Identifying Double-Source Plane Lenses for cosmological studies

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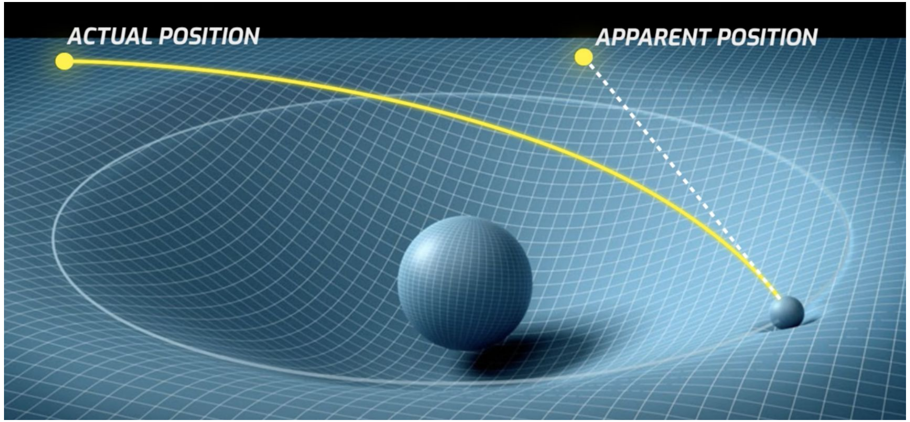
What is gravitational lensing anyway?

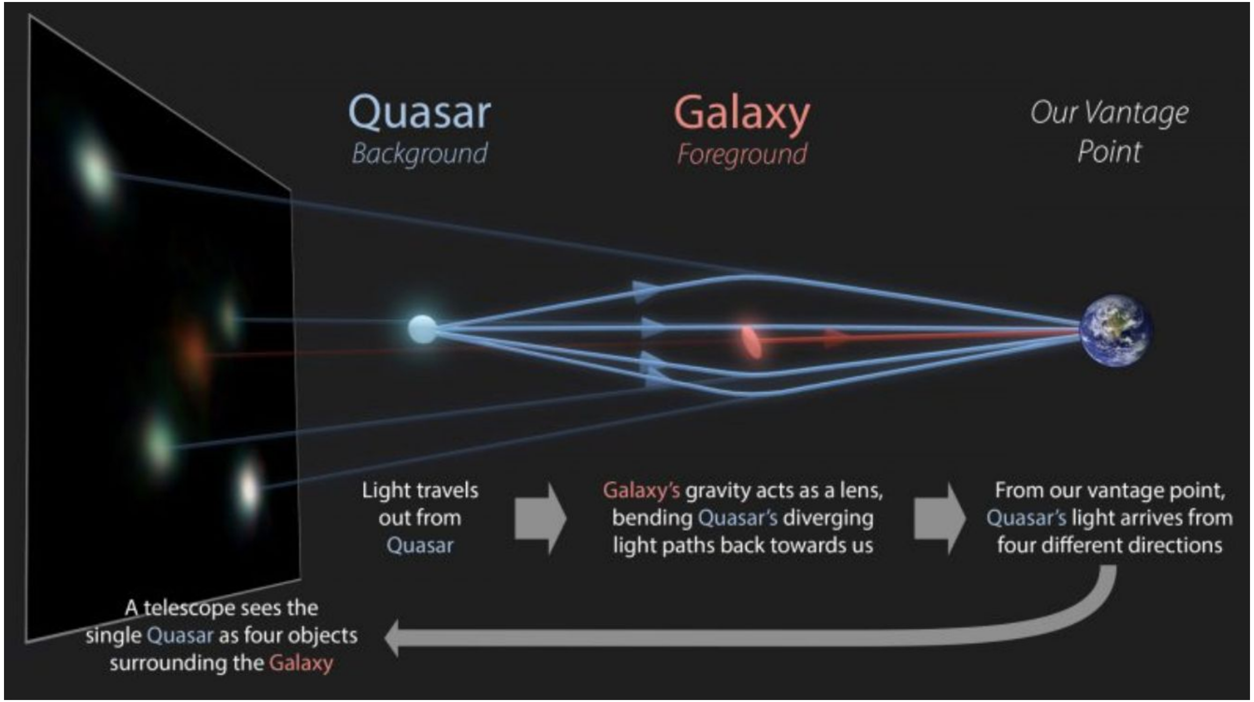
Gravitational lensing is a phenomenon that occurs when the gravitational field of some amount of matter changes the path of light from a distant galaxy in the same line of sight.

