Domain adaptation in application to gravitational lens finding

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Abstract

The anticipated tenfold increase in the number of strong gravitational lenses from upcoming wide-field imaging surveys drives the need for efficient automated detection methods. We assess the performance of three domain adaptation techniques – Adversarial Discriminative Domain Adaptation (ADDA), Wasserstein Distance Guided Representation Learning (WDGRL), and Supervised Domain Adaptation (SDA) – in enhancing lens-finding algorithms trained on simulated data (or real data) when applied to real observations from the Hyper Suprime-Cam Subaru Strategic Program. We combine domain adaptation techniques with classifier based on Equivariant Neural Network and find that: 1) the combination of ENNs and WDGRL domain adaptation method has a high potential of reducing the number of false positives; 2) the combination of ENNs and SDA improves the ability of the model to distinguish between the lenses and common false positives such as spiral galaxies.

1 Introduction

Strong galaxy-galaxy gravitational lensing, the distortion of light from a distant galaxy in the gravitational field of another massive galaxy between that source and the observer, is a powerful tool to study the universe. For example, sensitivity of the lensing observables to the distribution of mass in the lens provides a way to study the dark matter profiles of individual galaxies [4, 19, 31, 36, 40, 45], to probe the dark matter substructures on subgalactic scales [5, 8, 16, 17], and to test various dark matter theories [2, 3, 15, 22, 23, 35, 50].

Upcoming wide-field surveys like Euclid Wide Survey [20, 32] and Legacy Survey of Space and Time (LSST; [37]) are expected to yield an order of 10^5 strong lenses [14]. Given the rarity of these systems and the vast amount of data, efficient identification requires advanced automated algorithms. In recent years, deep learning models have become the primary tool for lens discoveries in wide-field surveys.

Typically the lens finding problem is treated as the image classification problem, which is well-suited for Convolutional Neural Networks (CNNs) [33]. Supervised CNN-based algorithms have demonstrated superior performance in the gravitational lens finding challenge [38] and over the last

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years have been applied to various wide-field surveys yielding a few thousands of lens candidates (e.g. [9, 10, 28, 34, 42, 44, 47]). To ensure that the supervised model is able to learn relevant features and generalize well to unseen data, the training dataset typically requires a large number of labeled samples (on the order of $10^3 - 10^4$), which exceeds the number of known lenses. Therefore it is common to use simulated lenses at the training stage (but see e.g. [24, 25] for supervised training only with observational data). However, the differences between the real observations and simulated images can significantly degrade the performance of the model [12, 13]. The gap between simulated and real data could be mitigated using domain adaptation (DA) methods.

Domain adaptation is a class of methods applied in situations when the training and test datasets come from different, but related domain, namely the source and the target domains. Based on availability of labels in the target dataset, DA methods can be divided into three categories: unsupervised domain adaptaion (UDA), when ground truth for the target data is unknown; semi-supervised domain adaptation (SSDA), where labels are available for a fraction of the target data; and supervised domain adaptation (SDA), where labels for the entire dataset are accessible.

We investigate the potential of domain adaptation techniques to enhance the performance of lens-finding algorithms. We examine two unsupervised domain adaptation methods, Adversarial Discriminative Domain Adaptation (ADDA) and Wasserstein Distance Guided Representation Learning (WDGRL), and compare them against the supervised classifier trained on the dataset containing simulated lenses. We also implement Supervised Domain Adaptation (SDA) method and compare it with the supervised classifier trained solely on the observational data.

2 Dataset

Domain adaptation requires two datasets, the source and the target. We use simulated lenses in the source dataset and real lens images in the target dataset, while non-lenses in both cases come from observations and are drawn from the sample of galaxies with magnitude brighter than 26 mag in the Hyper Suprime-Cam Subary Strategic Program (HSC-SSP) PDR2 Wide field [1].

Simulated lenses were created with `lenstronomy` [6, 7]. For the deflectors, we used preferentially red galaxies from HSC PDR2 Wide field that have spectroscopic redshifts and velocity dispersion measurements in the Sloan Digital Sky Survey (SDSS; [30]). As a background sources we used galaxies from Hubble eXtra Deep Field [26] with redshifts from Inami et al. [27]. The mass profile of the lens was approximated with a singular isothermal sphere (SIS) profile, set by velocity dispersion of the deflector: $\rho(r) = \frac{\sigma_V^2}{2\pi G r^2}$.

To construct the sample of real lenses, we compiled a list of known lens systems and lens candidates that were discovered in previous campaigns through various methods, including both machine learning and traditional approaches, including sources from the Master Lens Database[1] (version July 2021), SuGOHI Candidate List[2], and other published catalogs [9, 10, 18, 21, 24, 25, 28, 34, 41, 42, 44, 46, 47]. We crossmatched the full catalog with HSC PDR2 Wide layer and extracted cutouts in the *g*, *r*, and *i* bands. We performed a visual inspection of extracted images and excluded group-scale lenses or objects with barely visible or unclear lensed features in HSC, which is possible when the lens was discovered in a survey with higher resolution or depth. The final sample of the real lenses included 2254 objects. We left out 200 randomly selected lenses for the test set and used the rest in the domain adaptation.

