project_proposal

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0.1 Introduction and Objective

Transient Detection in astronomy is the process of detecting short lived celestial events. The process involves comparing new telescope images with reference images to see if there is a change in brightness or position of objects.

The objective of this project is to develop a physics informed computational imaging pipeline for astronomical transient detection. I aim to use plug-and-play ADMM with a deep model prior to provide robust guarantees and principled uncertainty quantification that end-to-end deep learning approaches cannot yet match.

From what I understand (I was insired by the recent computational imaging talk on the Rubin Telescope and don't have prior knowledge of this field), modern astronomical surveys rely on difference imaging to find transients. Classical subtraction techniques leave artifacts behind where the PSF or noise between reference and new images varies. End-to-End Deep Learning approaches may hallucinte or fail catastrophically when atmospheric conditions change the blur kernel and provide no principled uncertainty estimates. I hope that this work is able to decouple the physical forward model from the image prior and enable robustness to model mismatch and uncertainty quantification.

0.1.1 Problem Setup

The setup is this: Forward model:
$y = \mathbf{H}x + v$
where y is the observed image
$\mathbf{H}$ is the PSF (sensor blur, atmospheric turbulence)
x is the true clean image
v is Poisson-Gaussian noise mixture

ADMM Inverse Problem takes the form:
$x_{\text{recovered}} = \arg\min_x \frac{1}{2}\|\mathbf{H}x - y\|_2^2 + \lambda\phi(x)$
where ϕ is a pretrained deep learning model.

0.1.2 Robustness Studies

Our robustness studies on out of domain data can take the following form Factor1: PSF Model Mismatch In-distribution Moffat profile OOD Moffat with different β parameters and turbulance regime shift OOD Kolmogorov PSF to simulate turbulence if time permits, we can measure PSF from open source datasets and use these

Factor2: Noise Regime shifts by changing between fraction of Poisson and Gaussian noise added, and simulating bright moon conditions

Factor3: Spatial Variation Spatially uniform PSF vs PSF changes across focal plane

0.1.3 Datasets we could use include

Zwicky Transient Facility -> provides real transient alerts with reference cutouts, and PSF varies Dark Energy Survey -> Injected sources with known properties on real backgrounds with real PSFs (weak ground truth) Hyper Suprime-Cam -> provides PSF and can be used to compare against assumed vs true PSF

0.1.4 Uncertainty Quantification

There are many ways to do this. For the project, I may take a more empirical route

(1) add small noise to y, perturb the assumed PSF slightly, and enable dropout at inference if prior model supports this. Then take per-pixel standard deviation across runs to produce and uncertainty map

(2) Linearized Error Propagation. We could linearize around the fixed point and popagate noise covariance through linear system (will need jacobian approximation of the prior network)

(3) There exists better methods that use bayesian approaches and or conformal mapping, but may be out of scope for this project at this point in time

0.1.5 Baseline comparisons for project

We could compare to classical methods like the Richardson-Lucy, Alard-Lupton, and some end-to-end deep learning models that were trained for transient detection. Some metrics we can include are precision@k under uncertainty thresholds, coverage under OOD, Downstream classification F1, and PSNR for reconstruction fidelity

0.1.6 Milestones and Timelines

week1

- Dataset and noise pipelines up and running
- Deep DnCNN prior integrated

week 2

- Empirical uncertainty estimation
- 1-2 OOD conditions evaluation

week 3

- Final experiments and writeup

0.1.7 References

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