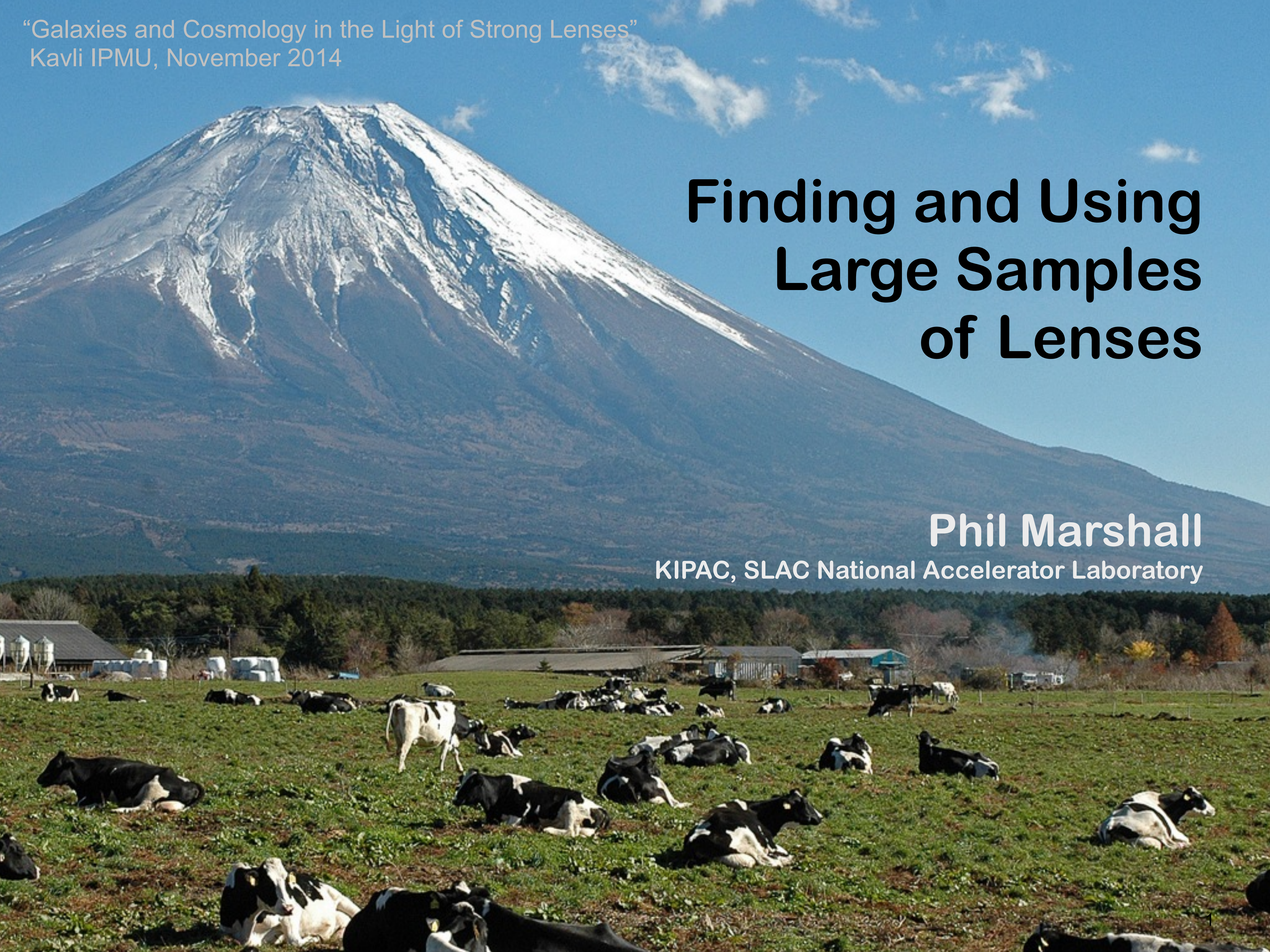

“Galaxies and Cosmology in the Light of Strong Lenses”
Kavli IPMU, November 2014

Finding and Using Large Samples of Lenses

Phil Marshall
KIPAC, SLAC National Accelerator Laboratory

Finding Lenses:

- Motivation
- Brief history
- Wide field imaging surveys
- Approaches to lens finding

Using Lenses:

- Hierarchical inference

Finding Lenses:

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Biases:
galaxy-scale
optical imaging

Length

Using Lenses:

- Hierarchical inference

Motivation

Motivation

Accuracy:

Motivation

Accuracy:

- **Large samples provide high accuracy on global parameters (cosmology, DM mass function, galaxy evolution models etc)**

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- **Diversity informs systematic modeling by probing unknown unknowns**

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Discovery:

Motivation

Accuracy:

- Large samples provide high accuracy on global parameters (cosmology, DM mass function, galaxy evolution models etc)
- Diversity informs systematic modeling by probing unknown unknowns

Discovery:

- Large samples will contain surprises, extreme or exotic lenses enabling new types of investigation

The first 10 years of industrial strong lensing

- **CLASS** (N lenses; Browne, Fassnacht)
- **SLACS** (N lenses; Bolton, Auger, Treu, Koopmans)
- **SQLS** (N lenses; Oguri, Inada)
- **HST** (N lenses; Moustakas, Marshall, Faure, Jackson, More, Pawase)
- **SL2S** (N lenses; Gavazzi, Sonnenfeld, More)
- **BELLS** (N lenses; Bolton, Brownstein)
- **SPT/Herschel** (N lenses; Vieira, Negrello)

$N \sim 10^{1-2}$

The first 10 years of industrial strong lensing

- **CLASS** (N lenses; Browne, Fassnacht)
  - Mine the FIRST images, follow-up with VLA snapshot imaging
- **SLACS** (N lenses; Bolton, Auger, Treu, Koopmans)
  - Mine the SDSS spectra, follow-up with HST snapshot imaging
- **SQLS** (N lenses; Oguri, Inada)
  - Mine the SDSS catalog, follow-up with UH88 snapshot imaging
- **HST** (N lenses; Moustakas, Marshall, Faure, Jackson, More, Pawase)
  - Mine the images, inspect
- **SL2S** (N lenses; Gavazzi, Sonnenfeld, More)
  - Mine the CFHTLS catalogs and images, follow-up with HST/AO imaging
- **BELLS** (N lenses; Bolton, Brownstein)
  - Mine the BOSS spectra, follow-up with HST imaging
- **SPT/Herschel** (N lenses; Vieira, Negrello)
  - Mine the source catalogs, follow-up with HST/ALMA imaging

$N \sim 10^{1\text{-}2}$

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$N \sim 10^{1\text{-}2}$

The next 10 years of industrial strong lensing

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- **SPT/Herschel/ALMA** (10^3 lenses)
  - Mine the Herschel/SPT catalogs, follow-up with ALMA imaging

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- **PS1** (10^{2-3} lenses)
  - Mine the PS1 catalogs and images, inspect, follow-up

The next 10 years of industrial strong lensing

- **SPT/Herschel/ALMA** (10^3 lenses)
  - Mine the Herschel/SPT catalogs, follow-up with ALMA imaging
- **PS1** ($10^{2\text{-}3}$ lenses)
  - Mine the PS1 catalogs and images, inspect, follow-up
- **DES/KIDS/HSC** (10^3 lenses each)
  - Mine the DES/KIDS/HSC catalogs and images, inspect, follow-up

The next 10 years of industrial strong lensing

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  - Mine the PS1 catalogs and images, inspect, follow-up
- **DES/KIDS/HSC** (10^3 lenses each)
  - Mine the DES/KIDS/HSC catalogs and images, inspect, follow-up
- **Euclid** (10^{4-5} lenses)
  - Mine the Euclid catalogs and images, inspect, follow-up

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  - Mine the Herschel/SPT catalogs, follow-up with ALMA imaging
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- **Euclid** ($10^{4\text{-}5}$ lenses)
  - Mine the Euclid catalogs and images, inspect, follow-up
- **LSST** (10^4 lenses)
  - Mine the LSST catalogs and images, inspect, follow-up

The next 10 years of industrial strong lensing

- **SPT/Herschel/ALMA** (10^3 lenses)
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- **PS1** ($10^{2\text{-}3}$ lenses)
  - Mine the PS1 catalogs and images, inspect, follow-up
- **DES/KIDS/HSC** (10^3 lenses each)
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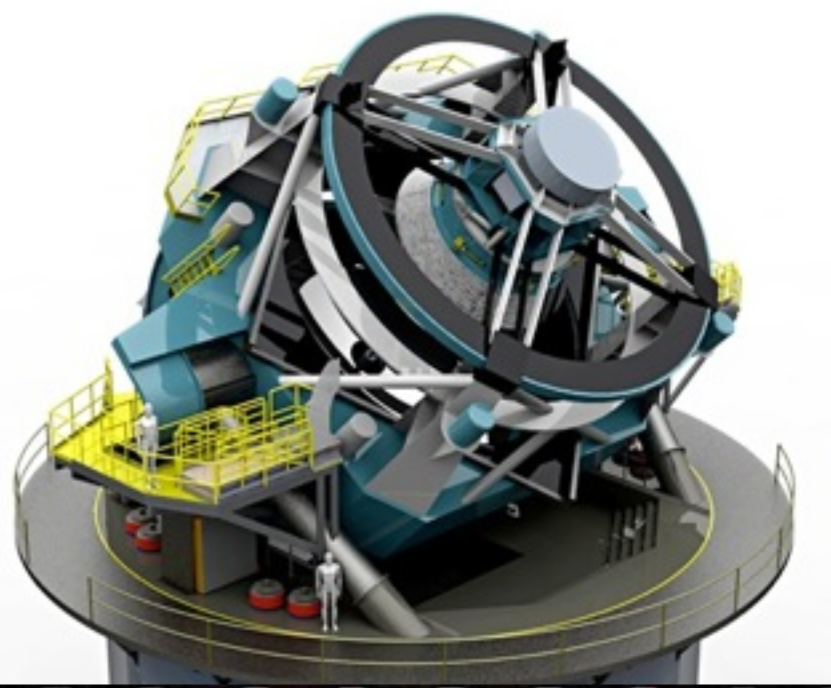
- **Euclid** ($10^{4\text{-}5}$ lenses)
  - Mine the Euclid catalogs and images, inspect, follow-up
- **LSST** (10^4 lenses)
  - Mine the LSST catalogs and images, inspect, follow-up
- **SKA** ($10^{4\text{-}5}$ lenses)
  - (Make and?) mine the SKA source catalogs, inspect, follow-up

Upcoming Imaging Surveys

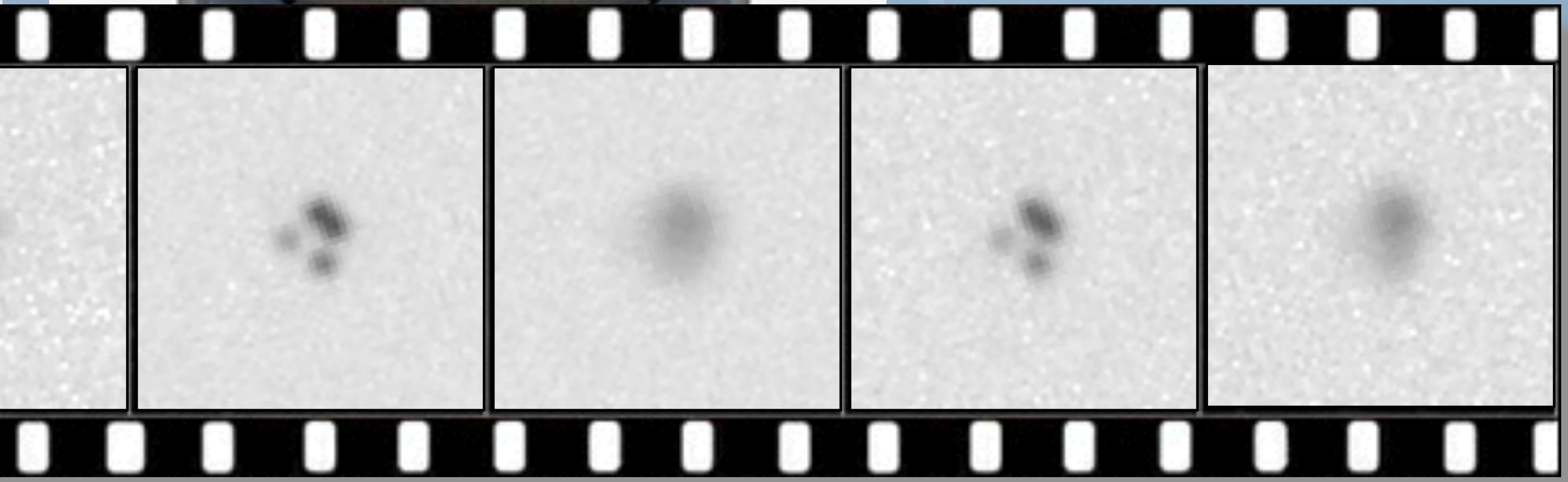
- PS1, DES, HSC, KIDS: ~1000 lensed quasars, 100s of group and cluster arcs
- LSST: $10^{3\text{-}4}$ lensed quasars, 100s of lensed SNe, 10^4 arcs and rings
- Euclid: 10^5 galaxy-scale lenses
- SKA: few 10^5 systems