3 Methods

We implemented two unsupervised domain adaptation methods: Adversarial Discriminative Domain Adaptation (ADDA, [49]) and Wasserstein Distance Guided Representation Learning (WDGRL, [43]), and Supervised Domain Adaptation (SDA, [39]).

The ADDA method aims to minimize the distance between source and target representations, $M_s(X_s)$ and $M_t(X_t)$, respectively, where M_s and M_t are source and target encoders. This is achieved through an adversarial training of the target encoder with respect to the discriminator. While the discriminator

[1] `https://test.masterlens.org/index.php`

[2] `https://www-utap.phys.s.u-tokyo.ac.jp/~oguri/sugohi/`

tries to distinguish between representations coming from different domains, the encoder learns to fool the discriminator and map target representations closer to the source ones. Once the distance between $M_s(X_s)$ and $M_t(X_t)$ is sufficiently small, then a classifier, trained on a source dataset in a supervised manner, can be applied to the target dataset.

The WDGRL method [43] adapts Wasserstein Generative Adversarial Networks (WGAN) concepts to domain adaptation. It uses Wasserstein distance to measure similarity between probability distributions, providing stable gradients even for distant distributions. The method iteratively trains three components: a domain critic D, which approximates Wasserstein distance between representations of source and target images; a feature extractor M, which maps input images to a lower-dimensional embedding space; and a classifier C, that is trained on the source dataset.

In the SDA method, the labels for the target dataset are available, allowing for contrastive semantic alignment to minimize the distance between representations while considering their class. The goal is to map same-class samples from different domains close together while keeping different-class samples well separated. The method employs semantic alignment loss $\mathcal{L}_{SA} = \sum_{a=1}^{N} d(M(\mathbf{X}_a^s), M(\mathbf{X}_a^t))$, and separation loss $\mathcal{L}_S = \sum_{a,b|a\neq b} k(M(\mathbf{X}_a^s), M(\mathbf{X}_a^t))$,, where d and k are pairwise distance and similarity metrics, respectively. As in other methods, the classifier is trained only on the source dataset.

We chose to base our encoder on the Equivariant Neural Network (ENN). ENNs are designed to preserve inherent symmetries in data through their architecture, making them particularly useful for gravitational lenses that often display rotational and reflectional symmetries. This approach leads to more efficient learning, better generalization, and reduced need for data augmentation. We implemented an ENN using the `e2cnn` package [11], incorporating the dihedral group D4, which includes identity transformation, rotations by by $\pm\pi/2$ and π, and horizontal/vertical reflections. Our model consists of six equivariant convolutional blocks, each containing a convolutional layer, batch normalization, and ReLU activation, with the final layer outputting a 256-dimensional representation. For the classification task, the encoder is followed by a simple network, consisting of two fully connected layers outputting binary classification.

4 Results

We examine the applicability of domain adaptation between mock lenses and real lens observations from HSC for the purposes of lens identification. For training we use 27,000 images per class in the source dataset, and 1,754 images per class in the target dataset. For validation, we use 3,000 images per class in the source dataset and 300 images per class in the target dataset. The size of the sample in the target domain is limited by the number of known lens candidates. We trained the base classifier for 100 epochs with a patience of 5 epochs, so the training stops if the validation loss of the model does not improve for 5 consecutive epochs. We use the Adam optimizer [29] to minimize losses and 1-cycle scheduler to adjust the learning rate. Learning rate was set to 1×10^{-5} and weight decay to 1×10^{-6}.

We employ the Receiver Operating Characteristic (ROC) curve and the area under this curve (AUROC) as our primary evaluation metrics. Additionally, we utilize $\mathrm{TPR}_{0.01}$ – the true positive rate at a false positive rate (FPR) of 0.01. This is particularly relevant for lens finding, where achieving low contamination while maintaining high identification rates is crucial. In typical automated lens searches, human experts validate positive examples as the final stage, so it is essential to minimize false positives while maintaining a high sensitivity.

We start by training an ENN classifier on the source dataset that contains simulated lenses. While this classifier achieves an AUROC of ~ 0.995, when evaluated naively (without domain adaptation) on the test dataset containing 200 real lenses and 20,000 non-lenses, its AUROC drops to 0.921. Application of domain adaptation results in improvement in AUROC: 0.942 for ADDA and 0.940 for WDGRL, shown in Fig. 1 (left). At the threshold, providing a FPR of 0.01, model adapted with WDGRL is able to recover 1.15 times more lenses than ADDA, and 1.49 times more lenses than the naive approach, which is summarized in Table 1

As a benchmark for the supervised DA, we trained a supervised classifier on the unbalanced dataset containing 1,754 real lenses and 28,754 real non-lensed galaxies. We also added 1,754 spiral galaxies drawn from a subsample of galaxies with redshift > 0.4 from a catalog of Tadaki et al.. Spiral