Why does this happen?

General Relativity.

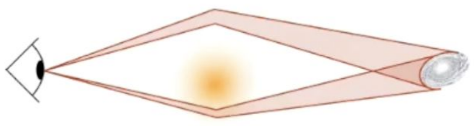
Mass causes curvature (in the "fabric" of spacetime) that a path of light can potentially "fall into" (& thus become bent) ; More mass, more curvature

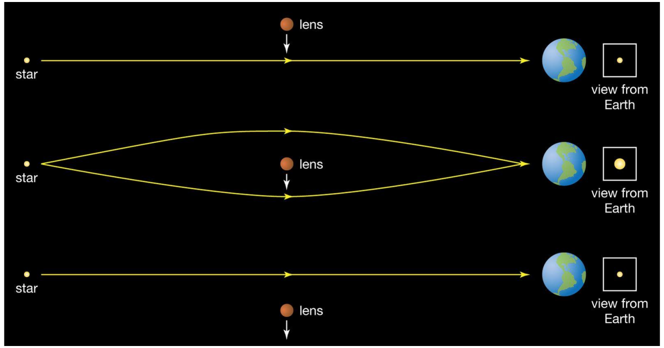




Strong Gravitational Lensing visualised

Types of Gravitational Lensing





Strong Lensing

- Caused by one gravitational lense with a lot of mass
- Creates multiple images and/or arcs (Ring/Circles are produced as the alignment approaches perfect symmetry)

Weak Lensing

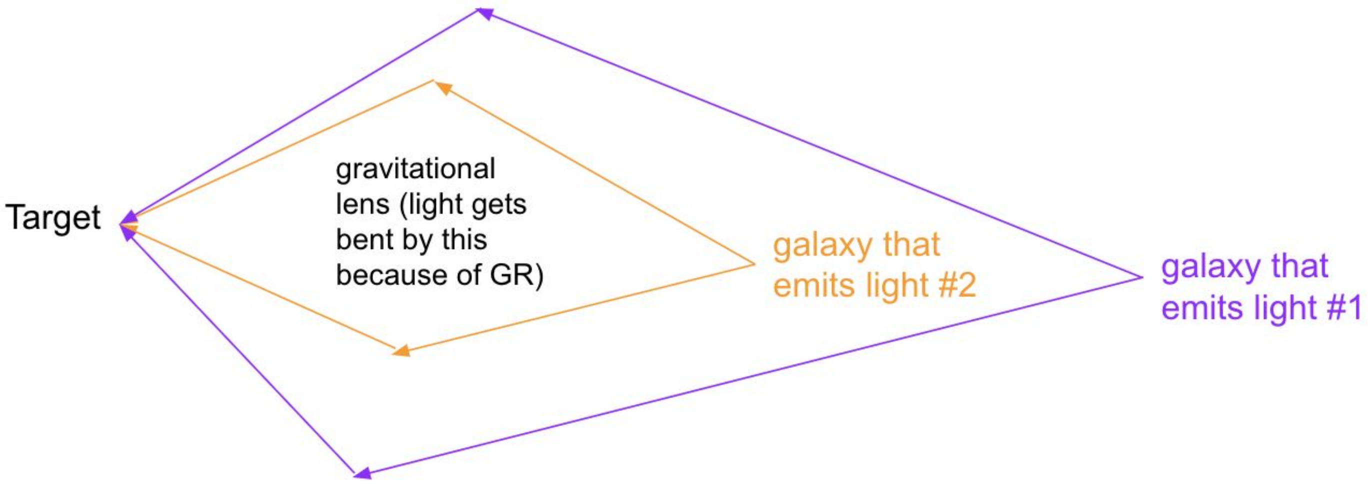
- Caused by many gravitational lenses with not a lot of mass & thus not a lot of curvature
- Creates one image that is distorted in some way (e.g. magnified or lengthened)

