to fool the discriminator, formulating a new baseline – AE_GANs:

$$\min_{\mathcal{F}} \mathbb{E}_{\mathbf{x} \sim P} \underbrace{\|\mathbf{x} - \mathcal{F}(\mathbf{x})\|_2}_{\text{reconstruction}} + \eta \underbrace{\mathcal{L}_{\text{GAN}}(\mathcal{D}(\mathcal{F}(\mathbf{x})), 1)}_{\text{fool } \mathcal{D} \text{ with reconstruction}}, \quad (26)$$

$$\min_{\mathcal{F}} \mathbb{E}_{\mathbf{x} \sim P} \underbrace{\mathcal{L}_{\text{GAN}}(\mathcal{D}(\mathbf{x}), 1)}_{\text{label } \mathbf{x} \text{ as real}} + \underbrace{\mathcal{L}_{\text{GAN}}(\mathcal{D}(\mathcal{F}(\mathbf{x})), 0)}_{\text{label reconstruction as fake}}, \quad (27)$$

where \mathcal{L}_{GAN} is the binary cross-entropy equivalent to the JS GANs [13]. Based on this, adversarial Mixup resynthesis (AMR) [117] constructs mixed hidden embedding which, after decoding, are indistinguishable from real samples. AMR first encodes a hidden pair $\mathbf{h}_i = \mathcal{G}(\mathbf{x}_i)$ and $\mathbf{h}_j = \mathcal{G}(\mathbf{x}_j)$ and then integrates them via Mix operation. The mixed representation is decoded by the decoder $\mathcal{H}(\cdot)$. AMR minimizes a tailored loss function that aims to fool the discriminator \mathcal{D} with output decoded from the constructed instances. Formally, one additional term $\mathcal{L}_{\text{GAN}}(\mathcal{D}(\text{Mix}(\mathbf{h}_i, \mathbf{h}_j))), 1$ is added to the loss function of autoencoder – Equation (26), and the other extra term $\mathcal{L}_{\text{GAN}}(\mathcal{D}(\text{Mix}(\mathbf{h}_i, \mathbf{h}_j))), 0$ is appended to the loss function of GANs – Equation (27). The Mix function can be Manifold Mixup or any other combination scheme.

4.6 Domain Adaption

Domain adaptation [256] is to transfer the model learned on a labeled source domain \mathcal{X}_s to an unlabeled target domain \mathcal{U}_t . Similar to SSL in Section 4.1, MixDA is an effective way to take advantage of unlabeled data.

Mao et al. present a novel general algorithm called Virtual Mixup Training (VMT) [257] to impose the linear combination constraint on the region in-between training data for improved regularization. VMT can be readily combined with most existing domain adaption models. Unlike conventionally mixing samples with labels, VMT constructs new data by combining multiple examples without supervision signal from the target domain. To do this, inspired by the virtual (or pseudo) labels [258], VMT synthesizes virtual samples as:

$$\begin{aligned} \tilde{\mathbf{u}} &= \lambda \mathbf{u}_i + (1 - \lambda) \mathbf{u}_j, \\ \tilde{\mathbf{y}} &= \lambda f(\mathbf{u}_i) + (1 - \lambda) f(\mathbf{u}_j), \\ \mathcal{L} &= \mathbb{E}[\text{D}_{\text{KL}}(\tilde{\mathbf{y}}, f(\tilde{\mathbf{u}}))], \end{aligned} \quad (28)$$

where \mathbf{u}_i and \mathbf{u}_j are the samples without label from target domain \mathcal{U}_t and D_{KL} denotes the KL divergence. However, training VMT with the conditional entropy loss may be unstable and even obtain a degenerated solution on some complicated tasks [259]. To tackle this problem, VMT mixes on the input of the softmax layer (i.e., logit values) rather than the output of the softmax layer (i.e., probabilities), as most of the probability values are encouraged to be zero due to the one-hot target vector, while the logits still have non-zero values.