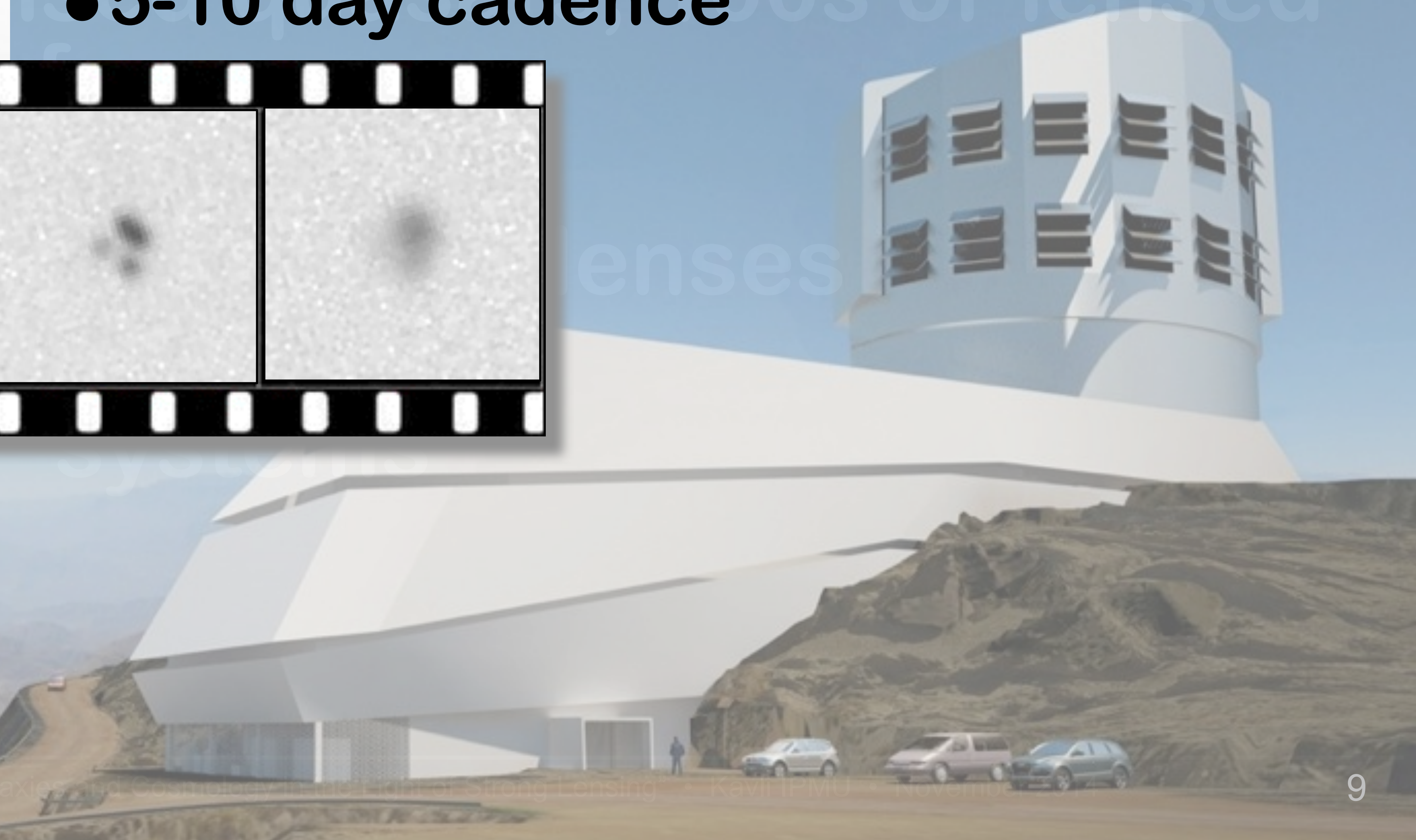
key words: "Science Book"

Imaging Surveys

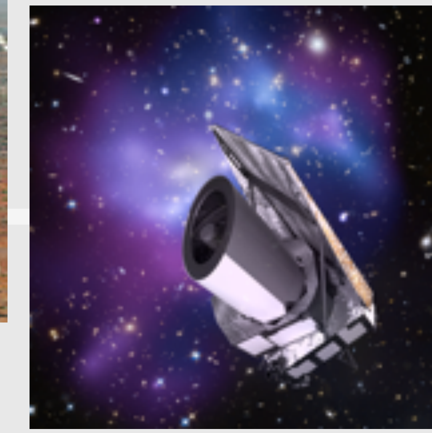


- 6m aperture, 10 sq deg field, 24th mag depth in 30 seconds, ugrizy
- 0.4-1.0" seeing (Cerro Pachon)
- 10 year, 18000 sq deg survey, 200 visits per object per band
- 5-10 day cadence

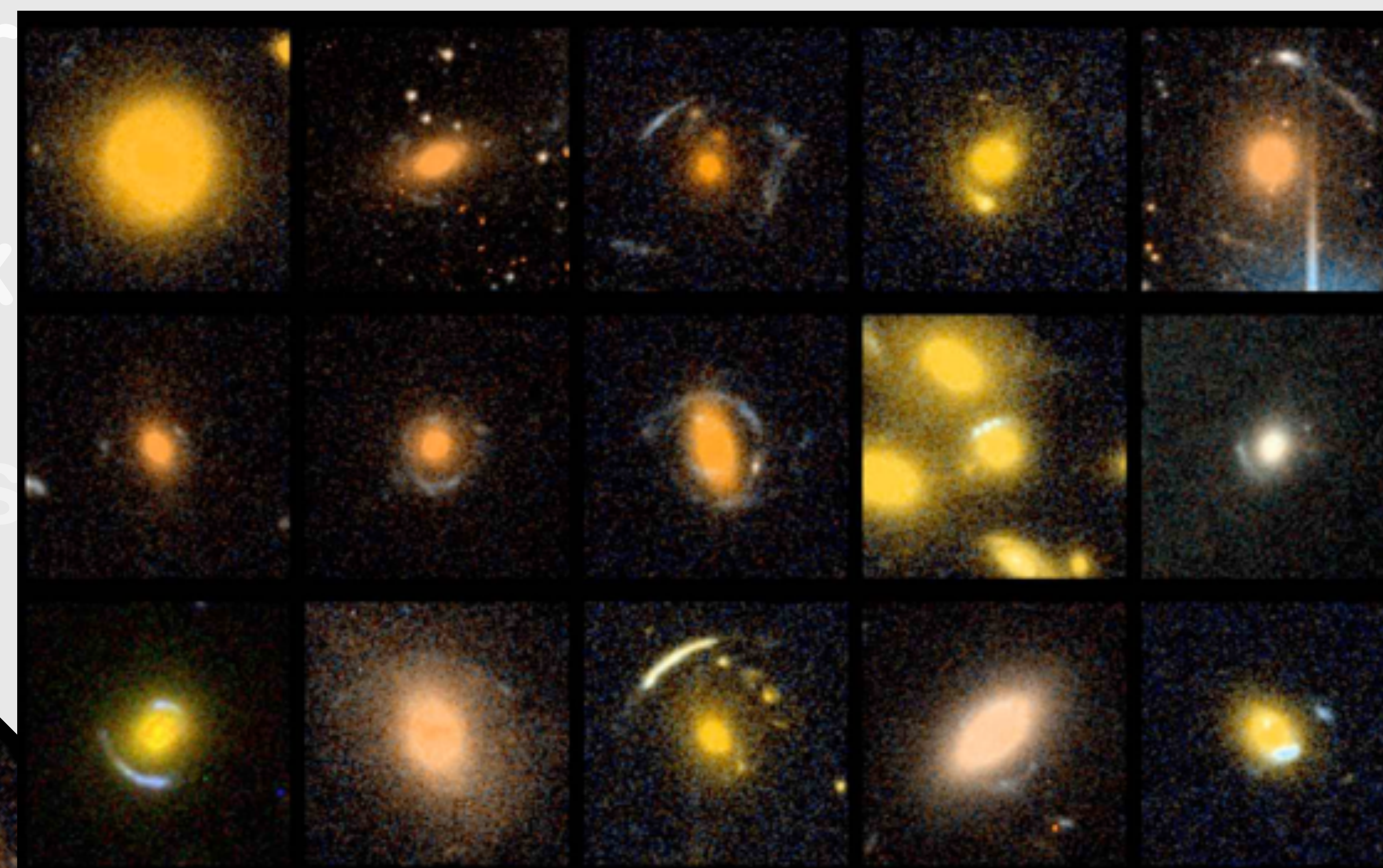




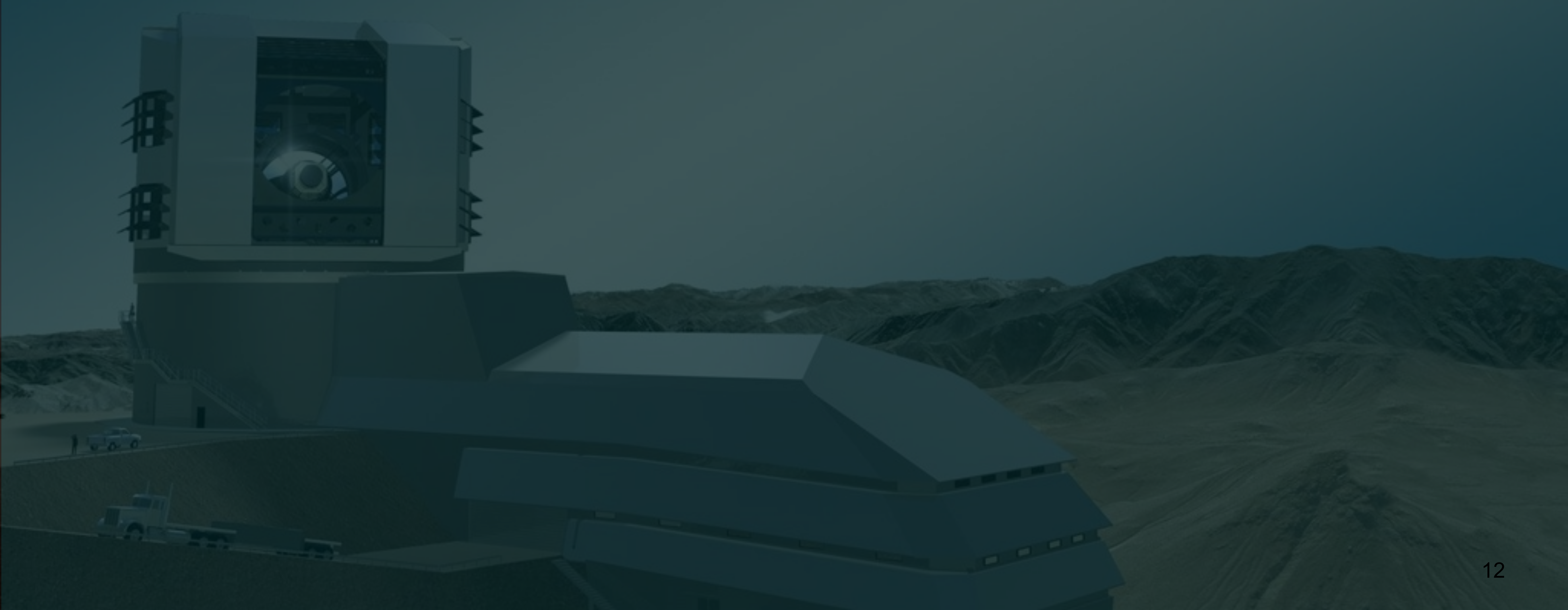
Euclid,SKA



- 0.1-0.3” image quality, 15000 sq deg
- Approaching the 10 lenses per sq deg seen in HST images (COSMOS, HAGGLeS): sources are mostly star-forming galaxies
- Galaxy structure and evolution studies, on a heavily industrialised scale



Wide-field high resolution imaging surveys will contain 100,000 strong lenses



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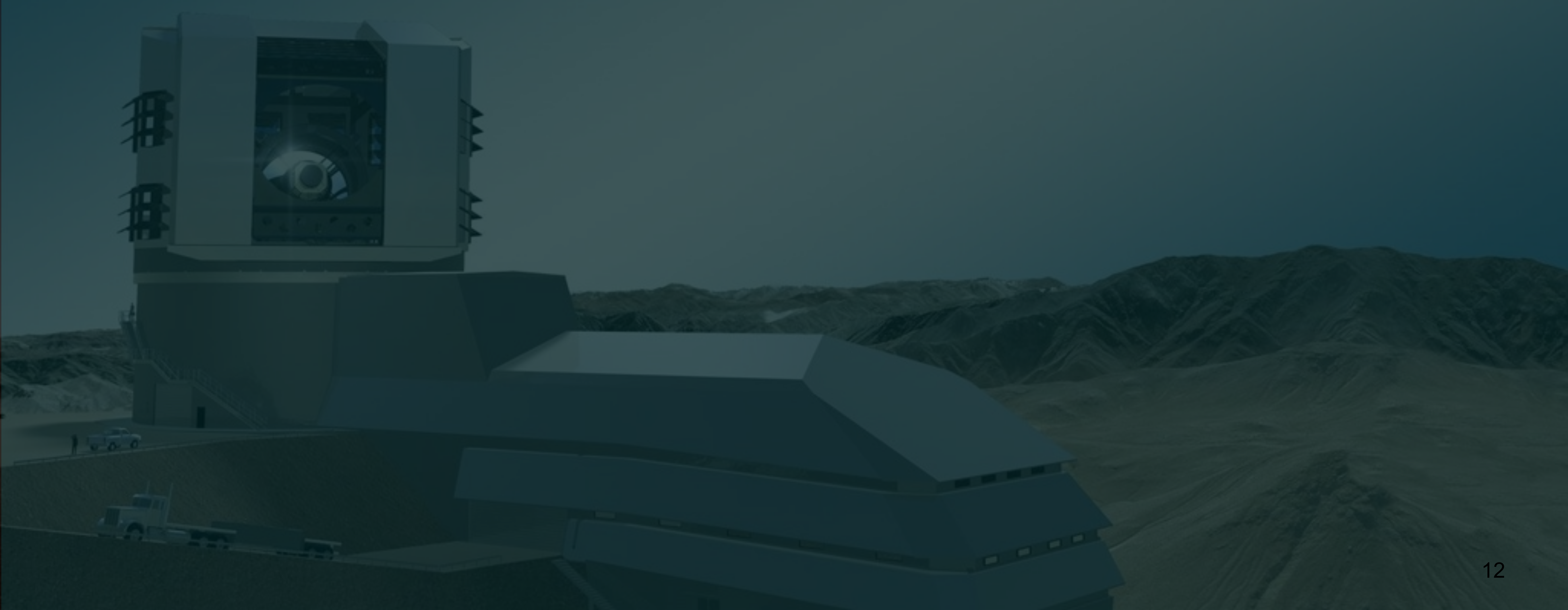

