MagNet: Deep Vision for the Cosmic Dawn

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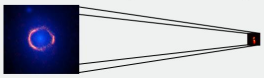
Motivation

We currently understand relatively little about how galaxies form. Much of our understanding could be enhanced if we were able to make detailed images of the most distant galaxies. These galaxies formed at the cosmic dawn, within the first billion years of the universe, and thus hold the keys to understanding the bulk of star formation throughout cosmic history.

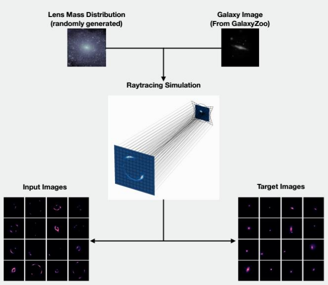


Much of our understanding could be furthered using gravitational lensing. Gravitational lensing magnifies background galaxies, making them detectable. Unfortunately, in doing so it causes significant image distortions. Correcting this distortion is critical to understanding how stars formed in the first galaxies.

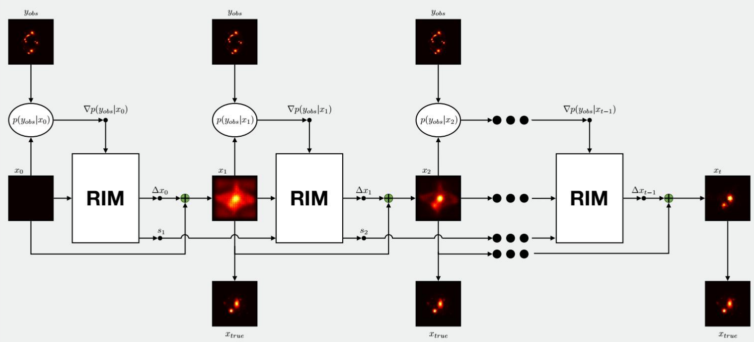
Current source reconstruction methods solve an inverse problem, and thus require *ad hoc* specification of a functional form of regularization. Most available choices are ill-suited to explain the structures observed in galaxies, and can potentially cause systematic biases. They are also expensive to evaluate.

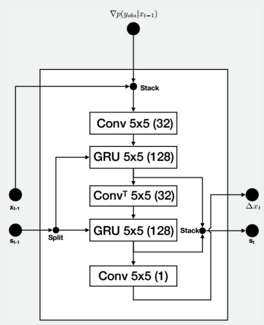
In this project, we propose to replace traditional source reconstruction methods with deep learning techniques.

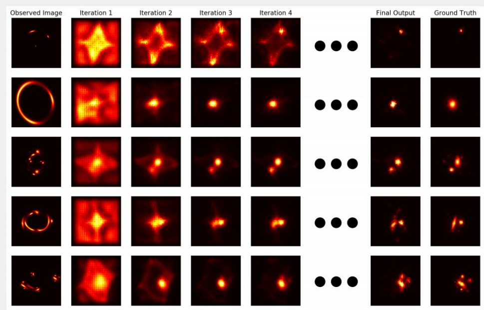
Training Set Generation



Network Architecture

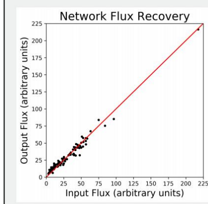


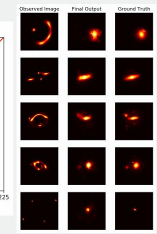




This figure shows the reconstruction process of the trained network applied to 5 example images in the test set. The leftmost column shows the observed image, which is highly distorted due to the effects of the lensing. The second column shows the output of the first pass through the RIM cell. Columns moving further to the right show the outputs of successive passes through the RIM cell. The rightmost column shows the ground truth image.

Results





Over the Ensemble of test images, the network accurately recovers the flux of the input images (left Figure). This is important, because the flux is the quantity of interest when predicting star formation rates in the early universe. The morphology is recovered as well, as can be seen in the right Figure. This recovery is independent of the size, ellipticity, or number of the source components.

Conclusions & Future Directions

- The RIM accurately reconstructs the source images of gravitational lenses, both in morphology and flux.
- Although we trained using 20 iterations in the RIM, it only needed 10 steps to find the optimal solution.
- Qualitatively, images with very compact sources resulted in worse reconstructions. This may be improved using a scalable source grid size.
- This project assumed that the images had significant SNR such that noise was essentially unobservable. Future iterations should train with larger noise levels.
- Much of the gains from this method will come from reconstructions of interferometric images. We defer this to future work.

References

1. Putsky, P, & Welling, M., *Recurrent Inference Machines for Solving Inverse Problems, arxiv: 1706.04008*