Inter- and Intra-domain Mixup training (IIMT) [260] imposes training constraints across domains using Mixup to enhance the generalization performance on the target domain. For potential domain discrepancy, IIMT utilizes an additional feature-level consistency regularizer to facilitate the inter-domain constraint. In addition, adversarial domain learning and Intra-domain Mixup are explored to further improve performance. Another work combining adversarial domain adaptation and Mixup is DM-ADA [261], which keeps domain invariance in a continuous latent space and trains a domain discriminator to discern examples relative to the source and target domains. The mixed domain label is then used to encourage the domain discriminator to align representations and constrain distance between mixed examples. Besides, domain Mixup is jointly implemented on both pixel and feature levels to lift the model’s robustness. Specifically, pixel-level Mixup (i.e., mixing inputs) encourages the domain discriminator to explore the underlying properties of source and target distributions. Feature-level Mixup (i.e., mixing embeddings) elicits a latent space with low domain shift to get a more consistent feature distribution. Similarly, Dual Mixup regularized learning (DMRL) [262] forces the model to output coherent predictions to boost the intrinsic structures of the hidden space by inherent structures carrying domain and category Mixup regularization.

The “negative transfer” – the dearth of domain invariance and distinction of the latent representation – is the main issue in partial domain adaptation, where the label space of the target domain is a subset of the source label space. To deal with this problem, a “Select, Label, and Mix” (SLM) framework [263] is developed to discriminate the invariant feature embedding. The “Mix” conducts domain Mixup with the “Select” and “Label” parts to scrutinize more intrinsic structures across domains, resulting in a domain-invariant hidden space. Also, the inter-domain, intra-source, and intra-target domain combinations have been investigated.

4.7 Natural Language Processing

Conventional data augmentation techniques for NLP [16] are different from image data that can directly leverage the human knowledge for label-invariant data transformation, such as cropping, flipping, or changing the intensity of RGB channels [3]. For example, slightly altering a word (token) in a sentence may dramatically change its meaning. Therefore, commonly used data augmentation methods in NLP are based on synonym replacement from handcrafted ontology word similarity [264], [265], inevitably limiting their scope of application because only a small portion of words have exactly or nearly the same meanings. However, MixDA is general enough to generate augmented data for NLP.

As the first NLP MixDA method, Guo et al. [137] adapt Mixup for NLP on the sentence classification task. They propose wordMixup to interpolate on the word embeddings and senMixup to interpolate on sentence embeddings. Experimental evaluation with CNN and Long Short-Term Memory (LSTM) network [266] verify their effectiveness. Another similar work is Mixup-Transformer [151] which incorporates Mixup with Transformer-based [188] pre-trained architecture. An issue for pre-trained language models is the miscalibration for both in-distribution and out-of-distribution (OOD) data due to over-parameterization. A regularized fine-tuning approach is developed [211] for improved calibration. The synthetic on-manifold examples are produced by interpolating in the data manifold to impose a smoothness constraint for better in-distribution calibration. Besides, the predictions for off-manifold instances are forced to be a uniform distribution to mitigate the over-confidence issue for OOD data.

Emix [142] generates virtual examples by interpolating hidden layer representations with word embeddings and takes the difference of text energies [267] of the samples into consideration. Existing embedding-based methods ignore one crucial property – language-compositionality, i.e., a complex expression is built from its sub-structures. A compositional data augmentation approach called TreeMix [152] is developed to decompose sentences into their constituent sub-parts by constituency parsing tree. It then mixes them to generate new data, increasing the diversity and injecting compositionality into the model.

In the context of semi-supervised text classification, MixText [209] is presented to generate new data with a novel combination strategy called TMix which generates the “guessed” low-entropy labels for unlabeled data and mixes the labeled and unlabeled data in the BERT-encoded [2] representation space. SeqMix [213] is a simple but effective data augmentation algorithm for sequence-to-sequence tasks. It generates samples by softly mixing input-output sequence pairs with two binary combination vectors (similar to Cutmix [15]) to encourage the neural model’s linear behavior. Another approach with the same name is proposed in [148], which instead aims to improve the efficiency of active sequence labeling by expanding the queried data and synthesizing new sequences in each iteration. Specifically, SeqMix mixes queried samples in both the feature and target spaces. It guarantees plausibility via a discriminator that computes the perplexity scores for all the constructed candidates and returns the ones with low perplexity. Besides, AdvAug [214] aims to minimize the expected risk over two vicinity distributions, one of which characterizes a smooth interpolation hidden space for sequence-to-sequence learning.

