Semi-Supervised Domain Adaptation for Cross-Survey Galaxy Morphology Classification and Anomaly Detection

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Abstract

In the era of big astronomical surveys, our ability to leverage artificial intelligence algorithms simultaneously for multiple datasets will open new avenues for scientific discovery. Unfortunately, simply training a deep neural network on images from one data domain often leads to very poor performance on any other dataset. Here we develop a Universal Domain Adaptation method DeepAstroUDA, capable of performing semi-supervised domain alignment that can be applied to datasets with different types of class overlap. Extra classes can be present in any of the two datasets, and the method can even be used in the presence of unknown classes. For the first time, we demonstrate the successful use of domain adaptation on two very different observational datasets.

Data

- Source domain: Galaxy Zoo 2 - SDSS [1];
- Target domain: Galaxy Zoo 3 - DECaLS [2].

Three filter images (i, r, g), 256 x 256 pixels and normalized to [0,1].

Training - validation: test = 60% : 20% : 20%.

Example images from the 3-class problem. Top row: source domain SDSS data (spiral and elliptical); Bottom row: target domain DECaLS data (spiral, edge-on without bulge, edge-on with bulge).

Experiments

3 classes:
- known (source and target) - barred spiral, round smooth elliptical;
- unknown target domain class - merging galaxy.

10 classes:
- known (source and target) - disturbed, merging, round smooth, cigar shaped smooth, barred spiral, unbarred tight spiral, unbarred loose spiral, edge-on without bulge, edge-on with bulge;
- unknown target domain class - gravitationally lensed galaxies.

Source domain classification is performed via cross-entropy loss $\mathcal{L}_{CE}$, while domain adaptation (DA) and clustering of similar objects into classes is performed via two loss functions (with weight $\lambda \approx 0.105$):

$$\mathcal{L} = \mathcal{L}_{CE} + \lambda (\mathcal{L}_{AC} + \mathcal{L}_{ES})$$

- Adaptive clustering $\mathcal{L}_{AC}$: semi-supervised clustering [3, 4] that groups unlabeled target domain samples into clusters by computing pairwise similarities among the extracted features, then forcing the class labels predicted by the classifier for samples with large pairwise feature similarities to be consistent.
- Entropy Separation $\mathcal{L}_{ES}$: align classes present in both datasets, while pushing away the classes present only in one of the domains [5]. This is possible because unknown samples often do not share features with known samples, which leads to larger entropies for unknown samples compared to entropies between shared classes [6].

Domain Adaptation with DeepAstroUDA

Top (3-class): left - target domain accuracies during training (elliptical in violet, spiral in navy and unknown merger class in yellow); right - loss functions during training (CE loss in yellow, AC loss in green, ES loss in dark green). Vertical dashed lines on the left plot show epochs in which hyperparameters of the ES loss were fine-tuned.

Bottom (10-class): left - target domain mean known class accuracy (dark blue), unknown gravitational lens class accuracy (red) and mean accuracy for all classes (black dashed line); right - target test set confusion matrix to illustrate confusion between morphologically similar classes (disturbed 7, merging 1, round smooth 2, cigar shaped smooth 3, barred spiral 4, unbarred tight spiral 5, unbarred loose spiral 6, edge-on without bulge 7, edge-on with bulge 8, lenses 9).

Aligning the data distributions allows the model to work well on unlabeled target data. Domain-invariant features make training harder, prevent overfitting on the source domain, and increase performance even on the labeled source data.

DeepAstroUDA can:
- perform well on complex domain shift problems, such as working with astronomical data originating from different surveys;
- handle any type of domain overlap and work in the presence of unknown classes, which can be used for anomaly detection tasks, such as merging galaxies or gravitational lens searches.

References