Machine Learning investigations for LSST

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Strong lens mass modeling and Photometric redshift estimation

Gravitational lensing

Based on general relativity, light gets deflected by mass. This effect is called gravitational lensing and the deflection strength depends on the mass of the lens, for instance a galaxy.

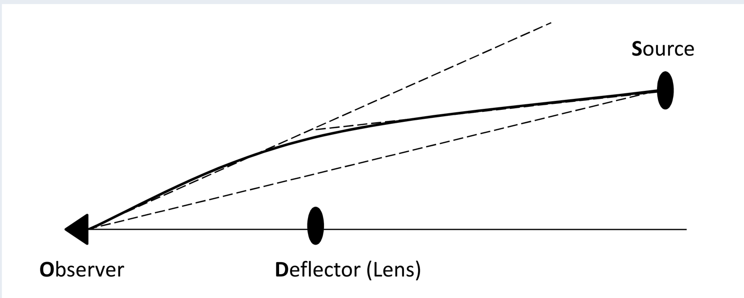
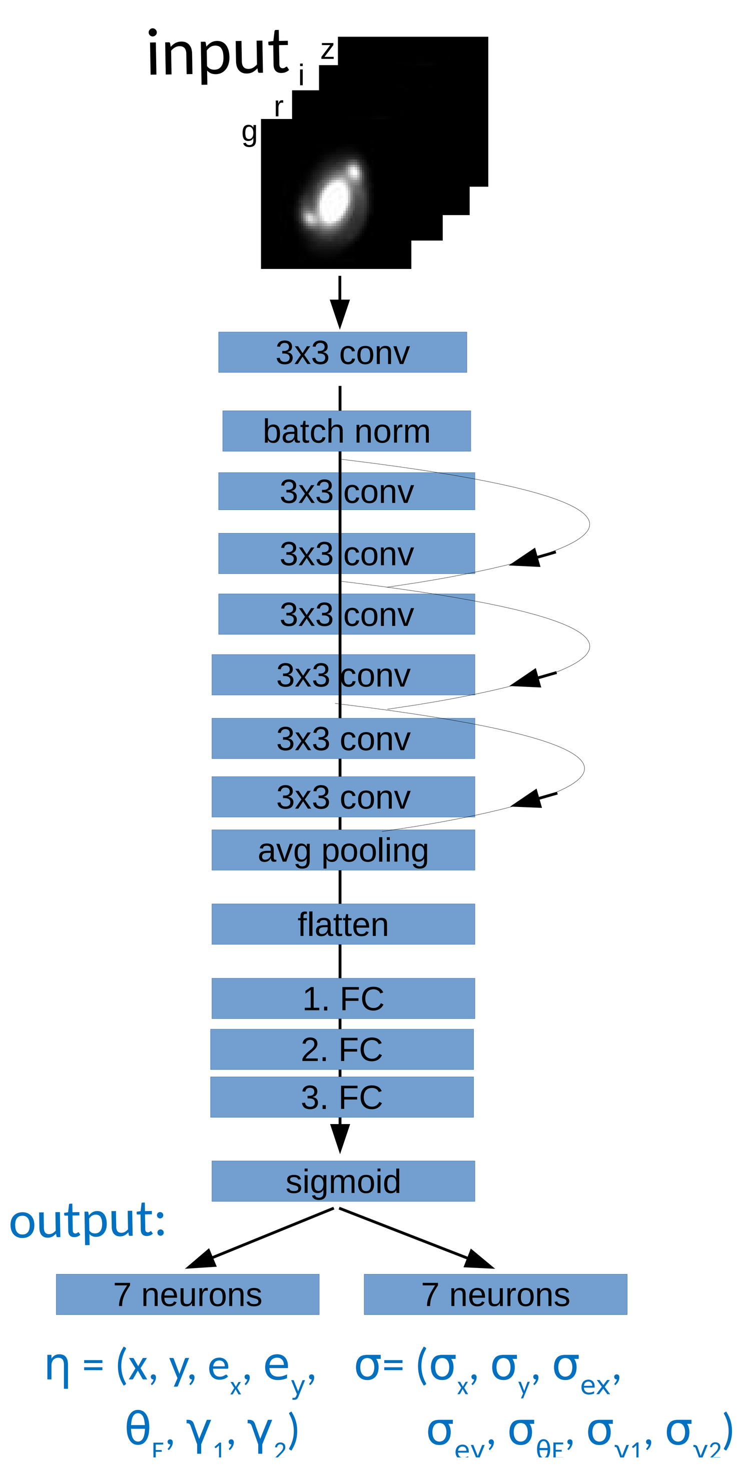


Figure 1: Gravitational lensing sketch.

