

LSST Catalog-level Realization of Gravitationally-lensed Quasars

Jenny Kim

*Kavli Institute for Particle Astrophysics & Cosmology,
P. O. Box 2450, Stanford University, Stanford, CA 94305, USA*

Phil Marshall, Mike Baumer, and Steve Kahn

*Kavli Institute for Particle Astrophysics & Cosmology,
P. O. Box 2450, Stanford University, Stanford, CA 94305, USA and
SLAC National Accelerator Laboratory, Menlo Park, CA 94025, USA*

Rahul Biswas

University of Washington

((LSST Dark Energy Science Collaboration))

(Dated: June 29, 2017)

The scale of the LSST dataset will be such that we should anticipate extracting as much information out of the its catalogs as possible, before ever turning to the pixel-level data. In this work we explore the use of simple, low-multiplicity Gaussian mixture models for realizing gravitational lens systems in LSST catalog space, to enable both large-scale sample simulation and direct model inference.

I. INTRODUCTION

The Large Synoptic Survey Telescope (LSST), a wide-field survey telescope with the diameter of 8.4m, will be start running in Chile in 2020 [?]. This telescope has a 3.5 *deg* of field of view, would cover around *deg*² in the sky, and use *u*, *g*, *r*, *i*, *z*, and *y* filters [?]. The telescope will give extensive amount of astronomical data that could be used for the study of Solar System, Extragalactic structures, near-Earth astroids, radiant radio sources, Dark Matter, and Dark Energy.

LSST Dark Energy Science Collaboration (DESC) also anticipate to detect around 7000 strongly lensed systems that will provide useful information such as cosmological time delay or lense mass distribution [?] [?] [?]. In order to do so, finding the lensed system among the enormous set of data is crucial. However, considering the amount of the data that LSST will produce, pixel-level data searching will be really inefficient and expensive. In order to solve the problem, we propose the lens classification with catalog-level searching with machine learning techniques.

The attempt to use Machine Learning to detect lensed system is not a new idea. [?] suggests that morphological classification of the lensed system using the Convolutional Neural Network(CNN) would be effective. [?] has developed 'lensextractor' that uses convolution neural network to train and test the software to detect the lensed system. Most of the previous attempts involved single-band image classification [?] [?].

Similarly, we propose to build a software 'SL Realizer' that does catalog-level lens search to detect lensed system. The 'SL Realizer' project largely consists of two major parts: producing large-sized catalogs of lensed systems and making the software to classify objects in the catalog as lenses or non-lenses. We first calculated the synthetic magnitude of simulated OM10 lenses to use as a training data set for SL Realizer [?]. Using the OM10 lenses as the training set and [?] as our data set, we were able to achieve

To be updated after the completion of III at the end of the summer

II. CATALOG GENERATION

A. Synthetic magnitude calculation

The OM10 mock lensed quasar catalog `qso_mock.fits` contains estimates of the lens galaxy i-band magnitudes, based on a simple Faber-Jackson scaling. With the `lenspopy` library we can compute synthetic magnitudes in *i*, *g*, *r*, and *z* filters. We validated the computation by plotting the difference in redshift, i-band magnitude, g-r magnitude, r-i magnitude, and i-z magnitude when

- comparing the synthetic magnitudes of the colored OM10 lens galaxies with those of SDSS LRGs.
- comparing the synthetic magnitudes of colored OM10 lens galaxies with those of 56 candidate galaxy-scale lenses that were imaged as part of the Canada-France-Hawaii Telescope (CFHT) Legacy Survey.
- comparing the synthetic magnitudes of colored OM10 lensed quasars with those of known SDSS Quasars.

1 contains the summary of the validations of synthetic magnitude calculation results, and more data could be viewed here. The OM10 lenses will be our training set for SL Realizer.

B. Visualization

Using the OM10 lenses whose magnitude was calculated in II A, we then visualized the lensed system. Here, in this notebook, we selected a lens system that has a lens ID of 48685211 and plotted it on different observation epochs. The result can be viewed in 2.

C. Mock Catalog Generation

D. Twinkles Catalog

The twinkles project also provides the simulation of LSST data [?]. This project uses LSST's *PhoSim* to generate a mock output of LSST. The table I contains a few samples of the Twinkles data set.