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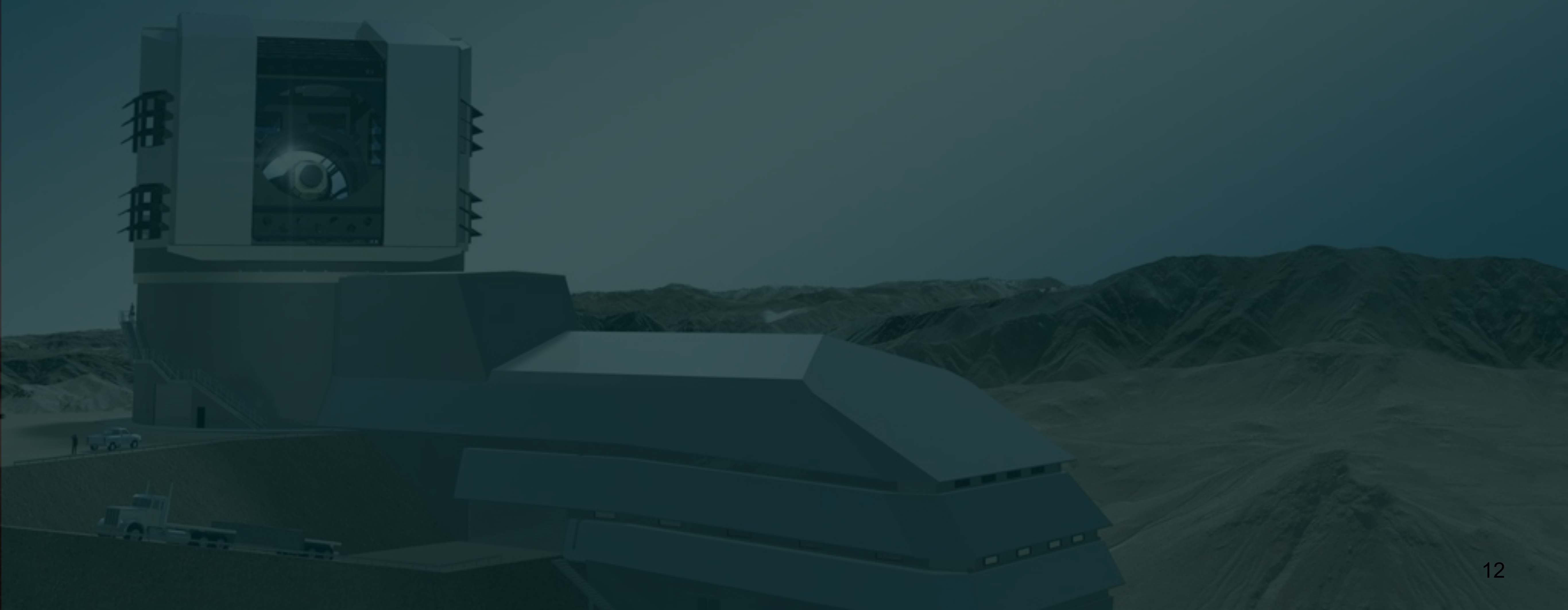
How might we find them?



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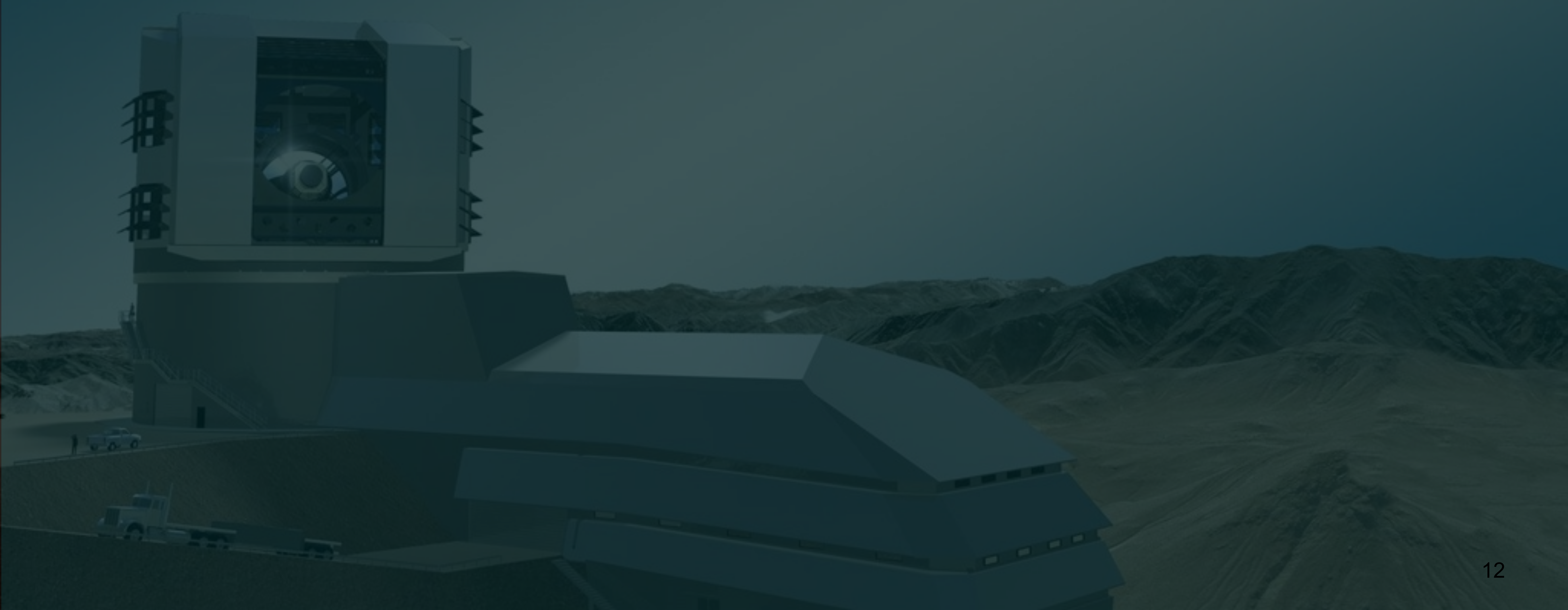
How might we find them?

- Automated, model-based lens target and candidate selection



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This talk:

Wide-field high resolution imaging surveys will contain 100,000 strong lenses

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This talk:

- How to think about lens finding

Wide-field high resolution imaging surveys will contain 100,000 strong lenses

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This talk:

- How to think about lens finding
- How to think about large samples

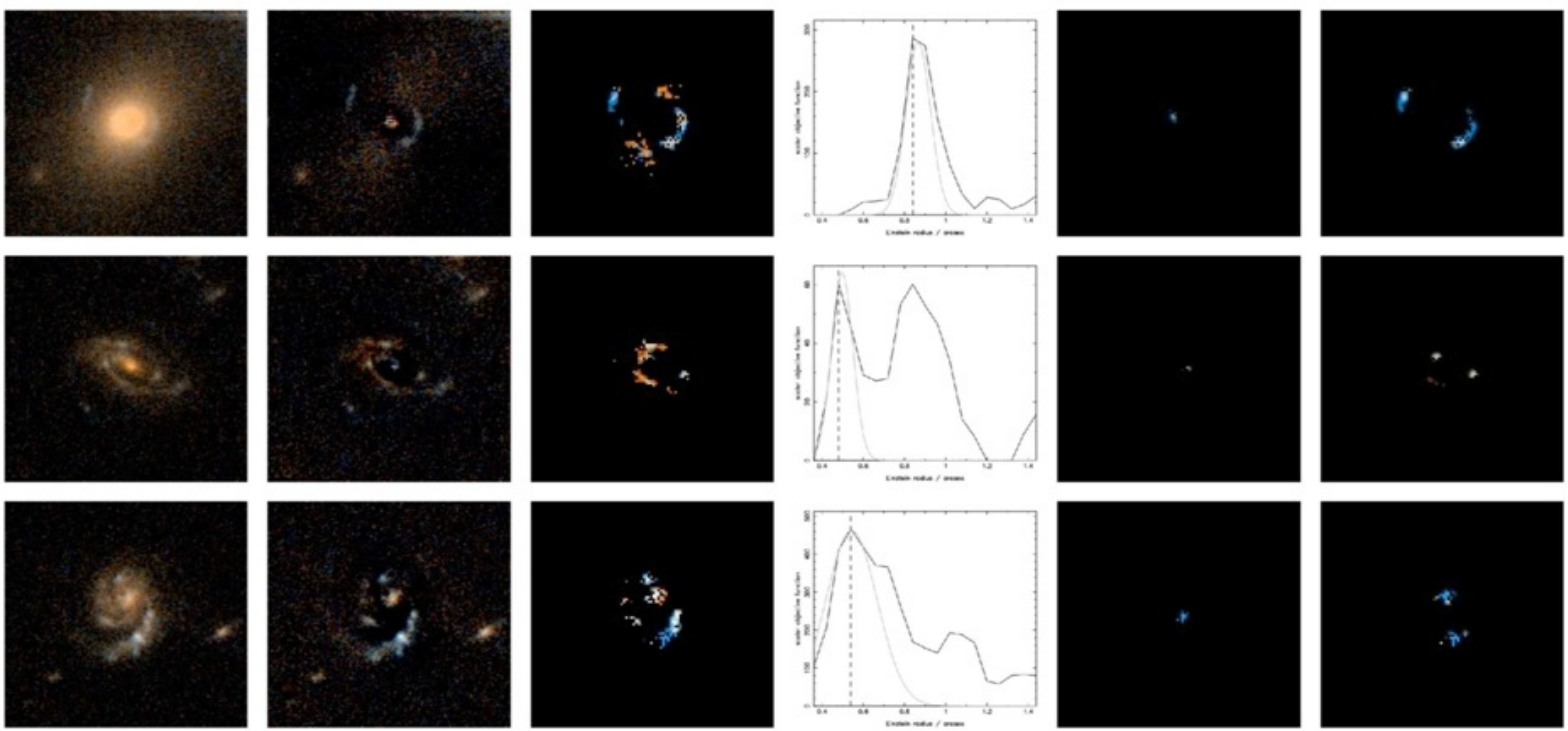
Thinking about Lens Finding

For a system to qualify as a lens candidate, it must be explained by a plausible lens model

Marshall et al 2009

Thinking about Lens Finding

For a system to qualify as a lens candidate, it must be **explained by a plausible lens model**



Marshall et al 2009

Thinking about Lens Finding

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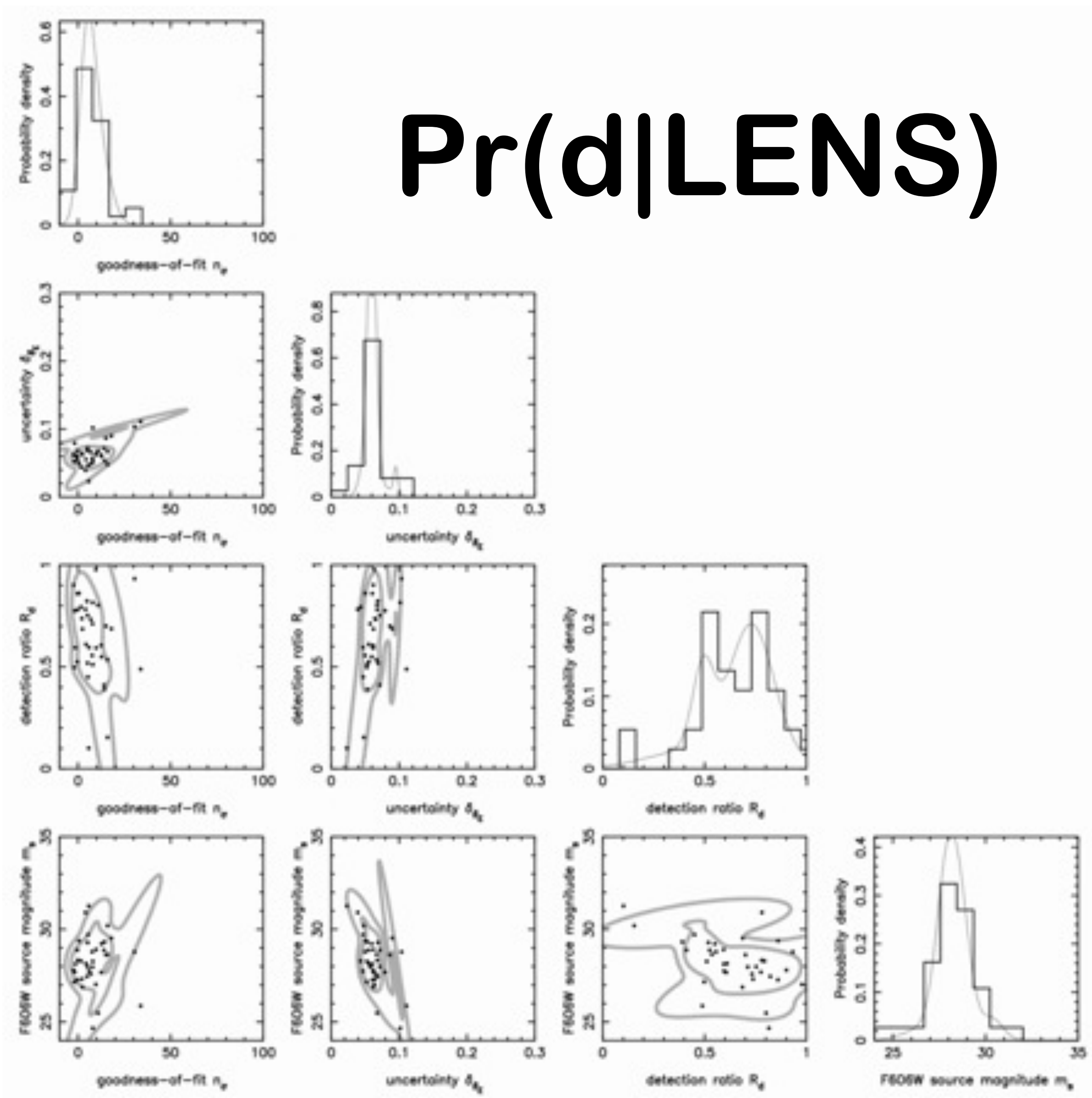
Pr(d|LENS)



