Debiased Learning from Naturally Imbalanced Remote Sensing Data

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Abstract

Deep learning has shown remarkable success in analyzing grounded imagery, such as consumer photos due to large-scale human annotations are available for dataset, e.g., ImageNet. However, such extensive supervision is not the case for remote sensing data.

We propose a highly effective semi-supervised approach tailored specifically for remote sensing data. Our approach encompasses two key contributions. We adapt the framework from semi-supervised learning approach, such as FixMatch, to remote sensing data by designing a set of robust strong and weak augmentations suitable for this domain. By learning from actual labeled data, combining with pseudo-labeled data, yet address the pseudo-labeling imbalance, we leverage a recently proposed debiased learning approach to mitigate the bias in pseudo-labeling.

Validated by extensive experimentation, our simple semi-supervised framework with 30\% annotations delivers significant accuracy gains over the supervised learning baseline by 7.1\%, and over recent supervised state-of-the-art, CDS by 2.1\% on remote sensing XView data.

1. Introduction

Deep learning has enjoyed remarkable success in analyzing natural images, primarily due to the extensive human annotation available in datasets such as ImageNet \cite{deng2009imagenet}. However, the scenario changes significantly when it comes to remote sensing data \cite{yu2016xview,yu2016xray}. While there is an abundance of remote sensing data available, there are limited annotations due to the challenges in annotating such data. The scarcity of annotations is primarily attributable to the uncommon viewing angles and the ambiguity present in the remote sensing data, making it difficult for humans to perform annotation accurately.

Previous works, such as transfer learning approaches, have shown significant success in handling specific data domains by starting with a model pretrained on ImageNet \cite{deng2009imagenet} and fine-tuning it with a few samples of the target domain. These approaches have been highly effective in medical imaging \cite{johnson2019cycada} and self-driving \cite{zhou2017neural} tasks. However, unlike these image domains, remote sensing data is characterized by a lack of high-resolution details and class-imbalanced properties, making it challenging to transfer from a pre-trained model directly \cite{park2017deep,yu2016xray,luo2019large}.

Additionally, several self-supervised learning methods \cite{noroozi2016unsupervised,grill2020bootstrap,caron2020unsupervised,chen2020improved} have been proposed, which can learn a representation without human-annotated data. However, learning self-supervised models without pretraining is expensive and time-consuming. Moreover, the ability to discriminate positive and negative pairs can be worse on remote sensing data than on natural images due to the ambiguity in the data.

In remote sensing scenarios with limited annotated data
and abundant unlabeled data, semi-supervised learning techniques hold significant promise. FixMatch [30] is a popular approach that combines weak and strong augmentations with pseudo-labeling to enhance the learning process. However, to adapt these techniques to remote sensing domains, we focus on the design of robust weak and strong augmentations specifically tailored for this context. We investigate the benefits of incorporating rotation, scaling, and horizontal flipping, aiming to improve the analysis and interpretation of remote sensing data. By thoughtfully integrating these augmentation strategies, we unlock the full potential of semi-supervised learning, enabling more effective and context-aware analysis techniques in remote sensing.

Furthermore, some previous studies have shown that machine-generated pseudo-labels often suffer from inherent imbalances [36]. This imbalance poses a challenge for learning models as it introduces a bias towards false majorities within the pseudo-labels. Similar issues have been observed in widely used datasets like CIFAR and ImageNet [36]. To address this bias problem specifically in the context of remote sensing data, we incorporate the DebiasPL [36] method, which aims to alleviate the bias associated with pseudo-labeling. In Figure 2, we illustrate the framework of our approach, and we summarize our key contributions in this work as follows:

1. We adapt the framework of semi-supervised learning approaches, such as FixMatch, to remote sensing data by designing a set of robust strong and weak augmentations specifically tailored to this domain.

2. We leverage the recently proposed DebiasPL method to mitigate the bias in pseudo-labeling by combining actual labeled data with pseudo-labeled data and addressing the imbalance in pseudo-labels.

3. We conduct extensive experiments that demonstrate the effectiveness of our approach. Validated through extensive experimentation, our simple semi-supervised framework with 30% annotations achieves significant accuracy gains over the supervised learning baseline by 7.1% and outperforms the recent supervised state-of-the-art, CDS, by 2.1% on remote sensing Xview data. This is illustrated in Figure 1.