Learning a good representation for end-to-end speech-to-text

translation (ST) with limited supervised information is important in NLP. Speech-TExt Manifold Mixup (STEMM) [268] leverages the representation divergence between modalities by combining the representations from different modalities. It feeds both unimodal and multi-modal blended sequences into the translation model in parallel with prediction in a self-learning manner. Another focus of machine translation is diversity, whose goal is to produce diverse target language translations for a given input sentence. MixDiversity [216] is developed to take advantage of the linearity in the hidden space via linear interpolation on different sentence pairs. To guarantee faithfulness and diversity simultaneously, two schemes are presented to choose diverse sentence pairs and assign appropriate weights for a good balance without additional training. For improved cross-lingual transfer performance, cross-lingual manifold Mixup (XMIXUP) [269] mitigates the representation discrepancy by mingling the representation from the source and target languages during training and inference. Another similar work is multilingual crossover encoder-decoder (mXEncDec) [217]. It integrates language pairs at the instance-level by mixing samples from different language pairs to form “crossover examples”, encouraging shared input and output spaces across languages. Besides, two strategies – simplified target interpolation and pairwise sampling – are designed to deal with the dissimilarity and data imbalance issues.

4.8 Graph Neural Networks

Graph neural networks (GNNs) [218] have attracted rising attention in recent years. However, directly applying existing MixDA methods is inappropriate since it is unclear how the synthetic nodes connect to the original nodes via constructed edges while preserving the topology of the whole graph.

To handle this problem, a network-agnostic method GraphMix [220] is presented to train an additional fully-connected network (FCN) using Manifold Mixup [43] to augment data. Specifically, only node features (excluding graph structure) are fed into the FCN. Compared to conventional GNNs that only aggregate information from the neighbors in a few hops due to the “over-smoothing” issue [270], [271], GraphMix conducts interpolation on randomly selected nodes, breaking the neighborhood limitation of GNNs and thus improving performance. Motivated by GraphMix, Graph Mixed Random Network Based on PageRank (PMRGNN) [224] expands neighborhood size for the random walk based graph neural networks. To combine both feature and structure information, NodeAug [221] is proposed with three variants: (1) the first one is NodeAug-I which only mixes nodes’ features and ignores the topology; (2) the second one is NodeAug-N which derives neighbor aggregation of virtual nodes by randomly choosing neighbors of two combined nodes with probability λ and $1 - \lambda$, and then appending edges from these selected nodes; and (3) the last one is NodeAug-S which scales all related source features accordingly, i.e., adding edges from all neighbors of the combined node to the mixed node.

Due to the similarity between the neighborhood and receptive field sub-graph, Wang et al. present Mixup-based methods for node classification and graph classification tasks [222]. In the node classification task, two-branch graph convolution is exploited to interpolate the irregular graph topology and mix their receptive field. The interpolation is conducted on the aggregated representations from the two branches after each convolution layer. As for graph classification, Mixup performs in the semantic space.

Another work GraphMixup [223] is designed for class-imbalanced node classification with 3 sub-modules: (1) feature Mixup performs in a constructed semantic relation space, (2) two context-based self-supervised strategies are developed to model both global and local structure information and conduct edge Mixup, and (3) a reinforcement Mixup scheme adaptively determines the number of combined nodes.

\mathcal{G} -Mixup [229] generates synthetic graphs by interpolating sampled graphons in the Euclidean space, which is a generator estimated for each class. To create more plausible samples, Graph Transplant [272] explicitly leverages the node saliency information (norm of the gradient) to guide the selection of sub-graphs and the label generation. Besides, mix-base schemes also are utilized to mix node embedding directly for better performance in the few-label scenarios [225].

MixDA is an effective means to get around the “over-smoothing” issue by mixing distant samples. Overall, the most important point for MixDA on graph learning is how to take advantage of structure information to compose new data. Mixing in the embedding space and combining with the help of sub-graphs or receptive fields are available solutions. Besides, how to directly create new nodes and their edges by MixDA in a principal manner is a burning problem.