This effect can be used to answer open questions in astrophysics, e.g., on dark energy, dark matter, and the expansion rate of the Universe. Depending on the alignment, the source can either be observed distorted or also multiple times (strong lensing).

Our ML approach

As shown in previous works [1, 2, 3] on space-based data, machine learning (ML) can be used to efficiently predict the values of an adopted lens mass profile. Therefore, we train a residual network (ResNet) to predict these parameters with uncertainties based on the input of LSST-like ground-based images.



$\eta = (x, y, e_x, e_y, \theta_E, \gamma_1, \gamma_2)$ $\sigma = (\sigma_x, \sigma_y, \sigma_{ex}, \sigma_{ev}, \sigma_{\theta E}, \sigma_{\gamma 1}, \sigma_{\gamma 2})$

Figure 2: ResNet architecture predicting 7 parameters together with uncertainties.

Automation of the traditional technique

So far lenses have been primarily modeled by maximum likelihood optimization, a very time and resource consuming procedure. A detailed analysis can take up to months of an expert. Thus, this techniques is not sufficient for the upcoming decade, such that we developed semi-automated pipelines to minimize the user input time.

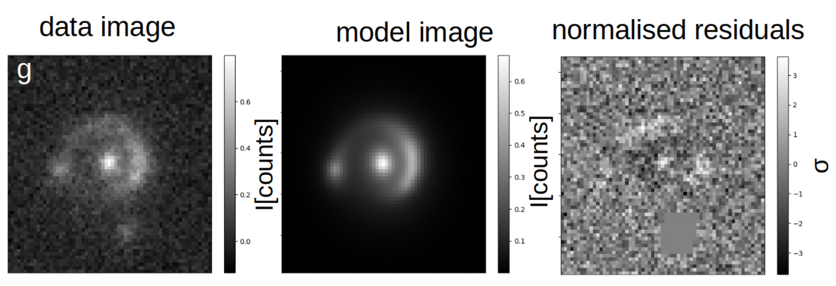


Figure 3: Example system modeled simultaneously in $griz$ with our automated code.

Network performance

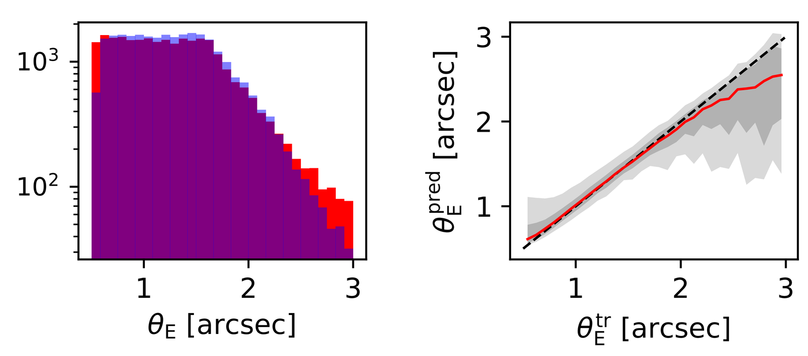


Figure 4: Comparison of the Einstein radius θ_E on the simulated test set.

