Searching for Strong Gravitational Lenses in the Dark Energy Survey

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INTRODUCTION

PROJECT WORKFLOW

IMPLEMENTING HTC & OSPOOL

IMPACT OF HTC & OSG

- Strong lensing
- Science applications
- Challenge context



1 - Training sample
2 - Machine Learning
Training
3 - Complete Search



- Before attending the OSG school
- Transition & challenges



- Quantitative impact
- Pushing the limits





Strong Lensing Observables:

- Image positions
 - Relative magnifications
 - Time delays between images

Science Applications:

Elliptical Galaxies	Cosmology				
Mass Structure	Dark Energy				
Formation	Dark Matter				
Evolution	Expansion History				

STRONG LENSING IN THE DARK ENERGY SURVEY





~0.1 deg



DES covers 5,000 sq deg. -> 500,000 times larger than the image shown.

Expectation: hundreds of strong lenses in complete data.

1- TRAINING SAMPLE: POSITIVE CLASS

Simulations



We control the quality of the simulations by setting constraints on simulation properties.

Created with Lenstronomy (Birrer & Amara 2018, Birrer et al. 2021)

Computational Limits:

- Need thousands of simulations: ~2 days (for 15,000 simulations)
- Tighter constraints require more time: 2 days -> 4 days
- Couldn't experiment much with simulations with different properties.

2- MACHINE LEARNING TRAINING



Machine learning model:

• Vision Transformer (ViT): 86 million parameters.

Computational Limits:

- Training is time consuming: ~3 days on personal laptop.
- The larger the training sample, the more time is needed.
- → Each training run is a big commitment.

3- COMPLETE SEARCH

Search: Must process 320 million images (1 TB)



Representation of 72 images

Computational Limits:

- On personal laptop: 7 years
- On a cluster running in series: 4.5 years
- When am I going to graduate?



CONTEXT: BEFORE THE OSG-USER SCHOOL

- Mostly doing simulations, and training. Taking ~2 weeks.
- Applying search to some images (80,000) to understand results. ~2 days
- Spending my time mostly waiting.
- Errors were expensive.

Elephant in the room: search on all the data.



IMPLEMENTING HTC: 1 - SIMULATIONS

How this task is parallelizable:

- Simulations are independent of each other.
- Each simulation only takes ~2 seconds.

Implementing HTC: straight forward

- Organization: input files, output files and software.
- Modify code to receive important information as arguments. Example: number of simulations & random seed.
- Lots of testing!





MOVING TO OSG: 2 - TRAINING

Challenge: Not easily parallelizable

• The learning process can't be divided into independent tasks.

OSG resources useful:

• A GPU made a large impact.





IMPLEMENTING HTC: 3 - TOTAL SEARCH

How this task is parallelizable:

- Images are independent of each other.
- The DES imaging data is divided into ~10,000 pieces (tiles), each containing 24,000 images.
- Processing each tile takes only 4 hours.

Implementing HTC:

- Challenge: All input data is heavy and not public.
- Solution: implementing HTC with the resources I had available: FermiGrid. Same concepts, just different syntax.



QUANTITATIVE IMPACT OF THE OSG SCHOOL

1- Simulations:



2- Training:



3- Complete Search

Expected:	39420
With HTC:	72

PUSHING THE LIMITS

Challenge for these searches: Purity rate of automatic searches: 1%



Possible to implement Interactive Machine Learning to improve our training sample:



SEARCH RESULTS



Random sample of candidates with probability ~ 1 (~ 900):

					14

CONCLUSION



State of the project:

- Preparing a crowdsourcing project in Zooniverse to extract the compelling candidates.
- More plans with OSG: characterizing the final candidates.

Thanks to the OSG consortium for allowing me to focus on the science, instead of the computational limitations.

EXTRA SLIDES: TRAINING SAMPLE



Created with Lenstronomy (Birrer & Amara 2018, Birrer et al. 2021)

We control the "quality" of the simulations by setting constraints: Magnification, position of the images, contrast of arc simulation, etc.



EXTRA SLIDES: THE VISION TRANSFOMER (VIT)



CHARACTERISTICS:

Larger receptive fieldBetter for global features





Performs the same or better than state of the art CNN models when pre-trained on large datasets.