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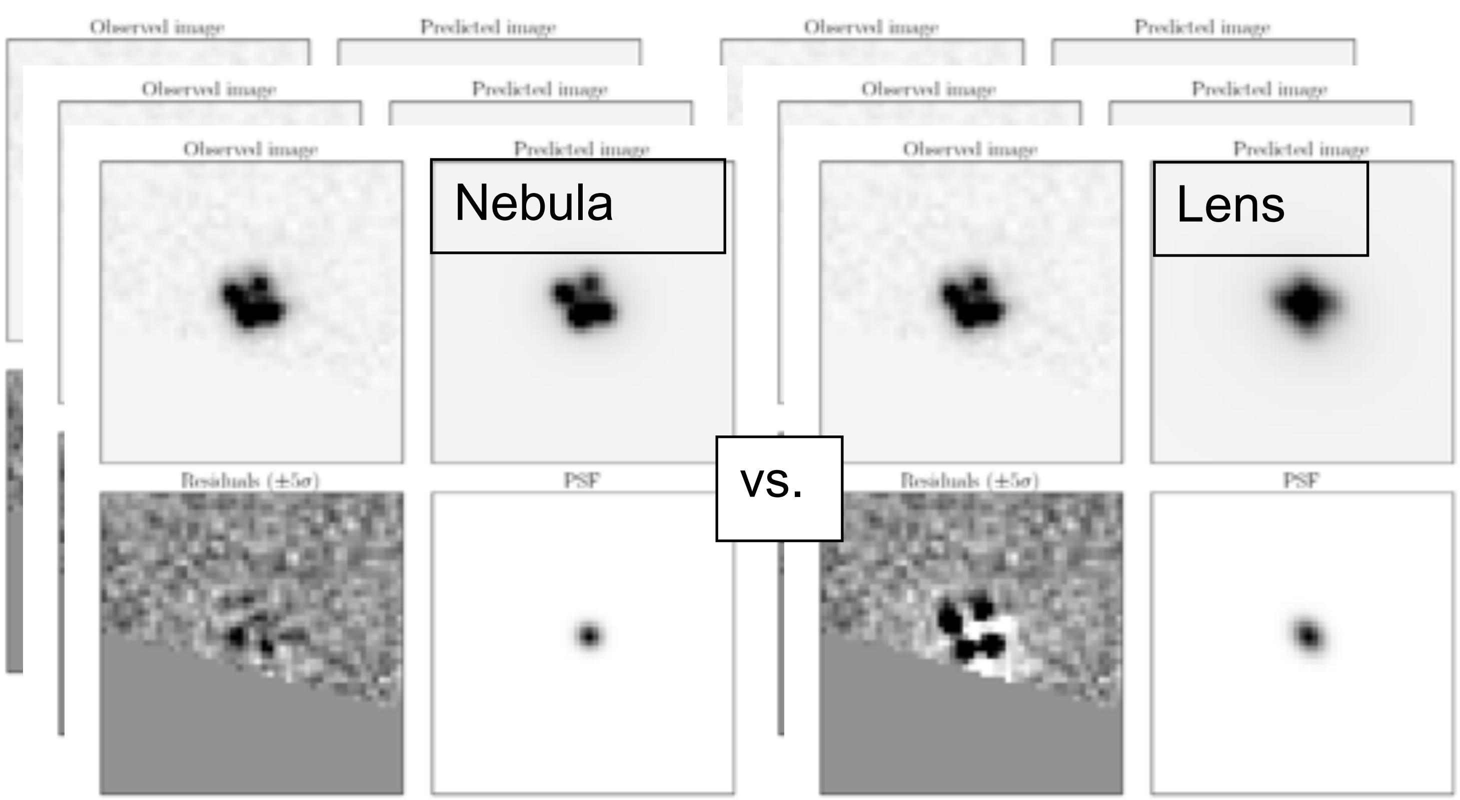

Multi-filter, multi-epoch data, unknown PSF

LensTractor
(Marshall, Agnello et al)

Robotic lensed QSO candidate detection

Classification based on explicit model comparison, Pr(d|LENS) / Pr(d|NEBULA)

Thinking about Lens Finding

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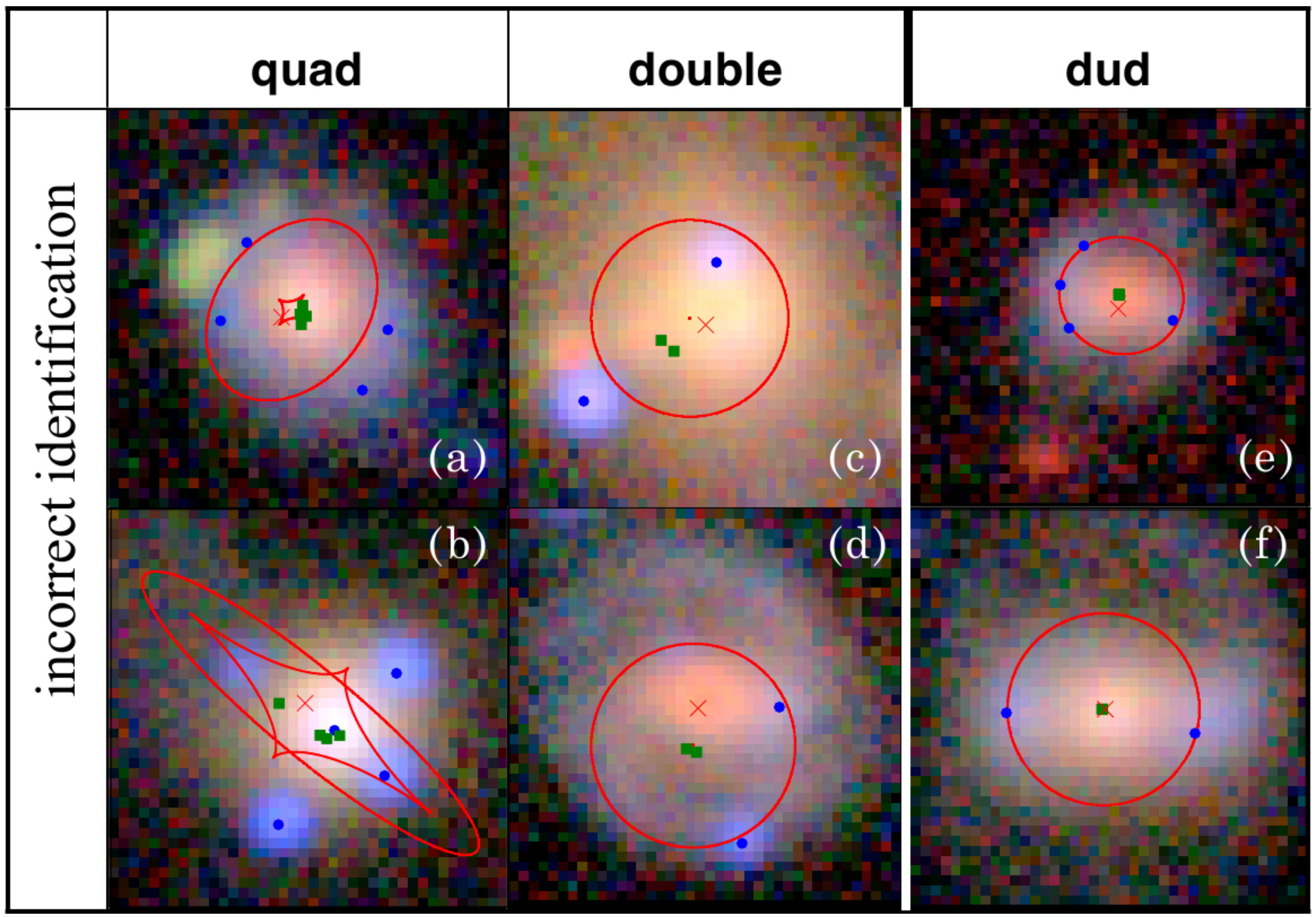


Chitah
(Chan et al 2014)

Robotic lensed QSO candidate detection

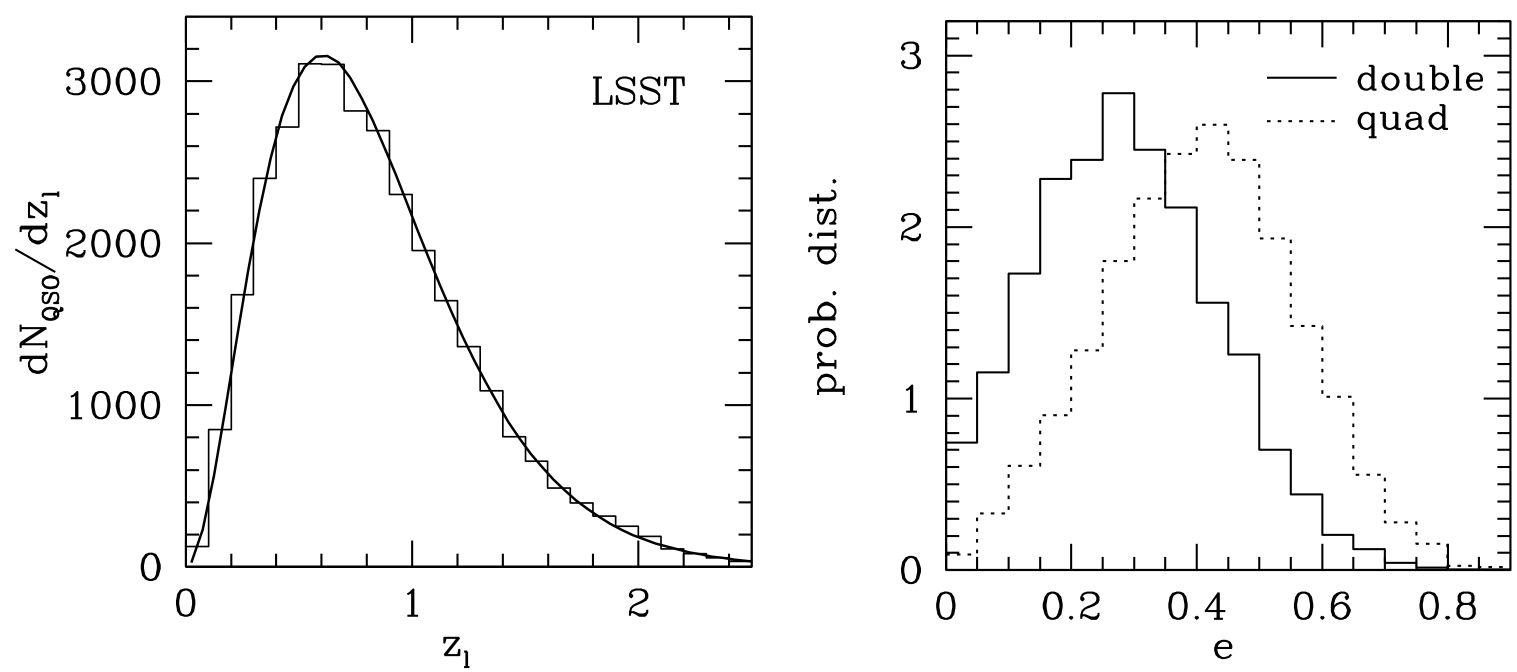
Classifies based on optimized Pr(d|x,LENS) from explicit model

Thinking about Lens Finding

For a system to qualify as a lens candidate, it must be explained by a **plausible** lens model

Pr(d|LENS) = \int Pr(d|x,LENS) Pr(x|LENS)

The lens model parameter prior Pr(x|LENS) is non-trivial, but was sampled by OM10...