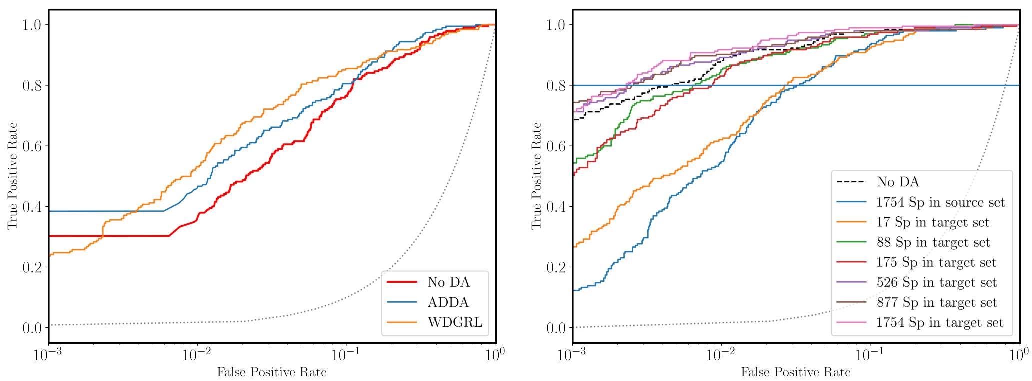

Figure 1: Left: Application of unsupervised domain adaptation between simulated and real lenses. Right: Application of supervised domain adaptation to a dataset containing spiral galaxies in addition to lenses and regular non-lensed galaxies. For the supervised domain adaptation (SDA), target datasets with varying number of spiral galaxies have been used, blue curve represents a setting where all spiral galaxies are added to the source dataset.

Table 1: Results for unsupervised domain adaptation algorithms

Method	AUROC	$\mathrm{TPR}_{0.01}$	$\mathrm{F1}_{0.01}$
No DA	0.921	0.354	0.303
ADDA	**0.942**	0.462	0.377
WDGRL	0.940	**0.528**	**0.416**

galaxies (along with ring galaxies and merging galaxies), are among the most common contaminants in lens searches because their spiral arms resemble the arc and ring-like features of the gravitational lenses.

We assess whether supervised domain adaptation can help distinguish spiral galaxies from lenses and test how the model's performance scales with the number of added spiral galaxies. To evaluate the models, we constructed a modified test dataset that includes 6,000 spiral galaxies, 200 lenses, and 20,000 non-lenses.

The results of the evaluation on the modified test dataset are shown in Fig. 1. The SDA model with all spiral galaxies included in the source dataset (blue curve) has the lowest performance. The other solid lines represent SDA models that do not have spirals in the source dataset but instead include an increasing number of spirals in the target dataset. The AUROC score improves as a larger number of spirals are added to the target dataset, suggesting that it is critical for the model to "see" a representative dataset during the adaptation stage. However, after approximately 500 added spirals, the improvement becomes negligible, and we plan to examine this in more detail in future. The black dashed line shows the ROC curve for the model without domain adaptation, trained on the observational unbalanced dataset. Despite the relatively small number of positive samples, it has only marginally lower performance than the models with supervised domain adaptation. In addition to examining the recall at a false positive rate of 0.01, we compared the false positive rate for spiral galaxies only at a true positive rate of 0.8. Overall, the number of misclassified spiral contaminants is low for the best-performing models. However, the top models with supervised domain adaptation outperform the model without domain adaptation and demonstrate three times smaller number of misclassified spiral galaxies, even though they had seen a lower number of spirals in the training dataset. The summary of results is listed in Table 2.

5 Discussion & Conclusion

In this work, we show that domain adaptation can enhance the performance and reliability of CNN-based gravitational lens detection algorithms, addressing the limited sample of known lenses and the shift between simulated training data and real observations. We used simulated mock lenses as positive examples in the source dataset and observations from HSC-SSP PDR2 Wide layer in the

Table 2: Results for supervised domain adaptation algorithm trained on a dataset with spiral galaxies.

N_{Sp} in tgt	AUROC	$\mathrm{TPR}_{0.01}$	$\mathrm{FPR}_{\mathrm{Sp}}$
No DA	0.988	0.882	0.009
1754 (in src)	0.968	0.549	0.134
17	0.971	0.621	0.113
88	0.987	0.851	0.022
175	0.984	0.831	0.028
526	0.989	0.892	0.004
877	0.985	0.903	0.004
1754	**0.994**	**0.918**	**0.003**

target dataset. For unsupervised domain adaptation, we implemented ADDA and WDGRL methods, with WDGRL showing the largest improvement in ROC score compared to naive inference. For supervised domain adaptation we also tested the model's ability to distinguish between lenses and spiral galaxies, finding that an algorithm adapted to the target dataset with spirals outperforms the naive classifier trained on the source dataset with spiral galaxies. In lens searches, algorithms are typically applied to large datasets (10^6-10^7 objects), with high-scoring candidates visually inspected by human experts. Our experiment showed that the combination of ENN-based algorithm and domain adaptation methods is particularly effective at low false positive rates, which is crucial for reducing the number of false positives in future surveys. In future, we plan to include other common types of contaminants (e.g. ring galaxies or interacting galaxies) to the dataset in order to improve the purity of the identified lenses.

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