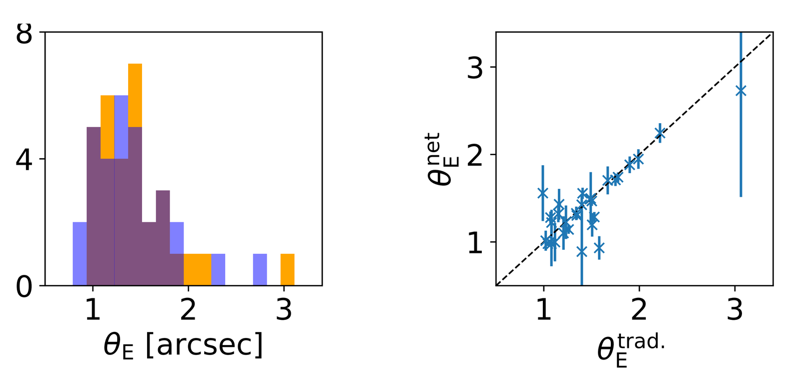


Figure 5: Comparison of the Einstein radius θ_E on 31 real lensing systems.

Conclusion

We present a ResNet predicting the lens mass and external shear γ values with uncertainties based on its LSST-like image. We compare the ResNet predictions of 31 real lenses to traditional obtained values. This demonstrates the reliability of the network and shows very good results on θ_E while difficulties remain on γ. Since the network needs only fractions of a second per lens system, we can handle the expected number of lenses in the near future.
For further details see [4, 5, 6].

photo-z from images

Good photo-z predictions are crucial given the huge amount of objects with only photometric data and the necessity of a redshift for nearly all applications. The traditional method is through template fitting, while in recent years great success with ML was obtained. However, so far these networks are based on catalog-level extracted properties from the image, while we have trained a convolutional neural network (CNN) directly on the images to predict the redshift.

Performance and comparison

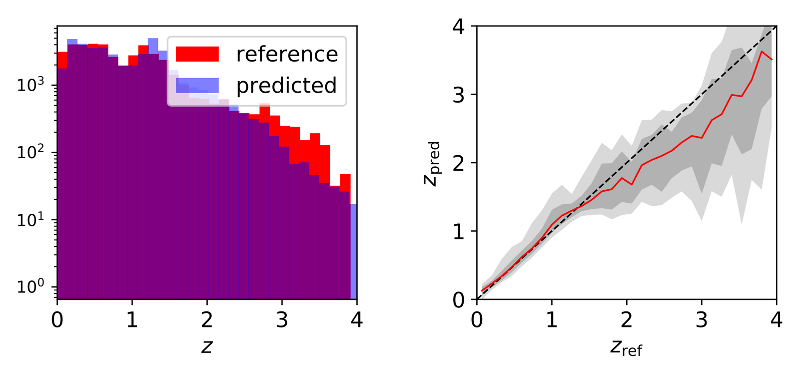


Figure 6: Performance of NetZ$_{main}$ on the test set, which are real ground based images with either spec-z or ∼30 band photo-z.

