Domain adaptation techniques for improved cross-domain study of galaxy mergers

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INTRODUCTION

In astronomy we often rely on complex simulations, which provide large labeled data sets suitable for training machine learning (ML) models, with the prospect of later applying these models to real observations. Simulated and real data will always have small differences, rendering standard ML models trained in one domain sub-optimal in others. ***We demonstrate the use of two techniques– Maximum Mean Discrepancy (MMD) and adversarial training with a Domain Adversarial Neural Network (DANN)– for the classification of distant galaxy mergers from the Illustris-1 simulation, where the two domains presented differ only due to inclusion of mimicked observational noise.***

METHODS

The effects of MMD and adversarial training are applied through the addition of a transfer loss component to the total loss backpropagated through a base network.

MAXIMUM MEAN DISCREPANCY

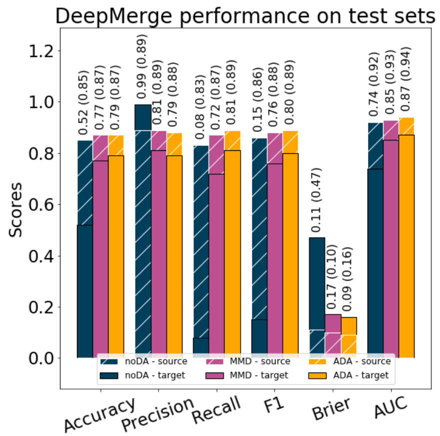
MMD as a transfer loss works by minimizing the distance between the means of the source and target distribution in latent space using kernel methods [1].

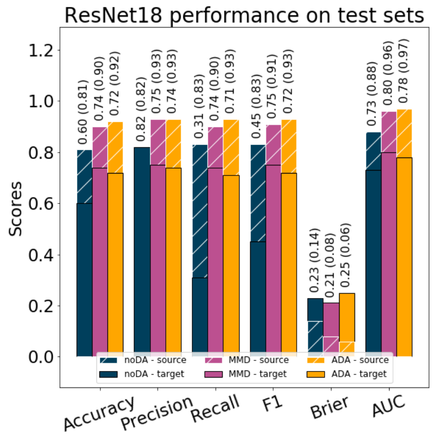
ADVERSARIAL TRAINING

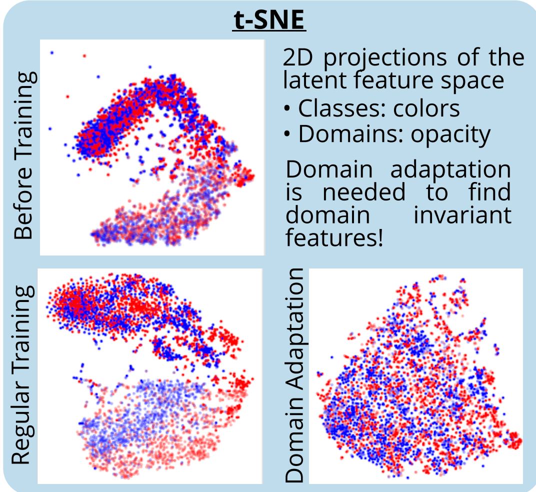
Adversarial training employs a DANN [2] to distinguish between the source and target domains. When the domain classifier fails to discriminate between the domains, domain-invariant features have been found and the classifier can be successfully applied across the two domains.

RESULTS

We present the performance of both domain adaptation techniques with two base networks: DeepMerge (DM) [3] and the more complex ResNet18 (RN18) [4]. We train our two classifier networks without any domain adaptation on the pristine labeled source data, as well as with the addition of MMD and adversarial training, which also use the unlabeled target data.



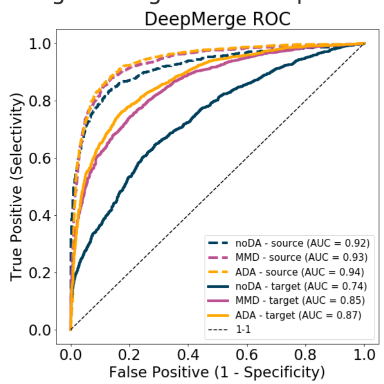


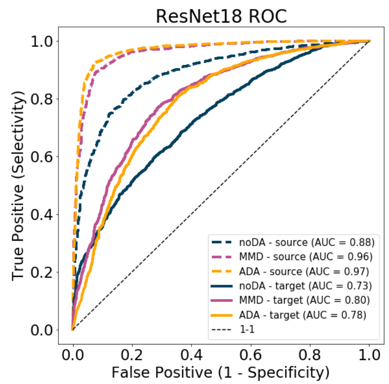


A slight decrease in source domain accuracy is expected with domain adaptation to compensate for recognition of shared features across domains. However, we actually observed an increase in source domain accuracy due to the regularizing effect of the additional transfer losses. Furthermore, we posit that the smaller improvements made with ResNet18 in the target domain are the result of much greater architecture complexity, rendering training more susceptible to source overfitting.

CLASSIFICATION ACCURACY

	Source Domain		Target Domain	
	DM	RN18	DM	RN18
noDA	84.8%	81.1%	52.0%	60.5%
MMD	86.9%	90.4%	76.6%	**73.8%**
DANN	**87.4%**	**92.3%**	**78.6%**	71.6%





CONCLUSION

Astronomy is entering the era of Big Data, with a plethora of simulations and many large-scale sky surveys. ***MMD and DANNs show great promise in astronomy to:***

- Substantially ***improve the performance of a source-trained model on a new and often unlabeled target domain*** data set and enable the harnessing of all available data.
- ***Increase robustness of ML models and help with uncertainty quantification*** due to modeling and inherent data characteristics.

REFERENCES [1] Gretton, A. et al. (2008) , arXiv:0805:2368. [2] Ganin, Y. et al. (2016), Journal of Machine Learning Research, 17, 1. [3] Ćiprijanović, A. et al. (2020), Astron. Comput., 32, 100390. [4] He, K. et al. (2015), arXiv:1512.03385.

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