Microlensing

- Caused by an object with not a lot of mass passing in front of a source of light
- Makes the source appear brighter
- Temporary

What are Double Source Plane Lenses?

DSPLs are a rare type of Strong Gravitational Lensing that occur when there are two sources (instead of just one) in a strong gravitational lens system.



DSPL visualised

How do we find DSPLs?

<Only 4 have been found>

Assumption that DSPLs are likelier to be found by further observation (looking at different wavelengths and in greater depth) of known single lense systems

Surveys:

- Looking for a central object surrounded by various sources
- Looking for higher redshift emission lines in the spectrum of galaxies

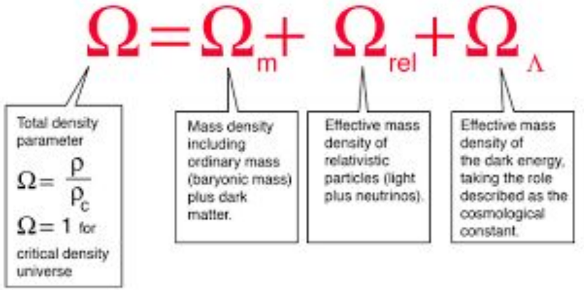
Why do we care about DSPLs?

DSPLs can help us determine the curvature of the universe with greater precision!

...how does it do that?

DSPL imposes constraints upon Dark Energy & Total Matter Density through distance ratios w/ the source and lens, and those constraints carry over to the density parameter equation that then tells us the curvature of the universe.

The density parameter equation



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Why do we care about DSPL continued...

The Dark Energy Equation of State

- The dark energy EoS characterises both the universe's accelerated expansion & the cosmic inflation of the early universe
- The *w* parameter of the dark energy EoS is defined as the pressure over the energy density of dark energy.
- DSPLs are the only way to constrain the *w* parameter without relying upon the Hubble constant; Has novel parameter degeneracy.
- It is important for us to further constrain the *w* parameter to both better understand the nature of dark energy and improve current constraints on other affected cosmological parameters.

How do DSPLs constrain Dark Energy EoS

By taking ratio of the two Einstein radii, we can use DSPLs to constrain the dark energy equation of state, as that directly measures the growth of angular diameter distances as varied based on redshift

(Collett 2012)

Equation (5b) holds if w is constant, whilst equation (5c) is general for any universe with a time-evolving equation of state. Neglecting the mass of the closer source, we define the quantity η as the ratio of the two Einstein radii,

$$\eta = \frac{\theta_{\mathrm{E},1}}{\theta_{\mathrm{E},2}}, \tag{7}$$

with 1 and 2 referring to the near and far sources, respectively. For an SIS lens, η is given by

$$\eta^{\mathrm{SIS}} = \frac{D_{\mathrm{ls1}} D_{\mathrm{s2}}}{D_{\mathrm{ls2}} D_{\mathrm{s1}}}. \tag{8}$$

The ratio, η, has the intrinsic advantage that it is independent of the Hubble constant and is only weakly dependent upon the mass distribution of the lens (in the case of an SIS model η is independent of the mass), so is a function only of w, Ω_{M} and the redshifts of the lens and sources (and the mass model).

(Einstein Radii Equation)

$$\theta_{\mathrm{E}} = \sqrt{\frac{4GM(\theta_{\mathrm{E}})}{c^2} \frac{D_{\mathrm{ls}}}{D_{\mathrm{ol}} D_{\mathrm{os}}}},$$

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To summarise…

We want to find more DSPLs.
Machine Learning could help us do that by automating a part of the process.