4.9 Federated Learning

Federated Learning (FL) [273] is a learning paradigm in which multiple agents collaborate to learn a model and are usually under the coordination of a central aggregator. This setup allows edge devices to jointly handle a learning problem without directly sharing data across devices, expelling the need to store data globally. Marrying the MixDA into FL can enhance FL performance while protecting privacy since it is not easy to reconstruct origin data from mixed examples without knowing the mix policy.

Oh et al. develop an efficient and privacy-preserving framework Mix2FLD [99] in which the local data is uploaded from different clients and then linearly combined at the server to preserve privacy and improve model accuracy. A notable distinction between FL and traditional machine learning is that data from the different clients in FL are *non-i.i.d.* (independent and identically distributed). XORMixup [119] utilizes a bit-wise XOR-based encoder and decoder to generate synthetic samples to solve the performance degradation as the across-client data heterogeneity increases. In particular, a device collects other clients’ encoded samples which are decoded using each one’s own data only. This bit-wise XOR operation is designed to warp the raw examples, ensuring data privacy. Another work sharing a similar motivation is Mean Augmented Federated Learning (MAFL) [100], where the transmitted data is averaged locally due to privacy issues. In MAFL, a novel augmentation method called FedMix is designed to obtain an approximation of global Mixup only on averaged data.

4.10 Other Applications

Compared to other DA methods, versatility is one of MixDA’s advantages, enabling it to be applied to various domains. In addition to the applications mentioned above, MixDA has succeeded in many other areas, which are briefly reviewed here.

Point Cloud. Directly transferring MixDA to point cloud data [231] may be difficult since there is no one-to-one correspondence between the points of two objects. Chen et al. formulate data augmentation on point cloud as a shortest path linear

interpolation problem and present PointMixup [232] to construct new samples by assigning an optimal path function for two point clouds, resulting in a linear and invariant interpolation. Another work is PA-AUG [236] which splits the objects into multiple sub-parts according to intra-object partition locations and then takes advantage of five separate augmentation methods (including Cutmix [15] and CutMixup [193]) in a partition-based way. To maintain topology information of the point cloud samples, Rigid Subset Mix (RSMix) [233] constructs synthetic examples by replacing an area of one sample with a shape-preserved part from the other sample. This extraction without distortion uses a carefully designed neighboring function considering the unordered structure and non-grid properties of the point cloud, thus preserving the structural information of the point cloud data.

Multi-modal Learning. Existing approaches for vision-language pre-training (VLP) [274] require well-aligned image-text pairs. However, obtaining adequate data is prohibitively expensive. To this end, cross-modal Cutmix (CMC) [275] is developed to utilize the large-scale image-only and text-only corpora for cross-modal alignment learning. CMC translates sentences from a multi-modal view by randomly replacing visually-grounded words in a sentence with diverse image patches and similar semantics. This may improve the data diversity while not changing the semantic meaning of scarce data and encourage the model to learn token-level interactions across modalities.

Potpourri. MixDA methods are also widely used in many other fields, such as medical imaging segmentation [276], object detection [277], semantic segmentation [278], [279], opinion mining [280], speaker verification [281], [282], automatic speech recognition [283], [284], [285], [286], video classification [287], meta-learning [288], pre-training [289], factorization machines [290], open set robustness [291], and contrast-agnostic applications [292].

In the above literature, generating more training by exploring unseen vicinity of original data and integrating more fine-grained information into training are two main factors of leveraging MixDA. We believe there will be a surge in applying MixDA methods in other fields in the near future.

5 EXPLAINABILITY ANALYSIS OF MixDA

Although numerous MixDA methods have been successfully used to solve a range of applications, it remains unclear why and how these methods work. In this section, we systematically recapitulate the explainability foundations of MixDA, focusing on explaining why mixed samples aid generalization from 3 different aspects: (1) vicinal risk minimization (VRM), (2) regularization, and (3) uncertainty & calibration. Besides, we also provide some interpretations of why MixDA works well.