2. Related Works

Semi-supervised learning (SSL) learns over both limited labeled data and relatively larger unlabeled data. A large portion of SSL approaches [2, 3, 19, 20] follow the self-training scheme that generates pseudo-labels to the unlabeled data based on the model learned from limited labeled data. FixMatch [30] learns to predict pseudo-labels using weakly- and strongly-augmented versions of an image and then matches both predictions via the cross-entropy loss. There are other lines of work such as consistency regularization [22,32] that apply perturbations to affect the classification loss. Transfer learning [7] approaches first learn a supervised or self-supervised model, then fine-tune the model with a supervised classifier via limited labeled data. Though previous SSL approaches achieve considerable success on natural image data and remote sensing data [37], the focus of this work is to leverage insights of SSL to remote sensing image data to develop a robust augmentation pipeline, yielding better performance.

Imbalanced-class learning learns representations that are suitable for rare classes without significantly reducing performance on majority classes. In most scenarios, the class imbalanced problem exists in real-world data [13,34], presenting a huge challenge to deep neural networks [1]. Previous works are composed of 1) re-balancing and re-weighting approaches [9, 23] that provide more weighting
to the rare classes, 2) margin-based approaches [5] that aim to impose a large margin to rare classes and have shown to be effective for the generalization of minority classes, and 3) ensemble-based approaches [35] that learn multi-expert models across classes to mitigate the data bias and variance. Unlike all the aforementioned works that mainly focus on imbalanced human annotation, we apply an approach that aims to alleviate the bias of machine annotation (i.e., pseudo-labeling) in the training data.

3. Debiased Semi-Supervised Learning

Our work provides a comprehensive review of recent advancements in addressing the data imbalance in remote sensing images. Specifically, we first review the FixMatch [30] and semi-supervised learning. We then discuss the two sources of imbalance in remote sensing data and review two methods for addressing them: debiased learning [36] to address pseudo-label imbalance and logit adjustment [21] to address training label imbalance. Finally, we present our new findings on the most effective augmentations in remote sensing data. Overall, our paper provides valuable insights for researchers and practitioners working in the field of remote sensing data.

3.1. FixMatch

FixMatch [30] is a semi-supervised learning approach based on pseudo-labeling. The two branches of inputs are based on weak- and strong-augmented images to generate augmented samples for unlabeled data. Suppose we have been given a mini-batch of labeled data $\mathcal{X} = \{(x^i_l, y^i_l) : i \in \{1, \ldots, B^l\}\}$ and of unlabeled data $\mathcal{U} = \{x^u_j : j \in \{1, \ldots, B^u\}\}$, and the loss function of labeled data $\mathcal{X}$ can be formed as:

$$L_s = \frac{1}{B^l} \sum_{i=1}^{B^l} \mathcal{H}(y^i_l, f(\mathcal{W}(x^i_l); \theta))$$

where $\mathcal{H}(\cdot, \cdot)$ is the cross-entropy function, and $\mathcal{W}(\cdot)$ is the weak augmentation. In order to deal with the unlabeled data $\mathcal{U}$, the widely used strategy is to generate the pseudo-label by obtaining the prediction via weak augmentation: $\hat{y}^u = \max (f(\mathcal{W}(x^u_j); \theta))$. Based on the given loss and pseudo-labels, we could express the loss $L_u$ for unlabeled data that computes the distance between the one-hot pseudo-label and model predictions on the strongly-augmented image $\mathcal{S}(x^u_j)$ as:

$$L_u = \frac{1}{B^u} \sum_{j=1}^{B^u} 1(\hat{y}^u_j \geq \tau) \mathcal{H}(\hat{y}^u_j, f(\mathcal{S}(x^u_j); \theta))$$

The objective function of FixMatch [30] consists of two components: $L = L_s + \lambda L_u$. Here, $L_s$ represents the loss term computed using labeled data, while $L_u$ represents the loss term computed using unlabeled data. The scalar hyperparameter $\lambda$ controls the relative importance of the two terms in the overall loss function.

3.2. Sources of Imbalance in Remote Sensing Data

One challenge in using semi-supervised learning approaches based on pseudo-labeling is to deal with the imbalanced nature of both 1) the training data and 2) the pseudo-labels. The debiased learning approach [36] illustrates that imbalances exist not only in the human-annotated labels but also in the machine-generated labels, i.e., pseudo-labels.