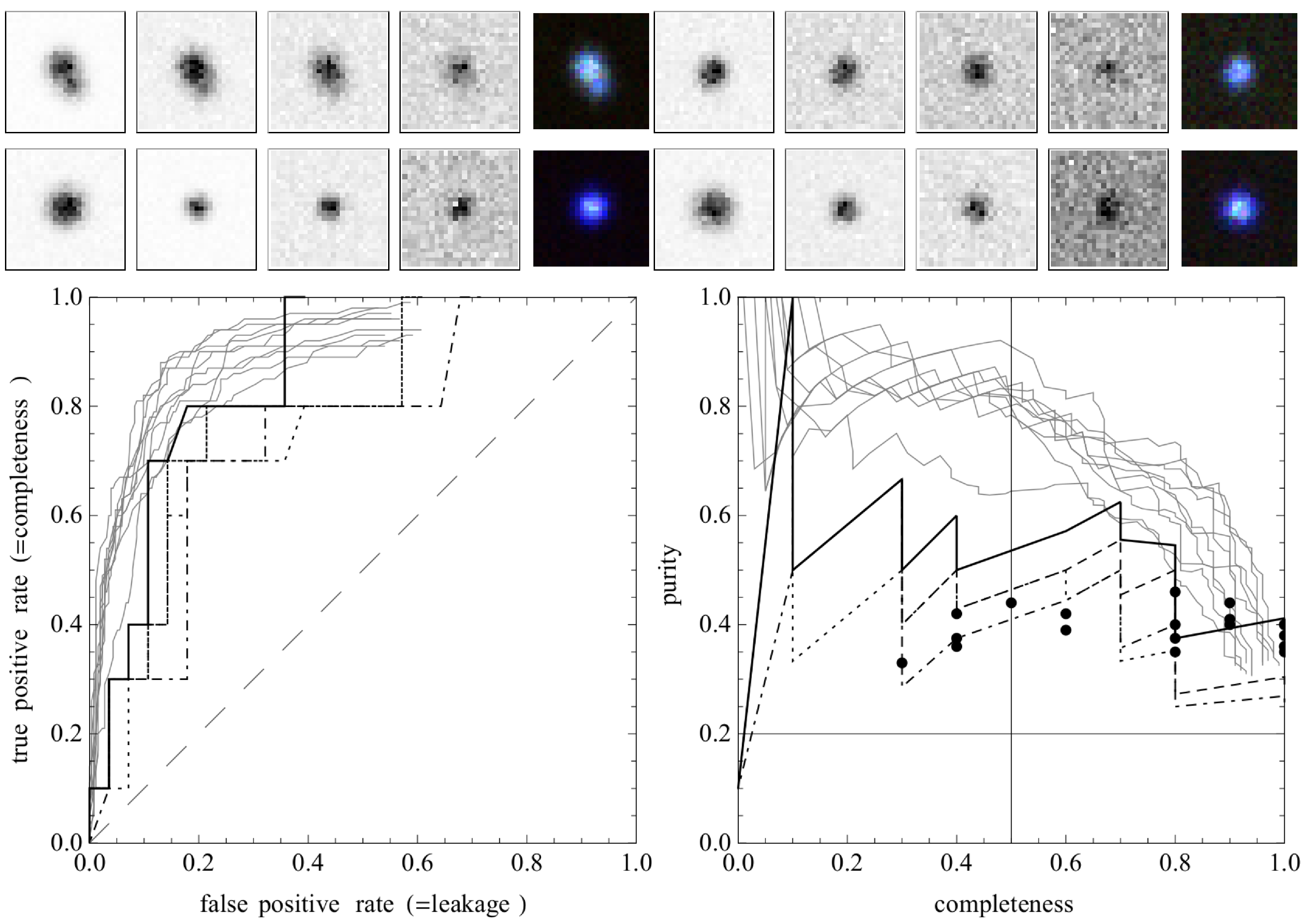


http://github.com/drphilmarshall/OM10

(Oguri & Marshall 2010)

Thinking about Lens Finding

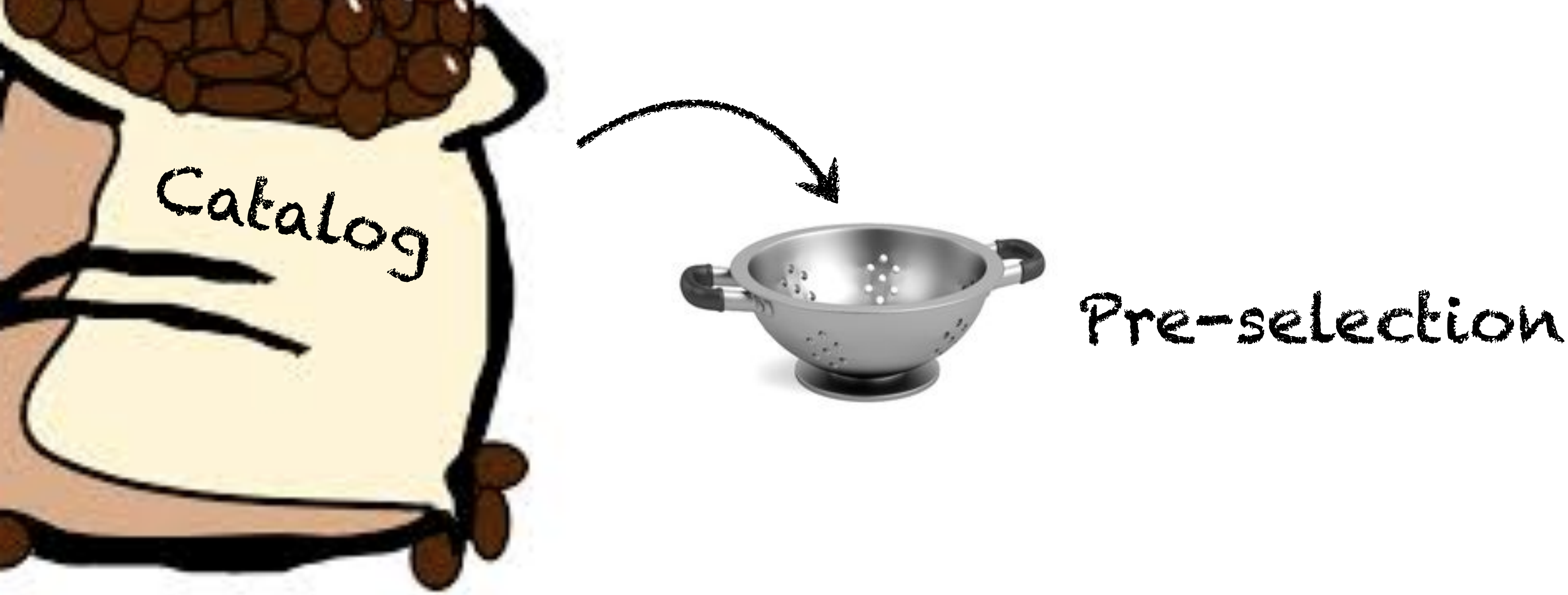
For a system to qualify as a lens candidate, it must be explained by a plausible lens model

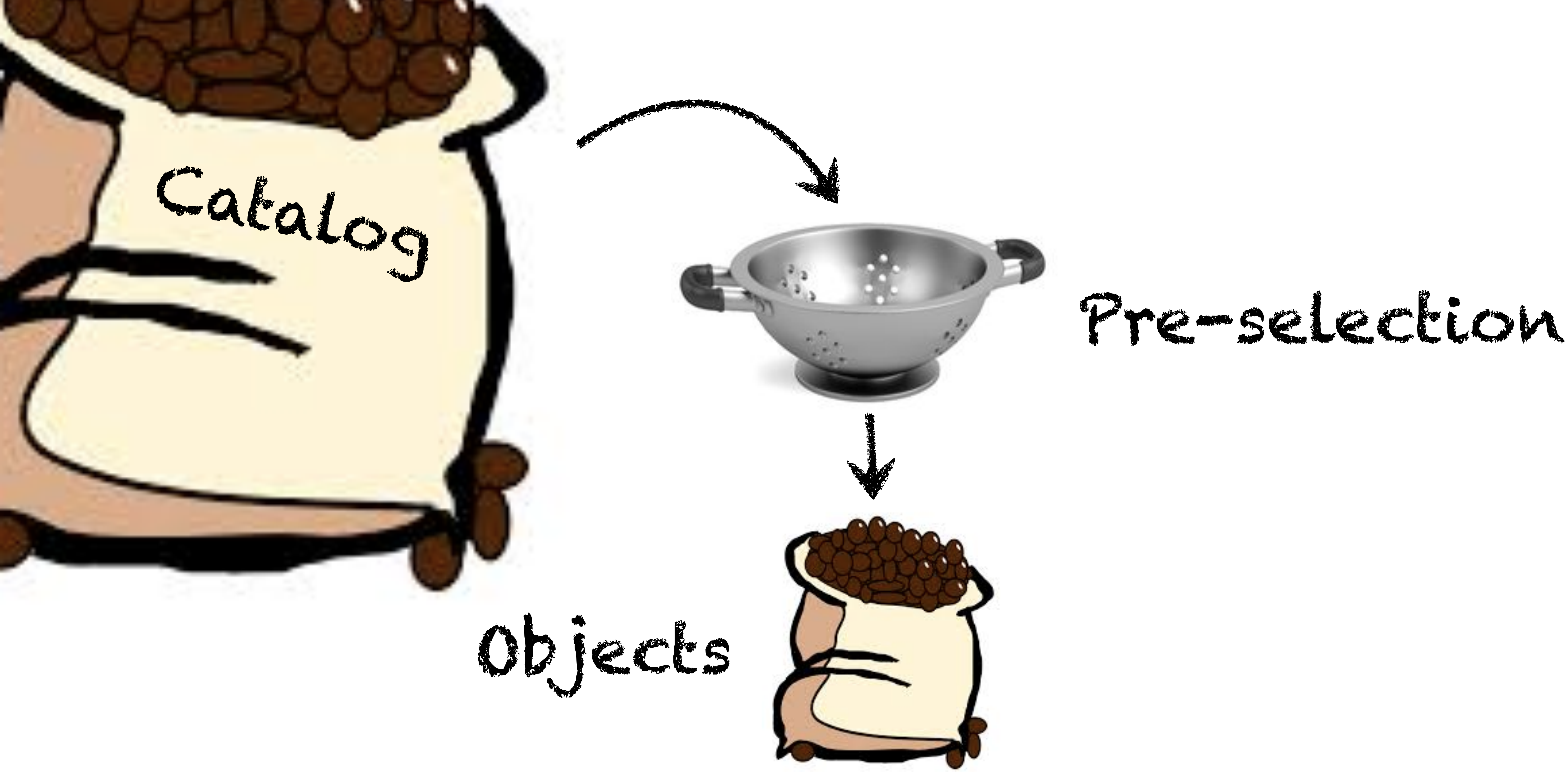


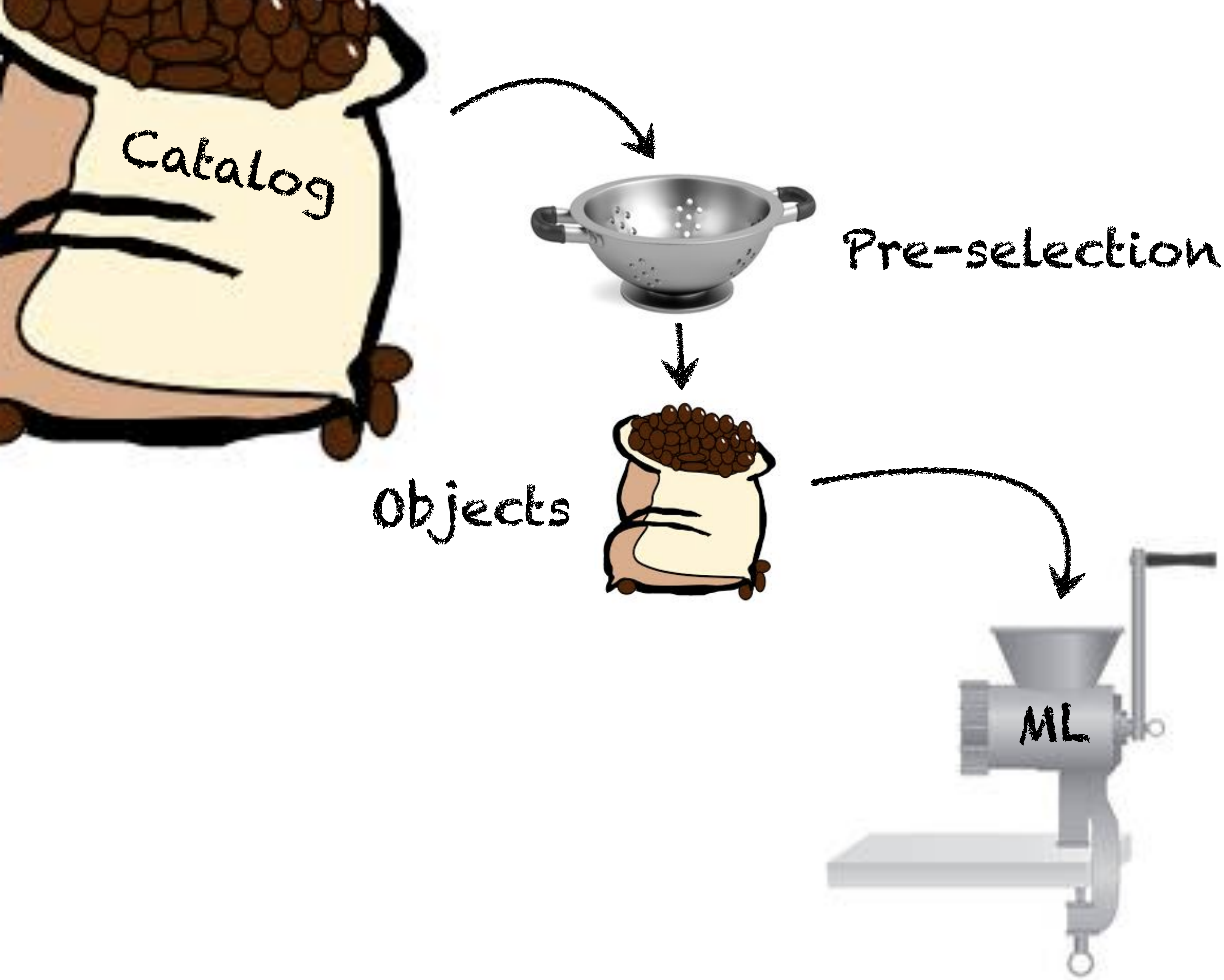
Lens Mining
(Agnello et al 2014)