5.1 Vicinal Risk Minimization

Supervised learning aims to find out a mapping function f in the hypothesis space \mathcal{F} that model the relationship between the input random variable \mathbf{X} and output random variable \mathbf{Y} . \mathbf{X} and \mathbf{Y} follow a joint distribution $P(\mathbf{X}, \mathbf{Y})$. To achieve this goal, a loss function \mathcal{L} is defined as the discrepancy between the model prediction $f(\mathbf{x})$ and the ground truth \mathbf{y} for samples $(\mathbf{x}, \mathbf{y}) \sim P$. An optimization algorithm is also required to minimize the average of the loss function \mathcal{L} over the joint distribution P to obtain the optimal function f^* :

$$f^* = \arg \min_{f \in \mathcal{F}} \int \mathcal{L}(f(\mathbf{x}), \mathbf{y}) dP(\mathbf{x}, \mathbf{y}). \quad (29)$$

Unfortunately, the joint distribution P is mostly unknown. As a remedy, the prevailing practice is to collect some training data $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^N$ – where N is the number of training examples and $(\mathbf{x}_i, \mathbf{y}_i) \sim P$ – and utilize the empirical risk to approximate the expected risk which is then minimized to attain the optimum, i.e., *empirical risk minimization* (ERM):

$$\begin{aligned} f^* &= \arg \min_{f \in \mathcal{F}} \int \mathcal{L}(f(\mathbf{x}), \mathbf{y}) dP_\psi(\mathbf{x}, \mathbf{y}), \\ P_\psi(\mathbf{x}, \mathbf{y}) &= \frac{1}{n} \sum_{i=1}^N \rho(\mathbf{x} = \mathbf{x}_i, \mathbf{y} = \mathbf{y}_i), \end{aligned} \quad (30)$$

where $\rho(\mathbf{x} = \mathbf{x}_i, \mathbf{y} = \mathbf{y}_i)$ is a Dirac mass centered at $(\mathbf{x}_i, \mathbf{y}_i)$. For ERM approximation, one of the major concerns is its generalization performance, i.e., when the size of the hypothesis space (measured by the number of model's parameters) is comparable to or larger than the number of training data N , the obtained model via ERM is prone to memorize training samples and, therefore, inevitably performs poorly when encountering new data. The reason is that the support of $\rho(\mathbf{x})$ is a one-point set $\{\mathbf{x}_i\}_{i=1}^N$, in this way, $P_\psi(\mathbf{x}, \mathbf{y})$ cannot approximate $P(\mathbf{X}, \mathbf{Y})$ exactly. To address this problem, *vicinal risk minimization* (VRM) [293] is proposed to improve the viability of ERM by replacing the Dirac mass with a vicinity function:

$$P_V(\tilde{\mathbf{x}}, \tilde{\mathbf{y}}) = \frac{1}{N} \sum_{i=1}^N V(\tilde{\mathbf{x}}, \tilde{\mathbf{y}} | \mathbf{x}_i, \mathbf{y}_i), \quad (31)$$

where V is the vicinity function that gauges the probability of the virtual example $(\tilde{\mathbf{x}}, \tilde{\mathbf{y}})$ appears in the vicinity of the training sample $(\mathbf{x}_i, \mathbf{y}_i)$. For example, a Gaussian distribution function $V(\tilde{\mathbf{x}}, \tilde{\mathbf{y}} | \mathbf{x}_i, \mathbf{y}_i) = \mathcal{N}(\tilde{\mathbf{x}} - \mathbf{x}_i, \sigma^2) \rho(\tilde{\mathbf{y}} = \mathbf{y}_i)$ is considered in [293] and this form of VRM can be interpreted as synthesizing data with additive Gaussian noise. In this vein, Mixup and Cutmix can be reformulated as a group of generic vicinal distribution:

$$\begin{aligned} \mathcal{V}_{\text{Mixup}} &= \frac{1}{N} \sum_j^N \mathbb{E}_\lambda [\rho(\tilde{\mathbf{x}} = \lambda \mathbf{x}_i + (1 - \lambda) \mathbf{x}_j, \\ &\quad \tilde{\mathbf{y}} = \lambda \mathbf{y}_i + (1 - \lambda) \mathbf{y}_j)], \\ \mathcal{V}_{\text{Cutmix}} &= \frac{1}{N} \sum_j^N \mathbb{E}_\lambda [\rho(\tilde{\mathbf{x}} = \mathbf{M} \odot \mathbf{x}_i + (1 - \mathbf{M}) \odot \mathbf{x}_j, \\ &\quad \tilde{\mathbf{y}} = \lambda \mathbf{y}_i + (1 - \lambda) \mathbf{y}_j)], \end{aligned} \quad (32)$$

where, for simplicity, we omit $(\tilde{\mathbf{x}}, \tilde{\mathbf{y}} | \mathbf{x}_i, \mathbf{y}_i)$ in the vicinity function. Obviously, Mixup and Cutmix can recover the vanilla ERM principle when setting λ as 1.