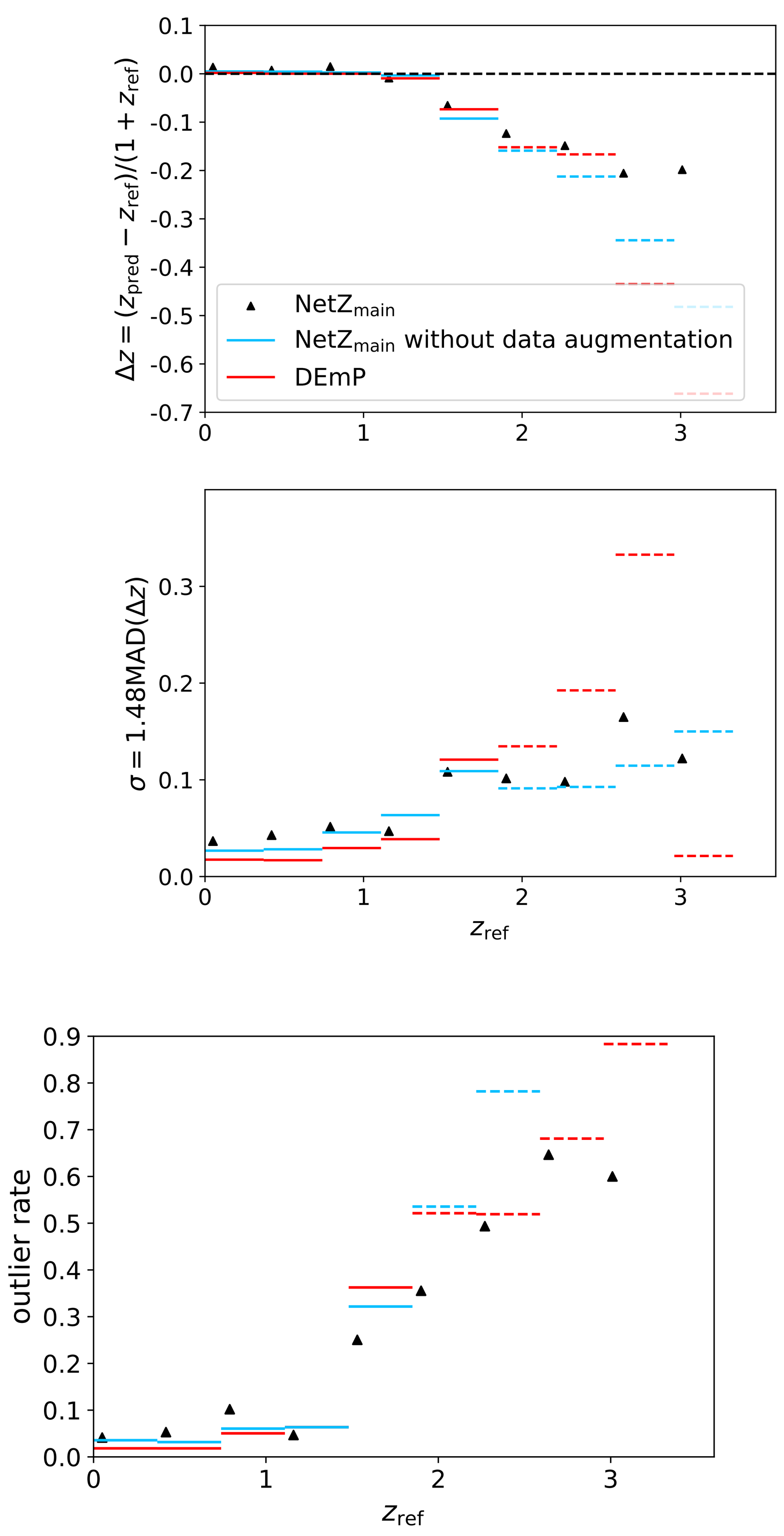


Figure 7: Comparison to a well tested hybrid photo-z method DEmP [7, 8, 9] on the exact same test set.

Dedicated networks

Beside NetZ$_{main}$, trained on all galaxy types and for a very broad redshift range ($0<z\lesssim4$), we present dedicated CNNs NetZ$_{lowz}$ and NetZ$_{LRG}$ for, respectively, the lower redshift range ($0<z\leq1$) and for luminos red galaxies (LRGs), which perform even better on their dedicated sample as NetZ$_{main}$.

NetZ architecture

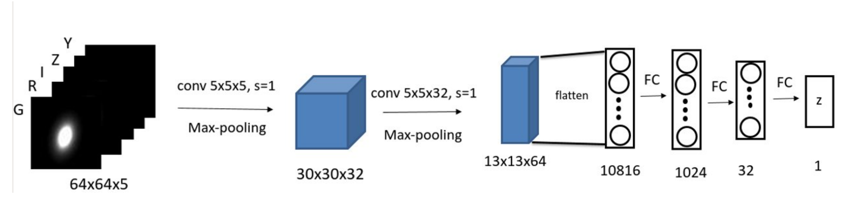


Figure 8: Network architecture of NetZ.

Conclusion

We present CNNs that are able to predict photometric redshifts of galaxies directly from the image cutout and publish more than 34 million new photo-z estimates from NetZ$_{main}$. The performance is competitive with other well established methods like DEmP [7, 8, 9], especially on the high-z range when the sample is more uniformly distributed thanks to data augmentation which is not possible on the catalog level.
For further details and references see [10].

References

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Acknowledgements

SS, SHS, RC, YS, and ST thank the Max Planck Society for support through the Max Planck Research Group of SHS. This project has received funding from the European Research Council (ERC) under the European Unions Horizon 2020 research and innovation programme (LENSNOVA: grant agreement No 771776). This research is supported in part by the Excellence Cluster ORIGINS which is funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy - EXC-2094 - 390783311.