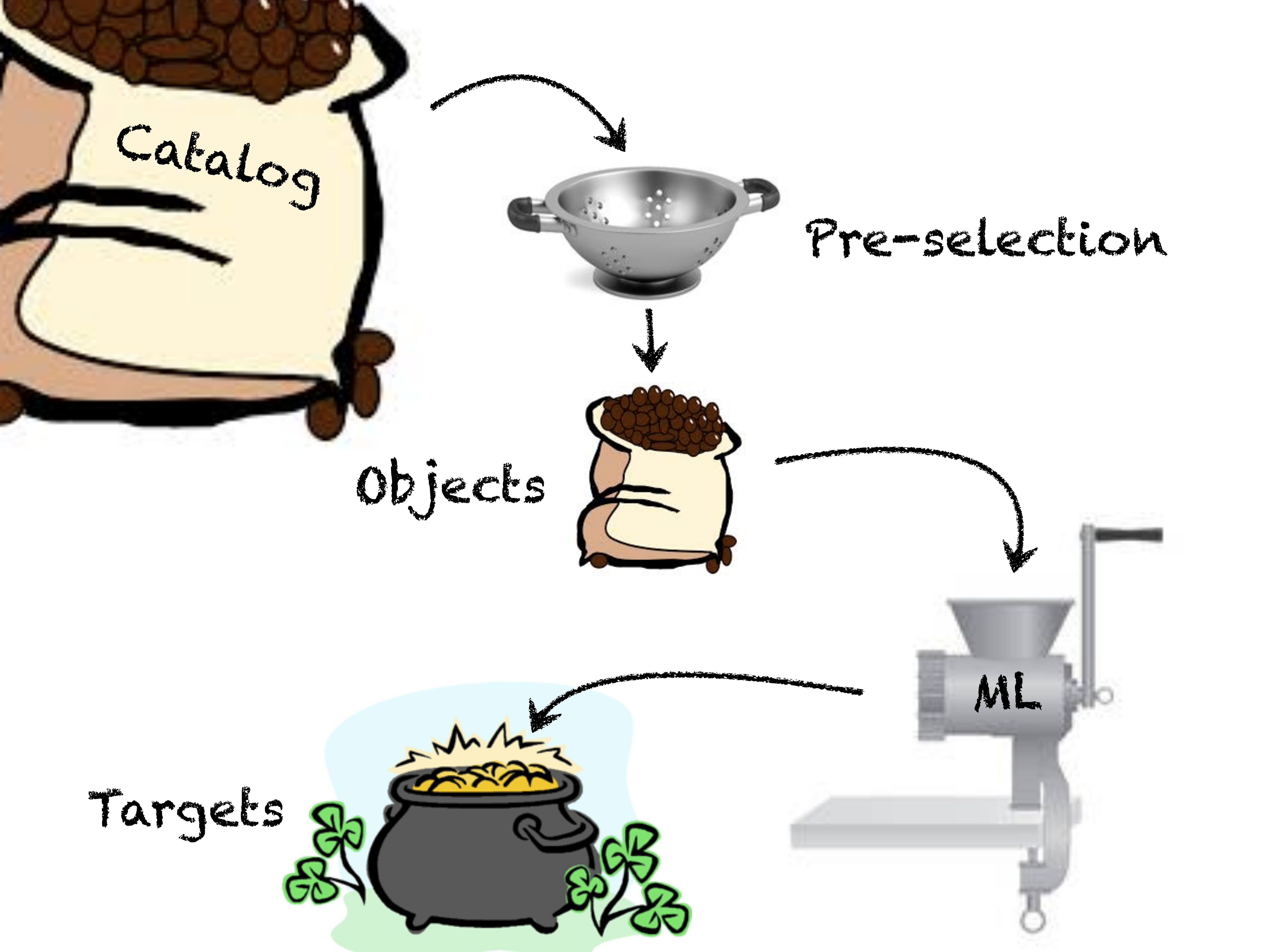
Supervised machine learning methods - implicit lens model (prior) enters via the training set