In order to gain a deeper understanding of this issue, we analyze the distribution (Figure 3) of imbalanced training data and pseudo-labels generated by the FixMatch [30] semi-supervised learning approach on xView [18], a remote sensing dataset. Our investigation reveals that these imbalances in the data sources can introduce notable biases during the learning process, ultimately affecting the model’s performance. Thus, our work aims to

1. apply the debiased learning method [36] to alleviate the imbalanced pseudo-labels.
2. incorporate logit adjustment [21] to mitigate the imbalanced training labels in the remote sensing data.

3.3. Debiased Learning (Pseudo-Labels)

Our approach applies a proposed debiased learning method, DebiasPL [36] on the semi-supervised learning task. The framework of DebiasPL is mainly based on FixMatch, and further embedded with an adaptive debiasing module and a marginal loss.

![Image](309x579 to 545x720)

**Figure 3.** Remote sensing data, such as xView [18], has two sources of imbalance. One is training label imbalance provided by humans, the other is pseudo-label imbalance generated by semi-supervised learning framework during learning on remote sensing data. Note that the average probability distributions of FixMatch [30] are computed by averaging over all unlabeled data. The class indices are then sorted based on their corresponding average probabilities.
Adaptive debiasing module. DebiasPL is motivated by Causal Inference [11, 24, 28] that has been shown to be effective in mitigating the selection bias in several tasks. The DebiasPL aims to integrate causality of producing debiased predictions via counterfactual reasoning. Based on [11, 25], the debiased pseudo-labeling could be performed via the debiased logit with counterfactual reasoning:

\[ \hat{\tilde{f}}_i = f(\mathcal{W}(x_i)) - \lambda \log \hat{p} \] (3)

\[ \hat{p} \Leftarrow m\hat{p} + (1 - m) \frac{1}{\mu B} \sum_{k=1}^{\mu B} p_k \] (4)

where \( m \) is the coefficient of momentum, \( f(\mathcal{W}(\cdot)) \) refers to logits of weakly-augmented unlabeled instance.

Adaptive marginal loss. Motivated by the issue that the biases in pseudo-labels usually come from inter-class confusion, the DebiasPL aims to have a larger margin between highly biased classes by designing an adaptive marginal loss \( L_{\text{margin}} \) to alleviate the inter-class confusion. The marginal loss can be expressed as:

\[ L_{\text{margin}} = -\log \frac{e^{(z_{\hat{y}_i} - \Delta \hat{y}_i)}}{e^{(z_{\hat{y}_i} - \Delta \hat{y}_i)} + \sum_{k \neq \hat{y}_i} e^{(z_k - \Delta k)}} \] (5)

where \( \Delta_j = \lambda \log \left( \frac{1}{p_j} \right) \) for \( j \in \{1, \ldots, N\}, z = f(\beta(x_i)). \) The \( \mathcal{H}(\hat{y}_i^n, f(S(x_i^n); \theta)) \) could be replaced as \( L_{\text{margin}} \), the final unsupervised loss could be updated by Eq. (2) with Eq. (3) and Eq. (5).

3.4. Logit Adjustment (Training Labels)

The performance of each majority and minority class can often be biased due to imbalanced training data. This is because the classifier may not have enough examples to learn how to distinguish the minority class from the majority class. [29] shows that the imbalanced remote sensing data also suffer from this bias, leading to poor class-wise performance. To address this issue, we aim to apply logit adjustment [21], a technique that can produce a more balanced class-wise performance during evaluation. Logit adjustment adjusts the logits of each class based on their frequency in the training data. Specifically, the adjusted logits are computed as follows:

\[ \hat{y}_i = \frac{\log(\frac{p_i}{1-p_i})}{\sum_j \log(\frac{p_j}{1-p_j})} \] (6)

where \( \hat{y}_i \) is the adjusted output for class \( i \), \( p_i \) is the frequency of class \( i \) in the training data, and the sum in the denominator ensures that the adjusted logits sum to 1. By applying logit adjustment, we expect to achieve more balanced performance across all classes in remote sensing data.

3.5. Our New Findings on Remote Sensing Data

Remote sensing data possesses unique properties that set it apart from natural images, such as pixel-level data and non-uniform ground sampling distance (GSD) [18]. Despite the impressive success of debiased learning in natural images [36], it remains uncertain whether these techniques can be effectively applied to remote sensing data. Furthermore, it is unclear

1. which types of data augmentation are most suitable for remote sensing data, and
2. what modifications may be necessary for existing techniques to achieve optimal performance.