5.2 Model Regularization

From the perspective of model regularization, MixDA methods try to minimize the standard empirical risk on transformed data with a class of specific perturbation [24]. Inspired by previous analysis of dropout [294], [295], a regularized objective is elicited to specify the regularization effects of blended examples [24]. It has illustrated that Mixup and Cutmix enjoy a benefit similar to dropout [6] (inject noise to input) and label smoothing [296] (inject noise to output). Meanwhile, this work proposes to interpret them to smooth the Jacobian of the model and upgrade the calibration. Based on this, a transformation is also exploited at

test time to improve model accuracy and calibrate the vanilla prediction:

$$\text{pred}_{f^*}(\mathbf{x}_{\text{test}}) = \bar{\mathbf{y}}(1 - \frac{1}{\bar{\lambda}}) + \frac{1}{\bar{\lambda}} f^*(\bar{\lambda} \mathbf{x}_{\text{test}} + (1 - \bar{\lambda}) \bar{\mathbf{x}}), \quad (33)$$

where $\text{pred}_{f^*}(\mathbf{x}_{\text{test}})$ is the calibrated prediction for test sample \mathbf{x}_{test} . $\bar{\mathbf{x}}$ and $\bar{\mathbf{y}}$ are the mean of the entire training input set and training output set, respectively. $\bar{\lambda}$ is the expectation of mixture ratio λ . It is found that the decision surface trained with mingled samples is smoother than that obtained by conventional ERM [38].

Another parallel and independent work has been done in [25]. It demonstrates that training with mixed samples is the same as approximating the regularized loss minimization. Specifically, mix-based approaches directly restrain the Rademacher Complexity [297] of the underlying model and give concrete generalization error bounds. Therefore, it can address the overfitting issue to some extent. Besides, Mixed sample data augmentation is proven as a pixel-level regularization exposed on the input gradients and Hessians in [26]. For example, Cutmix actually tries to regularize the input gradients based on pixel distances.

5.3 Uncertainty & Calibration

Consider the most commonly used calibration metric ECE (expected calibration error):

$$\text{ECE} = \mathbb{E}_{p \sim P_{\hat{p}}} [\|\mathbb{P}(\hat{y} = y | \hat{p} = p) - p\|], \quad (34)$$

where $P_{\hat{p}}$ is the probability distribution of \hat{p} – the largest item in the model output softmax vector. Following [118], we assume the model is a Gaussian classifier:

$$f(\mathbf{x}) = \text{sgn}(\boldsymbol{\omega}^\top \mathbf{x}), \quad (35)$$

where $\boldsymbol{\omega} = \sum_{i=1}^N \mathbf{x}_i y_i / N$ in which different from \mathbf{y}_i is a one-hot vector, y_i is the scalar label ($y_i \in \{-1, +1\}$). Given \mathbf{x} and $\boldsymbol{\omega}$, the prediction is obtained by:

$$y = f(\mathbf{x}) = \arg \max_{c \in \{-1, 1\}} p_c(\mathbf{x}), \quad (36)$$

where $p_c(\mathbf{x})$ is the probability of class c and is defined as:

$$p_c(\mathbf{x}) = \frac{1}{e^{-2c \cdot \boldsymbol{\omega}^\top \mathbf{x}_i / \sigma^2} + 1}, \quad (37)$$

where σ is the standard deviation vector. After applying MixDA (taking Mixup as an example), augmented data is $\{\tilde{\mathbf{x}}_{i,j}(\lambda), \tilde{\mathbf{y}}_{i,j}(\lambda)\}_{i,j=1}^N$, leading to another classifier:

$$f_{\text{mix}}(\mathbf{x}) = \text{sgn}(\boldsymbol{\omega}_{\text{Mix}}^\top \mathbf{x}), \quad (38)$$