But wait . . . if only <5 DSPLs have ever been found, and a machine learning model needs lots of data (*thousands* of instances) to avoid overfitting . . . how will machine learning be able to help us?!

SIMULATED DATA!

what data did we need to generate?

our **target** dataset is high-quality, simulated images

our **source** dataset is simulated images with survey-like conditions

what images are in those datasets?

images of DSPLs and Einstein Rings (ERs are a phenomenon that looks very similar to DSPLs)!

how did we make this simulated data / what went into this simulated data?

we utilised a software called deeplenstronomy that took our configuration files & outputted images.

what's in the configuration files though?

```yaml
DATASET:
  NAME: EinsteinRingFinalVariation
  PARAMETERS:
    SIZE: 2000
    OUTDIR: ER3

COSMOLOGY:
  PARAMETERS:
    H0: 70
    Om0: 0.3

IMAGE:
  PARAMETERS:
    exposure_time: 1000
    numPix: 100
    pixel_scale: 0.05
    psf_type: 'GAUSSIAN'
    read_noise: 0
    ccd_gain: 6.083

SURVEY:
  PARAMETERS:
    BANDS: g
    seeing: 0.0
    magnitude_zero_point: 40.0
    sky_brightness:
        DISTRIBUTION:
          NAME: normal
          PARAMETERS:
              mean: 23.5
              std: 1.5
    num_exposures: 100

SPECIES:
  GALAXY_1:
    NAME: LENS
    LIGHT_PROFILE_1:
      NAME: SERSIC_ELLIPSE
      PARAMETERS:
        magnitude:
            DISTRIBUTION:
              NAME: normal
              PARAMETERS:
                mean: 12.5
```

```yaml
        e1:
          DISTRIBUTION:
            NAME: uniform
            PARAMETERS:
              minimum: -0.1
              maximum: 0.1
        e2:
          DISTRIBUTION:
            NAME: uniform
            PARAMETERS:
              minimum: -0.1
              maximum: 0.1
    MASS_PROFILE_1:
      NAME: SIE
      PARAMETERS:
        sigma_v:
          DISTRIBUTION:
            NAME: uniform
            PARAMETERS:
              minimum: 200
              maximum: 300
        e1:
          DISTRIBUTION:
            NAME: uniform
            PARAMETERS:
              minimum: -0.1
              maximum: 0.1
        e2:
          DISTRIBUTION:
            NAME: uniform
            PARAMETERS:
              minimum: -0.1
              maximum: 0.1
        center_x:
          DISTRIBUTION:
            NAME: uniform
            PARAMETERS:
              minimum: -0.5
              maximum: 0.5
        center_y:
          DISTRIBUTION:
            NAME: uniform
            PARAMETERS:
              minimum: -0.5
```

```yaml
GEOMETRY:
  CONFIGURATION_1:
    NAME: EINSTEIN_RING
    FRACTION: 1.0
    PLANE_1:
      OBJECT_1: LENS
      PARAMETERS:
        REDSHIFT:
          DISTRIBUTION:
            NAME: uniform
            PARAMETERS:
              minimum: 0.1
              maximum: 0.8
    PLANE_2:
      OBJECT_1: SOURCE
      PARAMETERS:
        REDSHIFT:
          DISTRIBUTION:
            NAME: uniform
            PARAMETERS:
              minimum: 0.81
              maximum: 3.1
```

```yaml
GEOMETRY:
  CONFIGURATION_1:
    NAME: DSPLTakeThree
    FRACTION: 1.0
    PLANE_1:
      OBJECT_1: LENS
      PARAMETERS:
        REDSHIFT:
          DISTRIBUTION:
            NAME: normal
            PARAMETERS:
              mean: 0.222
              std: 1.5
    PLANE_2:
      OBJECT_1: SOURCE
      PARAMETERS:
        REDSHIFT:
          DISTRIBUTION:
            NAME: normal
            PARAMETERS:
              mean: 0.609
              std: 1.5
    PLANE_3:
      OBJECT_1: SOURCE
      PARAMETERS:
        REDSHIFT:
          DISTRIBUTION:
            NAME: normal
            PARAMETERS:
              mean: 2.4
              std: 1.5
```