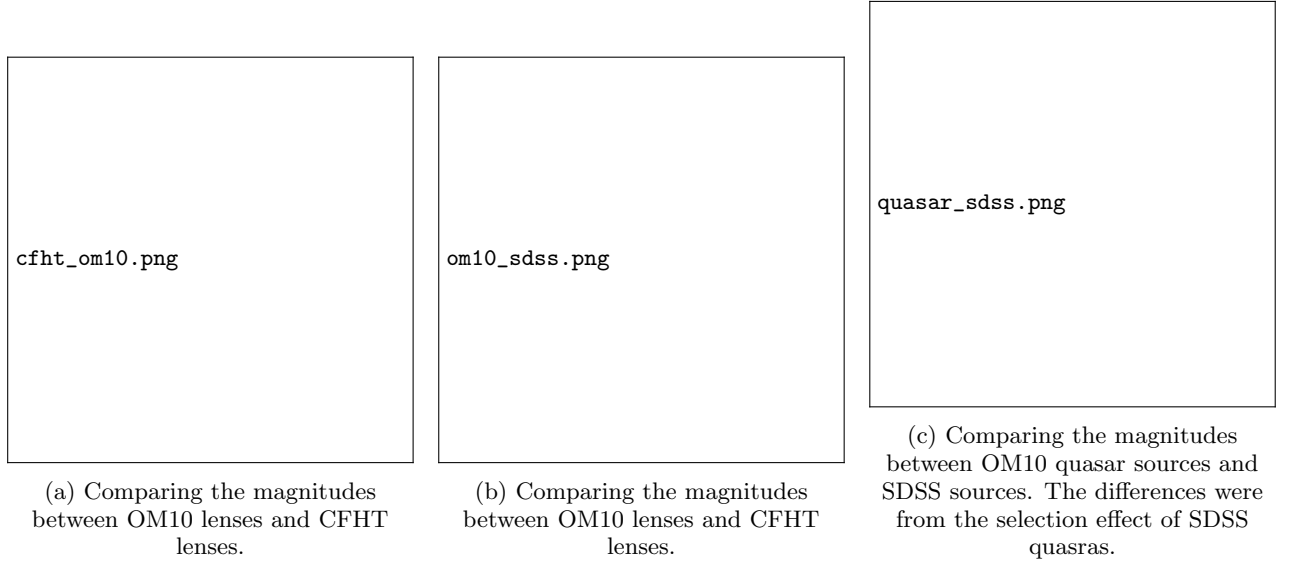


FIG. 1: Comparing OM10 data with SDSS and CFHT data set.

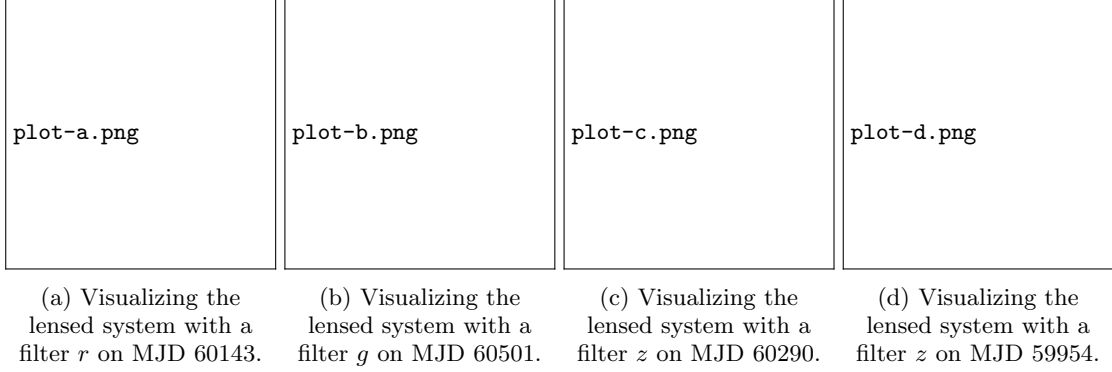


FIG. 2: Visualizing the lensed system in different epochs.

id	ra	dec	magnorm	redshift	majoraxis	minoraxis
21393434	53.0524882	-27.7029739	17.8301052	0.184	1.6126157	1.15325373
21393434	53.0524882	-27.7029739	17.8301052	0.184	1.6126157	1.15325373
21393434	53.0524882	-27.7029739	17.8301052	0.184	1.6126157	1.15325373
21393434	53.0524882	-27.7029739	17.8301052	0.184	1.6126157	1.15325373
21393434	53.0524882	-27.7029739	17.8301052	0.184	1.6126157	1.15325373

TABLE I: Sample of the Twinkles lensed system data DATA IS FAKE - NOT THE DATA WE ARE GOING TO USE IN RESEARCH

III. TRAINING SL REALIZER

Using the simulated data from IIA, this is what I am going to do during the summer!

IV. CONCLUSIONS

Here's a summary of what we just reported.

We can draw the following well-organized and neatly-formatted conclusions:

- This is important.
- We can measure some number with some precision.
- This has some implications.

Here are some parting thoughts.

Acknowledgments

Here is where you should add your specific acknowledgments, remembering that some standard thanks will be added via the `acknowledgments.tex` and `contributions.tex` files.

This is the text imported from `acknowledgments.tex`, and will be replaced by some standard LSST DESC boilerplate at some point.

Author contributions are listed below.

Jenny Kim: Led algorithm and code development, wrote paper.

Phil Marshall: Initiated project, advised on motivation, model construction and testing.

Mike Baumer: Advised on LSST data characteristics, model construction and testing.

Steve Kahn: Advised on LSST data characteristics, model construction and testing.

Rahul Biswas: Advised on LSST observing cadence, catalog characteristics, error model.