where $\boldsymbol{\omega}_{\text{mix}} = \mathbb{E}_{\lambda \sim P_\lambda} \sum_{i,j=1}^N \tilde{\mathbf{x}}_{i,j}(\lambda) \tilde{\mathbf{y}}_{i,j}(\lambda) / N^2 - P_\lambda$ is the distribution of mix ratio. The result is that MixDA helps calibration more when the feature dimension is higher:

$$\text{ECE}(f_{\text{mix}}) < \text{ECE}(f). \quad (39)$$

Besides, it has been proved that the above analysis also holds for semi-supervised learning [118].

Experiments conducted on several image classification benchmarks and models [106] demonstrate that mix-trained deep neural networks can significantly improve calibration. In other words, the generated softmax scores are much closer to the actual likelihood than the conventional models. Besides, solely mingling inputs or features cannot achieve the same degree of calibration. This suggests that the mix of targets, as a form of label smoothing [296], [298], plays an important role in improving calibration. In total, mixed training effectively mitigates the over-confident in data with noise or from out-of-distribution.

5.4 Properties & Interpretations of MixDA

MixDA has many appealing properties which have been extensively surveyed in this work. However, few works have explicitly summarized these properties and interpreted their functions in improving the model performance. Here we bridge this gap.

- MixDA methods such as Mixup and Cutmix oblige linear behavior in-between training examples. This property can significantly decrease the probability of oscillations when predicting examples that are *not* from training distribution. It also facilitates model generalization through averting memorization.
- As a kind of “local linearity” regularization, MixDA training encourages the decision boundaries to transit linearly between classes, which accordingly smooths the estimate of uncertainty [43], [52], [91]. Through the lenses of label-smooth [298], the manipulation of mixing class labels of the λ -blended images with the ratio $\lambda : (1 - \lambda)$ prevents excessively pursuing the rigid $0 - 1$ estimation. It, in turn, enables the model to account for uncertainty. These merits also boost the calibration and performance in unbalanced scenarios (e.g., in PUL learning [96], [97]).
- Training with mixed instances is more stable regarding gradient norms and model predictions, which is crucial for generative models such as GANs [14] and DDPM [254]. Besides, MixDA bears some similarities with adversarial training as both of them aim to explore some area out of the data manifold. Also, as a typical data augmentation method, MixDA heals the data-hungry issue in adversarial training [249], [250], [251].
- Either Mixup or Cutmix methods are simple enough to be accommodated into existing learning models. More importantly, mix operations are usually data-independent and model-agnostic. Therefore, MixDA methods are generic for a wide range of application domains, as summarized in Section 4.

6 DISCUSSION

In this section, we present findings w.r.t. the current research of MixDA and provide insight into remaining open challenges in this domain. In this way, future researchers can pinpoint promising future research directions therein.

6.1 Revisiting MixDA

By revisiting current MixDA methods, we have the following important findings.

- **Finding 1: Research attention for Mixup and Cutmix.**

Despite the similarity between Mixup and Cutmix, their adaptions focus on different points. For Mixup, considerable work aims to adaptively determine mix ratio λ (Section 3.1.3) or choose more appropriate samples (Section 3.1.4) for mixing. As for Cutmix, in contrast, existing methods studied how to select the cut patch and the location to paste (Section 3.2.2 and Section 3.2.3). The main reason is that Cutmix was proposed from a local perspective with the constructed rectangle region, while Mixup was designed from a holistic view with a global mix ratio.

- **Finding 2: Tradeoff between plausibility and diversity.**

In general, MixDA has undergone the following evolutionary process. In the beginning, vanilla Mixup and Cutmix blindly

combine training samples. Later, saliency information has been leveraged to guide the combination of mixed examples (cf. Section 3.1.5 and Section 3.2.2) for generating more plausible augmented data. However, the informative patches are limited, making generated data less diverse. In turn, overemphasizing diversity could construct many irrational training data. Therefore, future work could focus on how to get a favorable tradeoff between these two factors.