determining the ranges & distributions for these parameters

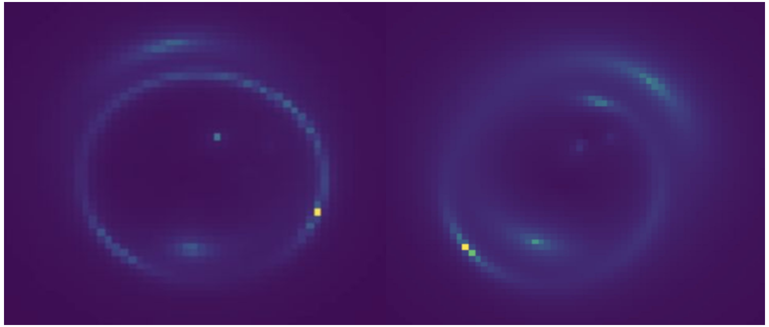
a mix of educated trial & error and literature review

e.g. inferring from observed trends in strong lensing, averaging the redshifts of the known, real DSPLs to determine a mean and forming a bell curve around that

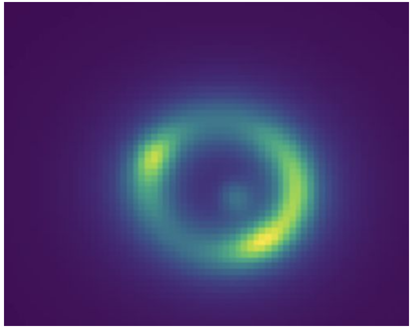
it is very important for us to have a wide range of images of both DSPLs and einstein rings because if our dataset does not accurately represent “what is out there”, it will cause biases in detection and could lead to incorrect scientific conclusions

Excerpts from our Final Datasets

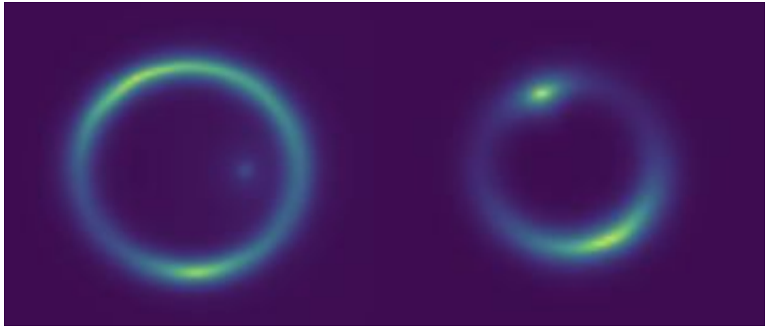
Simulated DSPLs high-quality



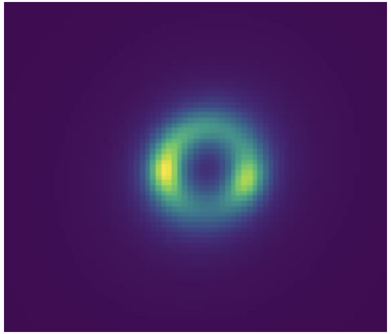
Simulated DSPLs DES survey



Simulated ERs high-quality



Simulated ERs DES survey



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aside from the overarching domain adaptation project, what other uses will our dataset have?

- predicting what future surveys using existing tools (hubble space telescope .etc) will look like (even if the classification hasn't been fully automated yet, it can assist scientists by telling them what to look for)

- determination of "at what point" a DSPL is considered distinct (by a computer) from an ER

acknowledgements

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THANK YOU!