Catalog

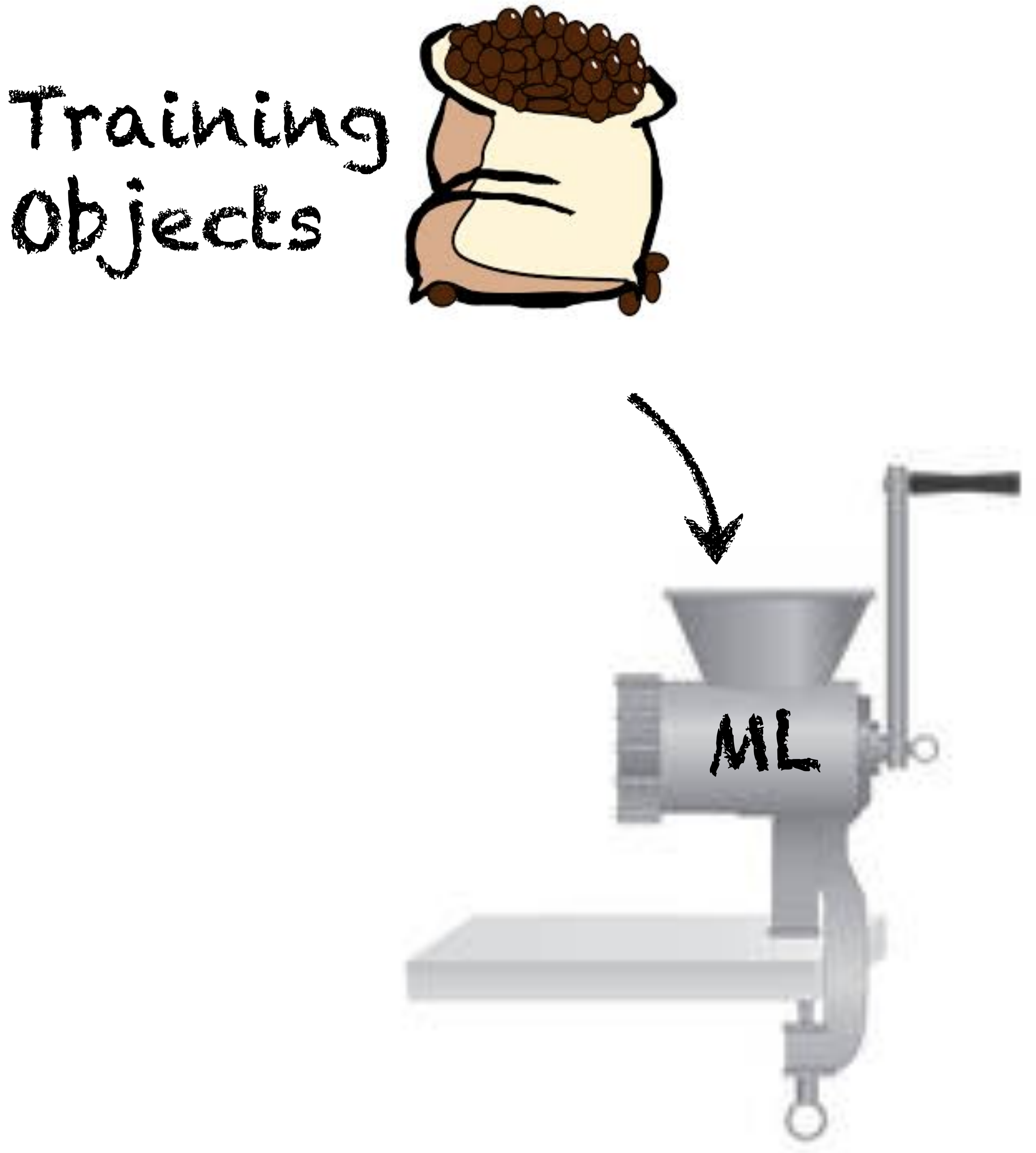

Catalog
Pre-selection

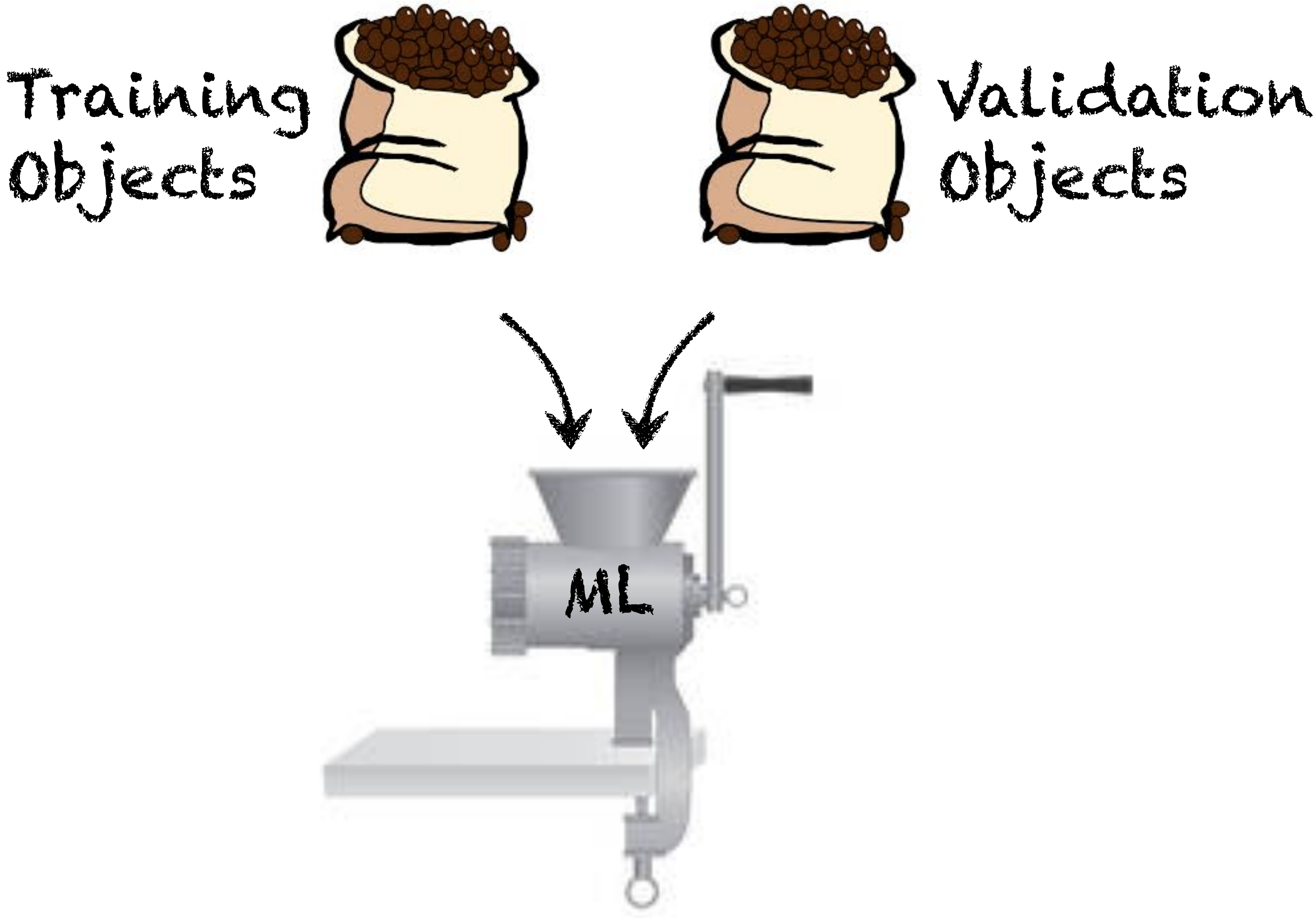

Catalog
Pre-selection
Objects

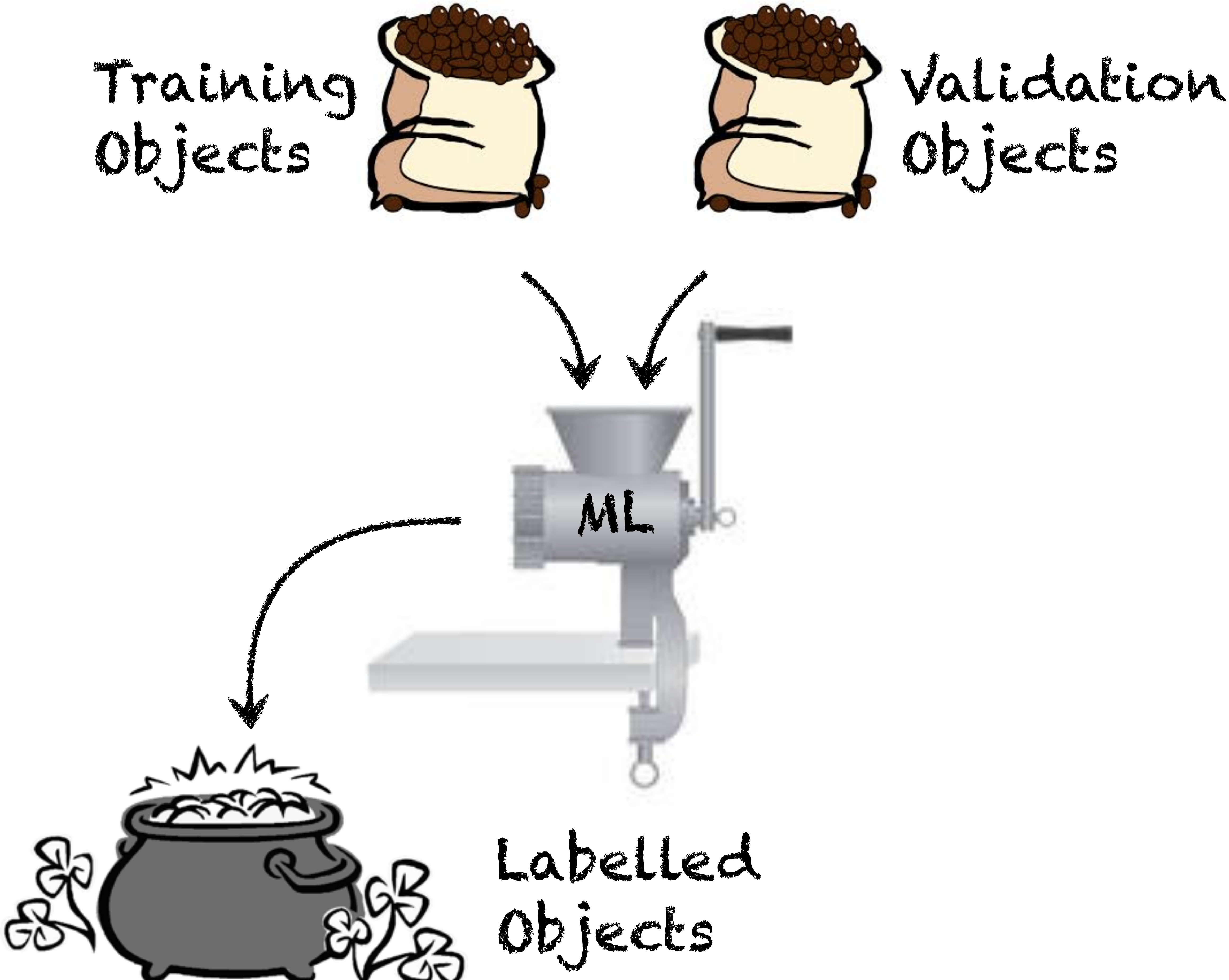

Catalog
Pre-selection
Objects
ML

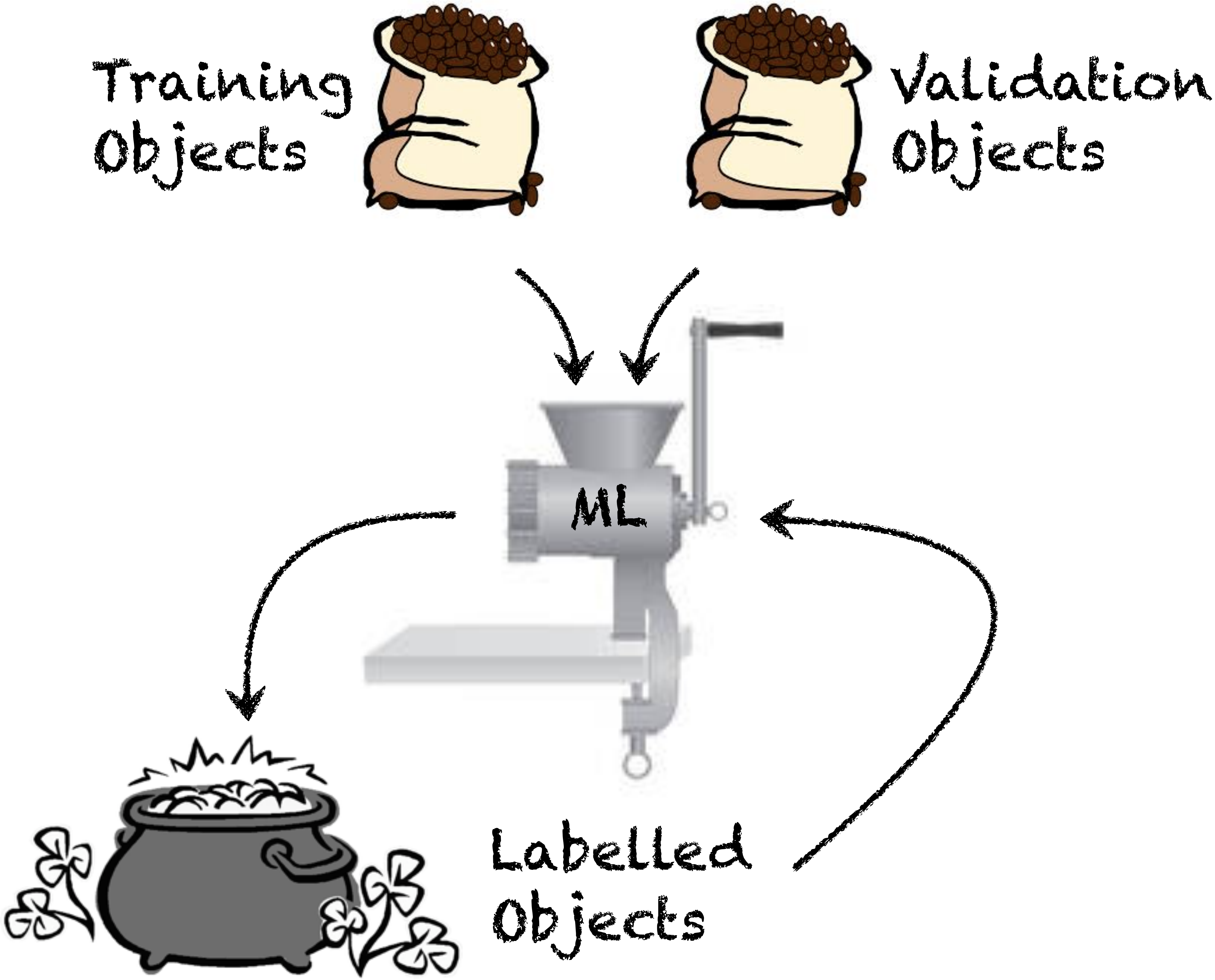

Catalog
Pre-selection
Objects
ML
Targets


ML


Training
Objects
ML


Training
Objects
Validation
Objects
ML


Training Objects
Validation Objects
ML
Labelled Objects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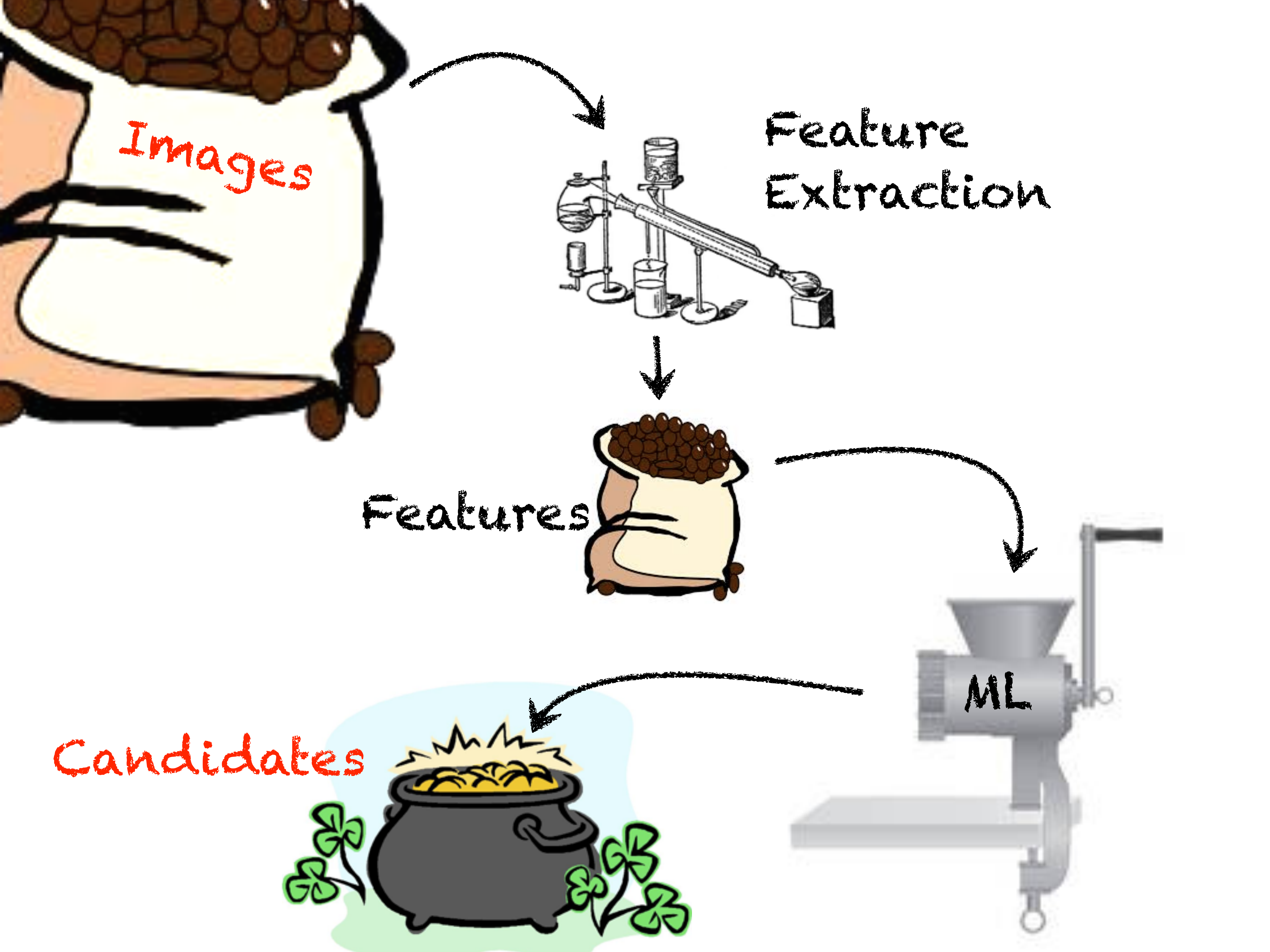

Images
Feature
Extraction
Features
ML
Candidates

Thinking about Lens Finding

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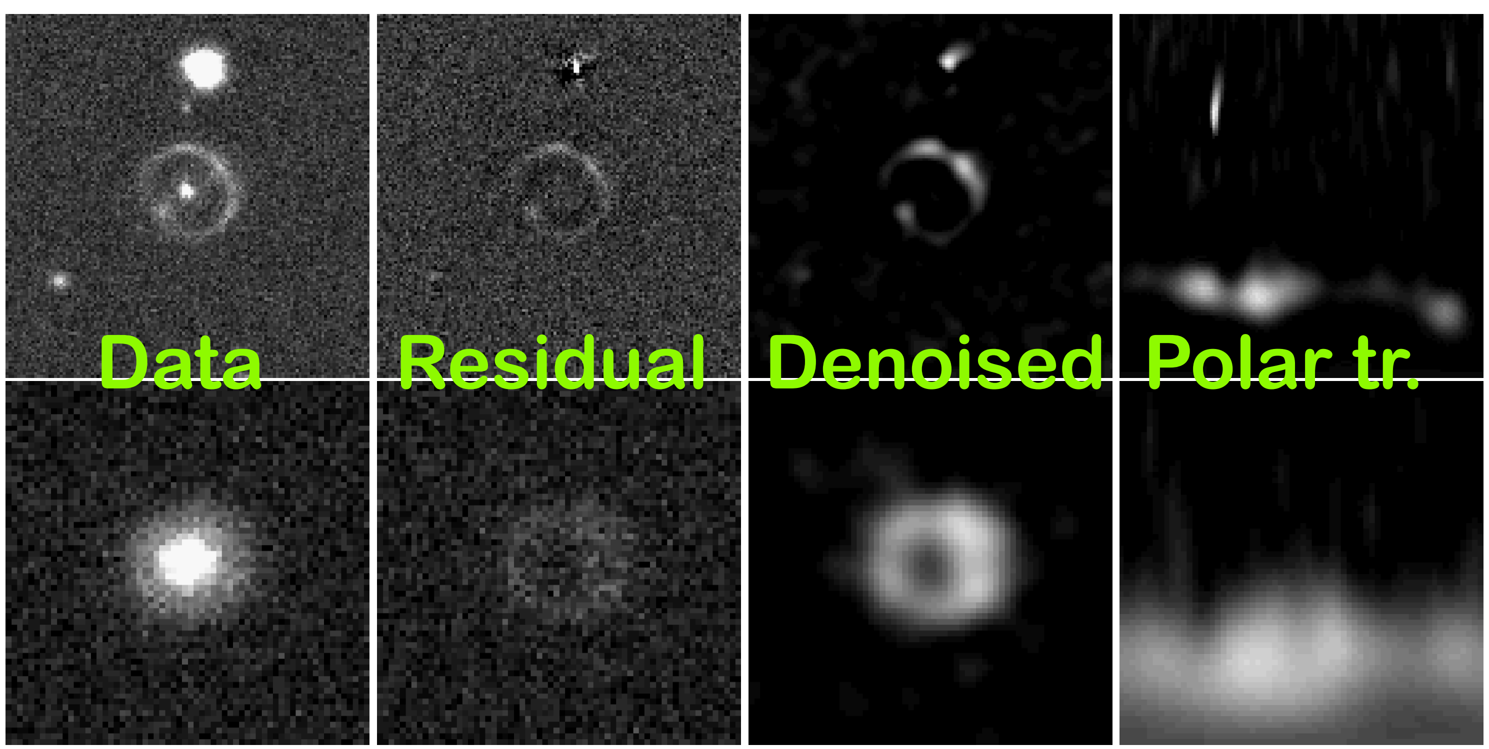

RingFinder
(Gavazzi et al 2014)

PCAFinder
(Joseph et al 2014)

Subtract lens light, process residuals, provide ranked candidates for **inspection**