- **Finding 3: Mixing more samples and the mix of MixDA.**

Most reviewed methods consider how to mix 2 training samples, while some researchers begin to investigate how to combine more examples in each mix process to increase augmentation diversity (cf. Section 3.1.6). Besides, combining MixDA methods (i.e., the mix of MixDA) becomes popular which has been demonstrated effective for further improving model performance (cf. Section 3.3).

6.2 Open Challenge Problems

Although MixDA methods have achieved desirable performance on a number of applications, several challenges remain in training MixDA models.

- **Challenge 1: Distortion in Mix.** MixDA methods inevitably distort the origin input in some way, potentially leading the vicinal distribution to mismatch with the true data distribution. Although this property benefits robustness, mixed examples introduce some noise into the data manifold. Therefore, how to reduce or even take advantage of this perturbation is a critical challenge in MixDA domain.

- **Challenge 2: Combining multiple DA.** Integrating various data augmentation methods into a pipeline is a natural choice for deep learning methods. Nevertheless, determining the order of multiple data augmentation is a challenging task. For example, it is widely believed that Mixup after rotation performs better than rotation after Mixup. Unfortunately, a principled way and theoretical understanding remain elusive in the literature.

- **Challenge 3: The function of λ .** The role of mix ratio λ is not well identified. In the conventional Mixup and Cutmix strategies, its value is determined via a Beta distribution which is empirical and casual. Although some research has developed methods to decide this important coefficient adaptively, there are few studies explaining the implication behind this ratio and how to determine its value efficiently.

6.3 Research Opportunity

Finally, we outline several exciting research opportunities for future researchers in the area of MixDA.

- The relationship between MixDA and regularization methods (e.g., weight decay) should be further investigated. For example, training with Mixup requires $5\times$ lower amount of weight decay on CIFAR-10 [33]. It is evident that MixDA has some cross-cutting and complementary effects with regularization approaches. Reformulating MixDA as some form of regularization or reinterpreting the regularization method from the perspective of MixDA benefits both lines of work. For example, identifying the relationship between MixDA with Lipschitz continuity is a potential proposal.

- Mix training has demonstrated its effectiveness for uncertainty estimation and calibration. However, mix-based test-time augmentation for estimating uncertainty and calibrating

- model output, similar to spatially transforming images or adding noise into images in [299], is less explored. For instance, generating test-time augmented versions for each testing sample by mixing it with examples randomly sampled from training data is a straightforward solution, however, maintaining a buffer for all training data is prohibitive. Therefore, finding prototypes or proxies for training examples is also an interesting problem that needs to be well-studied.
- How to help time series problems or reinforcement learning tasks with MixDA methods, such as generating extensive plausible scenarios for autonomous driving, is also an urgent issue due to the temporal dependence and the cumulative error issues. For example, blending environment perception results from adjacent timestamps can provide more fine-grained information for downstream tasks.
 - Combining more than 2 examples is still an under-explored field that can significantly increase the diversity of augmented data. Iterative execution of Mixup and Cutmix to mingle multiple samples can improve the diversity of augmented data and benefit from the advantages of Mixup’s global view and Cutmix’s local perspective.
 - Identifying the limits of this line of work also is necessary for both understanding existing MixDA methods and designing improved MixDA approaches. Take MixDA on graph learning as an example, generated soft label for the newly constructed node will aggravate the under-confidence issue in GNNs [300].

7 CONCLUSION

Data augmentation is always an important research topic in machine learning and deep learning research. In this survey, we systematically review the mix-based data augmentation methods by providing an in-depth analysis of techniques, benchmarks, applications, and theoretical foundations. First, we introduced a new classification for MixDA methods. In this context, a more fine-grained taxonomy categorizes existing MixDA approaches into different groups based on their motivations. Then we thoroughly reviewed various MixDA methods while recapping their advantages and disadvantages. Additionally, we comprehensively surveyed more than ten categories of MixDA applications. Besides, we provide readers with theoretical examinations of MixDA through the lens of ERM, regularization, and uncertainty & calibration, respectively, while explaining the success of MixDA by examining the critical properties of MixDA. Finally, we summarize our important findings w.r.t. the tendency of MixDA research and the main challenges in existing studies, and outline the potential research opportunities for future works in this field. With this review, we hope researchers and practitioners find a technical brochure of MixDA methods and their applications, as well as directions to address fundamental problems and advance this field.

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