Studying Morphology & Quenching of Galaxies in the All-Sky Era Using Interpretable Bayesian Convolutional Neural Networks

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Link to poster

Introduction & Outline

• We introduce Galaxy Morphology Posterior Estimation Network (GaMPEN), an ML framework that can estimate posteriors for a galaxy's bulge-to-total light ratio (L_B/L_T), half-light radius (R_e), and total flux (L_T).

• Using a log-likelihood loss function and the Monte Carlo Dropout technique, we incorporate both aleatoric and epistemic uncertainties in our predictions.

• A Spatial Transformer Network (STN) embedded within GaMPEN learns to make helpful transformations on the input image without any additional supervision.

• By first training on a large set of simulated galaxies and then transfer learning on a small amount of real data, we significantly reduce the number of real labeled galaxies needed to train GaMPEN.

• We have tested GaMPEN, and its classification precursor (GaMorNet) on a variety of different surveys -- SDSS, CANDELS, HSC.

• We used different CNN visualization techniques to investigate and shed light on GaMorNet's decision-making process, making our results interpretable.

• We use the fact that morphology traces the merger history of galaxies to learn about galaxy evolution using a large sample of galaxies with morphological classifications.

Primary Takeaways

• GaMPEN can robustly estimate Bayesian posteriors of galaxy morphology parameters.

• GaMPEN automatically crops crowded cutouts to focus on the object of interest

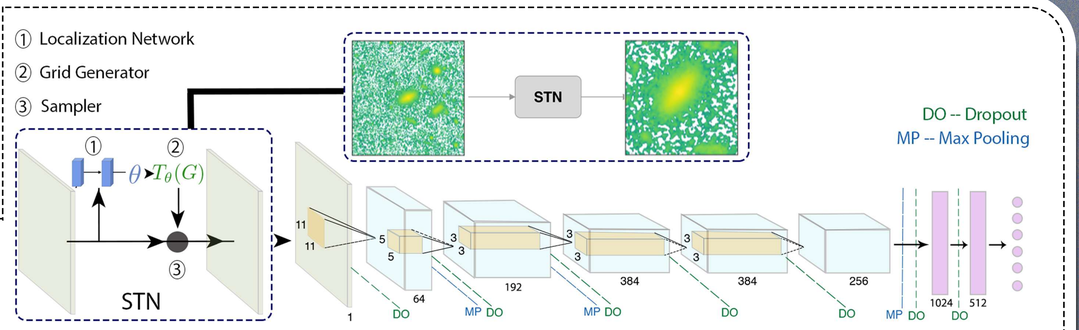
• GaMPEN doesn't need a large training set of real galaxies & works on multiple datasets.

• GaMPEN's decision-making process is interpretable

• Using morphology separated color-mass diagrams at z ~ 0 and 1, we identify two separate evolutionary pathways for disk- and bulge-dominated galaxies.

Methodology

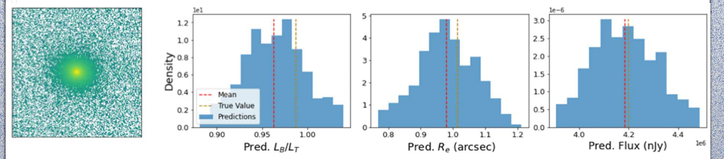
Uniform distributions of parameters in magnitude, radius, position angle with ranges typical at target redshift → Simulate galaxies -- some with a single Sersic component; and some with both disk and bulge components using GalSim → Convolve these galaxies with a representative PSF and add representative noise → Train GaMPEN on these simulated galaxies → Fine-tune the already trained network using a small amount of real data (Transfer Learning) → Process the real data through the trained network for which posteriors are to be estimated



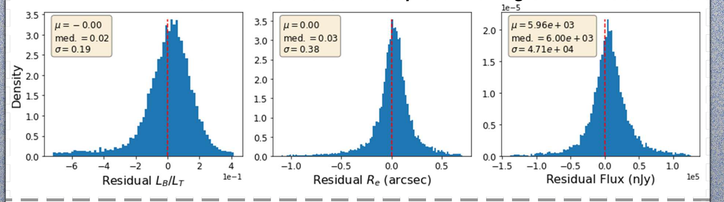
Schematic Diagram of GaMPEN. The numbers below each layer refer to the number of filters/neurons. An example of the transformation performed by the STN on a Hyper Suprime-Cam cutout is shown in the top inset.

Results

Predicted distributions for a randomly selected simulated galaxy. The coverage probabilities obtained for 1σ and 2σ are 68% and 95% respectively, showing that our uncertainties are well calibrated

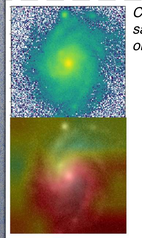


Residuals obtained for real HSC-W z < 0.25 galaxies. All histograms are centered at ~ 0 and have a reasonable spread showing GaMPEN is accurate.

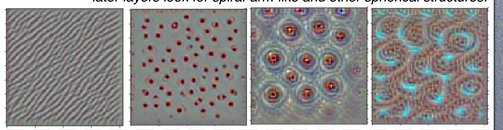


Interpretability Tests

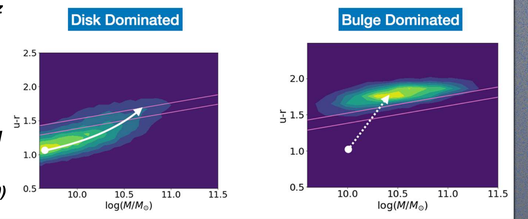
Class activation map visualized for a spiral galaxy in our sample. As can be seen, the network bases its decision on the presence of spiral arms in this image.



Patterns that shallower (leftwards) and deeper (rightwards) convolutional filters are responsive to. Earlier layers look for simple features (like edges), while later layers look for spiral-arm-like and other spherical structures.



Color-Mass diagram for z ~ 0 SDSS galaxies separated by morphology. Disks evolve secularly, and bulge-dominated galaxies quench rapidly after formation. Obtained using GaMorNet (precursor to GaMPEN) (Ghosh et al. 2020)



GaMorNet (classification precursor to GaMPEN) is publicly available with trained models. →

GaMPEN will be publicly available after further testing. But to use it for your work now, contact me! →