These questions have yet to be fully addressed in debiased learning approach [36] or other related works [29, 30]. Our research aims to bridge these knowledge gaps by exploring the efficacy of debiased learning techniques in remote sensing data and identifying appropriate modifications and practices to achieve superior performance.

3.6. Data Augmentations for Remote Sensing Datasets

In semi-supervised learning (SSL) settings, the debiased learning method [36] has been shown to be effective, using random resize cropping and horizontal flipping for weak augmentation and RandAugment [8] for strong augmentation on natural images. However, these augmentation techniques do not generalize well to remote sensing data due to the distinct properties of the latter, such as a lack of details in the imagery. In Figure 4, we illustrate examples by apply-
ing RandAugment [8] with different intensities of the transformations. RandAugment appears to be too complicated for remote sensing data. To address this issue, we empirically select appropriate augmentations that can improve the SSL performance on remote sensing data. Our approach includes random resize cropping and horizontal flipping for weak augmentation, and horizontal flipping, rotation, and scaling for strong augmentation.

Table 1 shows the augmentations that were selected for use with remote sensing data, along with the reasons for their selection. Rotation and scaling were both used to simulate variations in imaging angles and ground sampling distances, respectively, which are important factors in generalizing to remote sensing data. Additionally, horizontal flipping was included to simulate mirror-reflected scenes. RandAugment was not used due to potential overfitting to the training set of remote sensing data [39].

<table>
<thead>
<tr>
<th>Augmentations</th>
<th>Used</th>
<th>Reason</th>
</tr>
</thead>
<tbody>
<tr>
<td>RandAugment [8]</td>
<td>×</td>
<td>The use of RandAugment with high intensity of transformations may result in overfitting to the training set, which can be detrimental for generalization on remote sensing data.</td>
</tr>
<tr>
<td>Rotation</td>
<td>✓</td>
<td>random rotation (± 10 degrees) can simulate variations in remote sensing imaging angles.</td>
</tr>
<tr>
<td>Scaling</td>
<td>✓</td>
<td>scaling(0.8, 1.2) can simulate variations in ground sampling distances, which is important for generalization on remote sensing data.</td>
</tr>
<tr>
<td>Horizontal Flip</td>
<td>✓</td>
<td>horizontal flipping simulates mirror-reflected scenes in remote sensing data.</td>
</tr>
</tbody>
</table>

The effectiveness of each augmentation method varies, and we present a table in Section 4 to illustrate the performance gain from each augmentation strategy we leveraged. Notably, the augmentations used in previous SSL works, such as debiased learning, may not always be beneficial to SSL settings in remote sensing images.

4. Experiments

We assess the effectiveness of our semi-supervised learning approach, on the imbalanced classification task using the xView remote sensing dataset by 1) comparing the instance-wise accuracy and class-wise accuracy of our model and baselines; 2) conducting several ablation studies on data augmentation, data preprocessing, and the learning recipe for optimizing the proposed method on remote sensing data. We note all experiments are carried out on a single machine equipped with four Nvidia RTX 2080 Ti GPUs.

4.1. Experimental Setup

Dataset. We conducted a thorough evaluation of the performance of our semi-supervised learning approach on the xView [18] dataset, which has large-scale multi-spectral images featuring 8-band channels obtained from satellite data.

The data contains ten individual classes and has the properties of a highly imbalanced distribution, which is also shown in Figure 3.

To ensure consistency with previous studies [29], we preprocessed the data by selecting a subset of 10 categories out of 60 classes, namely StorageTank, Helicopter, Pylon, Maritime Vessel (MV), ShippingContainer, Fixed-Wing Aircraft (FWAircraft), Passenger Vehicle (PV), Truck, Railway Vehicle (RV), and Engineering Vehicle (EV). These categories are illustrated in Figure 5. The dataset consisted of 20431 training samples, 2270 validation samples, and 63279 test samples. Notably, we selected the R, G, B bands from the 8-band channels to form RGB images.

Baseline methods. As our baseline methods, we employed FixMatch [30] for its straightforward implementation and proven performance in semi-supervised learning. In addition, we included a ResNet-18 supervised learning baseline and the recently proposed complex-valued model, CDS [29], to demonstrate the effectiveness of our semi-supervised learning approach.

Training and evaluation. In the semi-supervised learning setup, we employed ResNet-50 [15] as the backbone and adopted the same set of hyperparameters used in FixMatch.
Figure 6. Improve the performance of our semi-supervised learning framework by increasing the amount of labeled data. The instance-wise accuracies of our method are shown with 5% to 30% of labeled data. We improve the performance and outperform the 100% labeled data trained state-of-the-art, CDS [29] by including more labeled data.

Table 2 shows a comparison of our approach against semi-supervised and supervised learning baselines. In our initial setup, we had our framework learn on 10% labeled data with a ResNet-50 backbone pretrained on ImageNet. As shown in Table 1, the our approach achieved 80.8% accuracy, outperforming the semi-supervised learning baseline, FixMatch, by 4.6%, and the supervised learning baseline by 5.5%, respectively.

Further improved by increasing the amount of labeled data, surpassing supervised CDS approach.

### 4.2. Instance-wise Comparisons

Table 2 shows a comparison of our approach against semi-supervised and supervised learning baselines. In our initial setup, we had our framework learn on 10% labeled data with a ResNet-50 backbone pretrained on ImageNet. As shown in Table 1, the our approach achieved 80.8% accuracy, outperforming the semi-supervised learning baseline, FixMatch, by 4.6%, and the supervised learning baseline by 5.5%, respectively.

Moreover, our method outperformed the best setting of the state-of-the-art complex-valued model for remote sensing, CDS [29], which was trained with 100% labeled data, by a 0.5% gain. In Figure 6, we demonstrate that the performance of our semi-supervised learning framework can be further improved by increasing the amount of labeled data, surpassing supervised CDS approach.

### 4.3. Class-wise Comparisons

Figure 7 displays the class-wise performance of the models, showcasing their ability to classify majority and minority classes. Moreover, by incorporating logit adjustment [21], the performance of our method for each class can be further boosted.

### 4.4. Ablation Studies

The ablation study focused on evaluating the effectiveness of selected augmentation strategies on the remote sensing dataset, xView [18]. We observed that the augmentation strategies in DebiasedPL were not directly applicable to this domain due to the complexity of RandAugment [8]. Therefore, we carefully selected and adapted appropriate augmentations to improve the performance of the model.
We found that the RandAugment [8] strategy in DebiasedPL [36], which performed well on other image classification datasets, was too complex and not applicable to remote sensing data. Our findings involved carefully selecting and adapting augmentations to improve performance on the remote sensing dataset [18].

<table>
<thead>
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<th>Weak augmentation</th>
<th>✓</th>
<th>✓</th>
<th>✓</th>
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<tbody>
<tr>
<td>Random Resize Cropping</td>
<td>×</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Horizontal flipping</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
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<tr>
<th>Strong augmentation</th>
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<th>✓</th>
<th>✓</th>
<th>✓</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResizeCropping + Horizontal flipping</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Rotation (± 10 degrees)</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Scaling (0.8, 1.2)</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>RandAugment (m=10)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>×</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>RandAugment (m=5)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>×</td>
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<td>×</td>
</tr>
</tbody>
</table>

Table 3 summarizes the performance gain achieved through selected augmentations on xView. Our findings suggest that the adapted augmentations can effectively improve the performance of the model, achieving a top-1 accuracy of 80.8%, by 5.2% gain from the original DebiasedPL augmentations. These results demonstrate the importance of selecting and adapting appropriate augmentations for remote sensing datasets, which can significantly improve the accuracy of the semi-supervised learning model.

5. Conclusion

We proposed a semi-supervised approach specifically designed for remote sensing data. Our paper addressed both training label and pseudo label imbalances in this domain. Our paper has two key contributions.

Firstly, we adapt the framework of FixMatch, to remote sensing data by designing robust strong and weak augmentations tailored for this context. Secondly, we leverage a recently proposed debiased learning approach to mitigate the bias in pseudo-labeling, effectively combining actual labeled data with pseudo-labeled data.

The results of our study highlight the significant potential of our straightforward semi-supervised framework, which effectively utilizes limited annotations (30%) to achieve notable performance enhancements. These findings contribute to the advancement of remote sensing data analysis and underscore the importance of developing tailored methodologies to tackle the challenge of limited annotations in this specific domain.

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Table 3. Performance gain from selected augmentation strategy.

References