Thinking about Lens Finding

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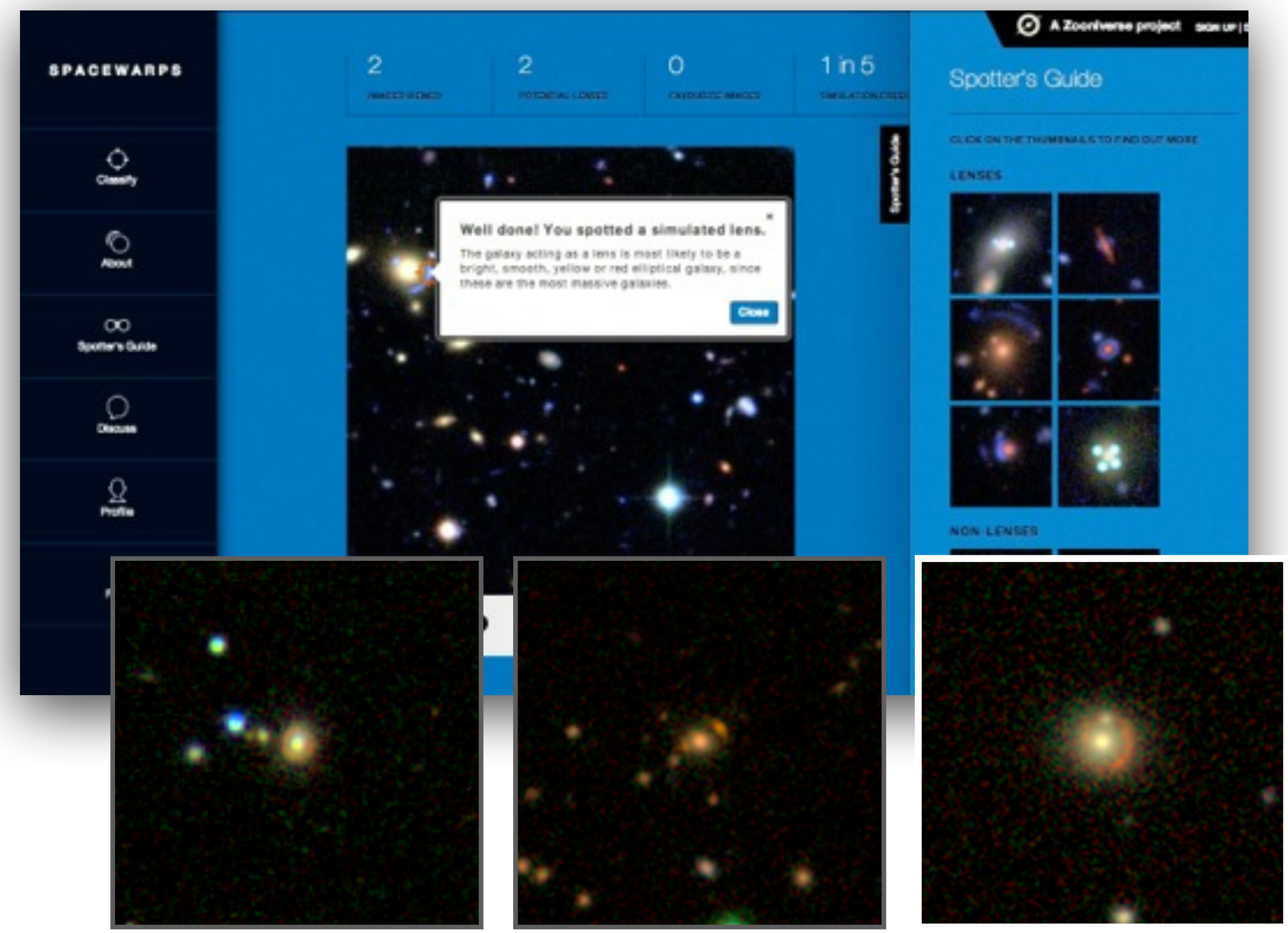
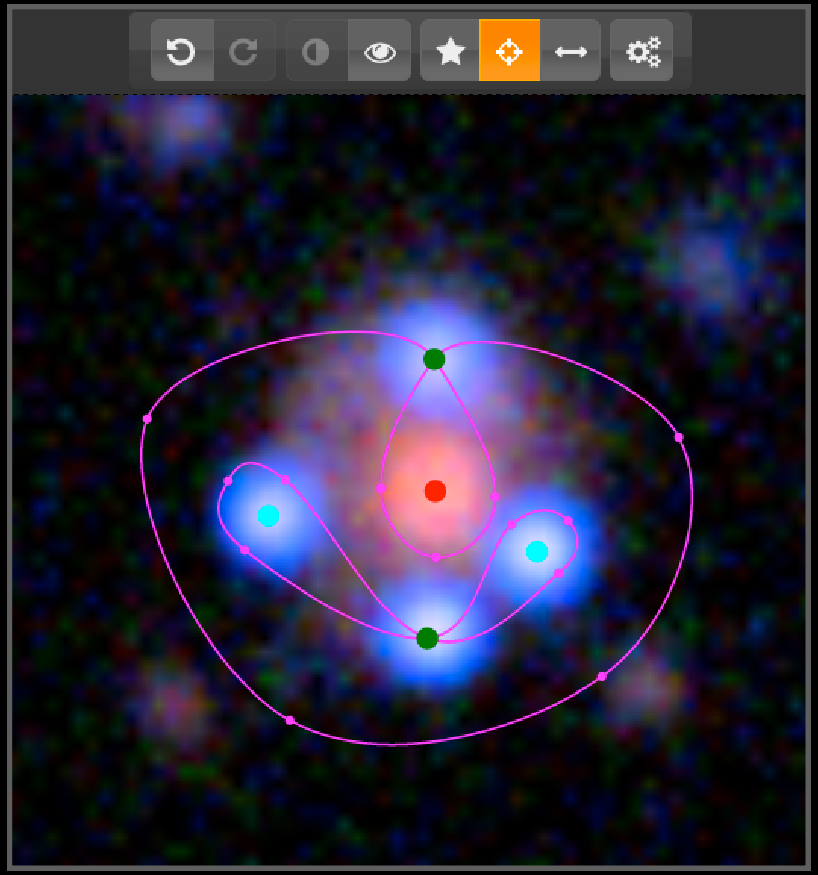


Space Warps
(Marshall, More, Verma et al)

Crowd-sourced image inspection, mental modeling. Supervised via training set (but imagination remains)

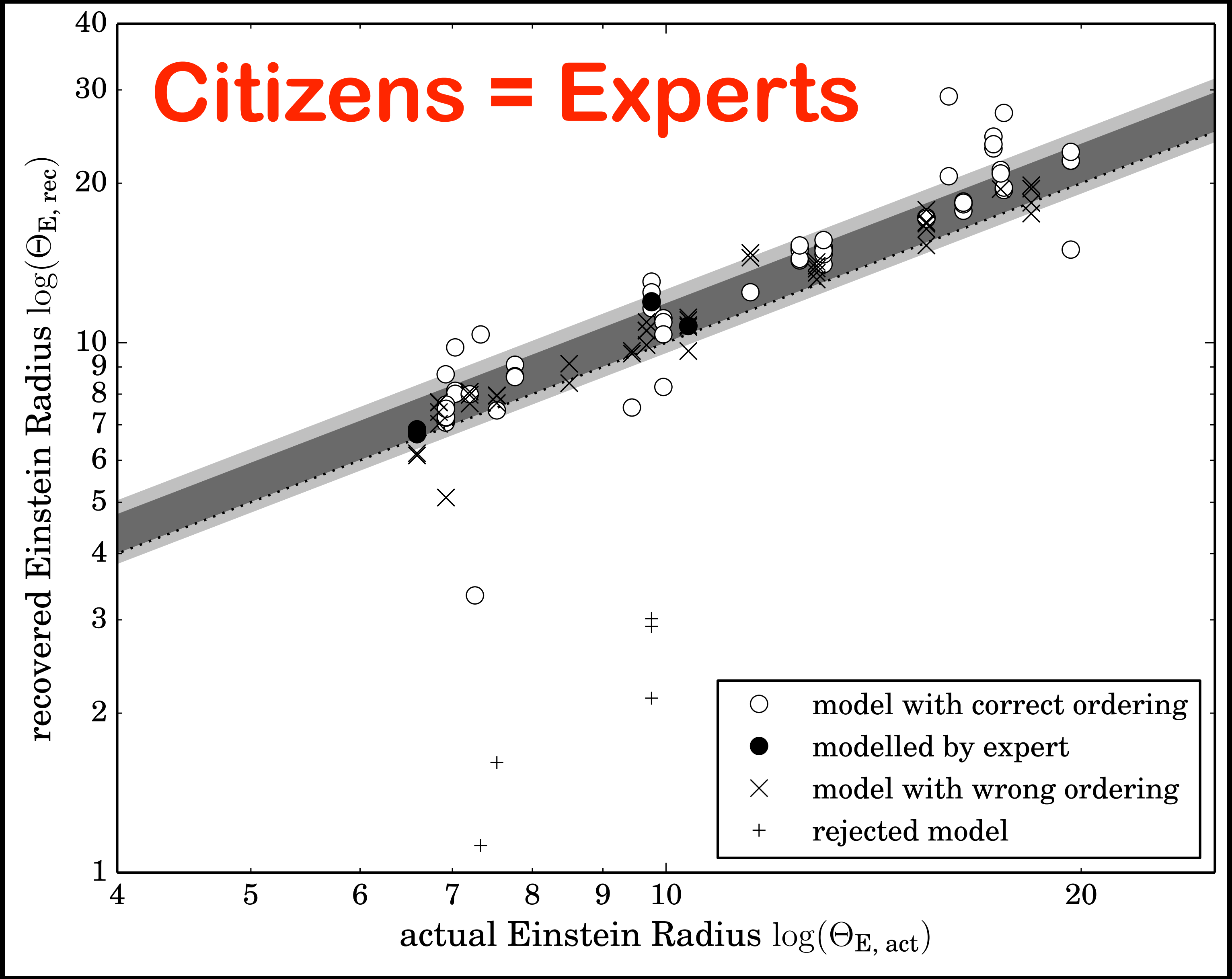
Crowd-sourced Lens Modeling

Visual inspection for candidate quality control: can we do better than "mental modeling"?



"SpaghettiLens"

Kueng et al 2014



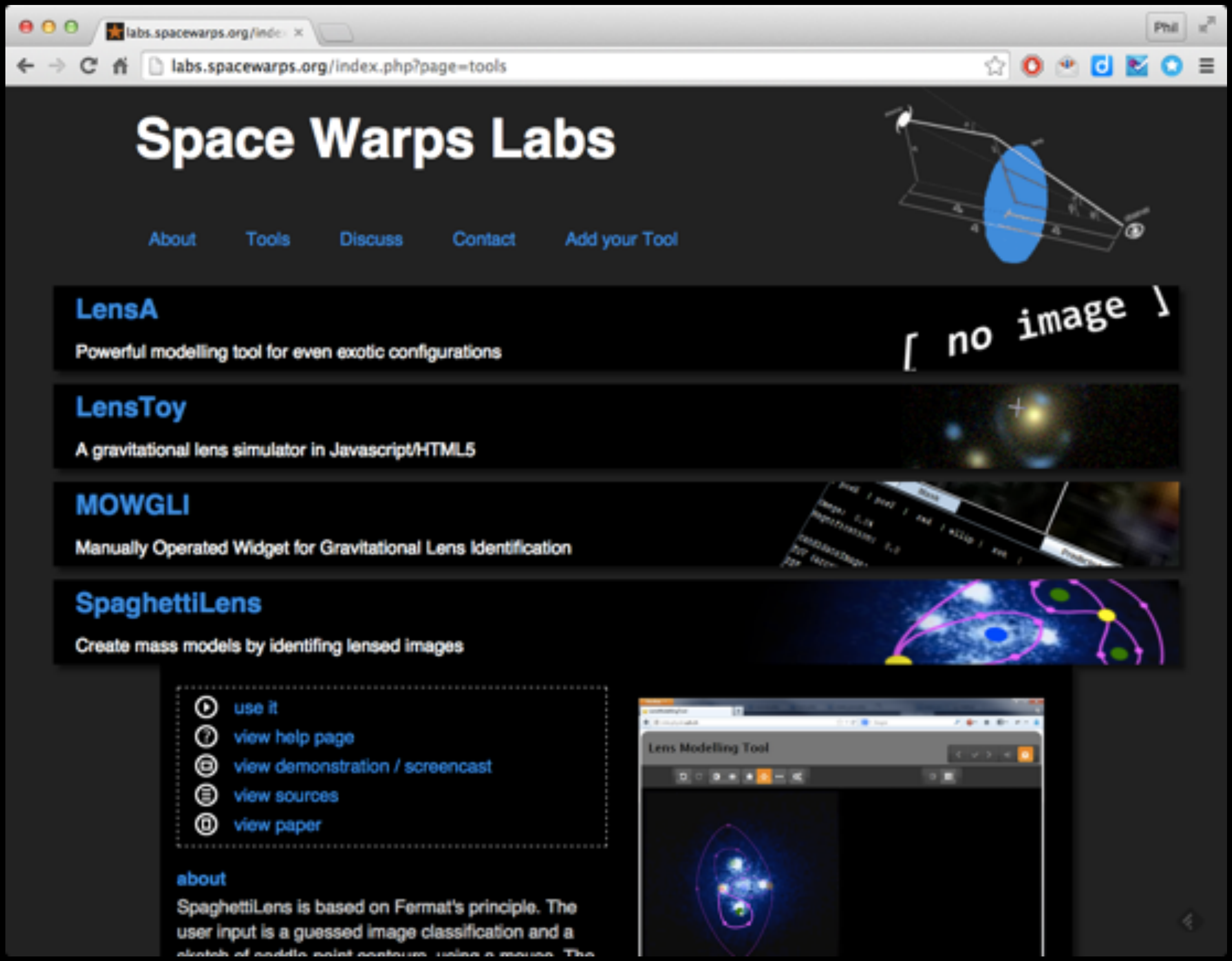
Crowd-sourced Lens Modeling

Visual inspection for candidate quality control: can we do better than “mental modeling”?

Under construction: labs.spacewarps.org

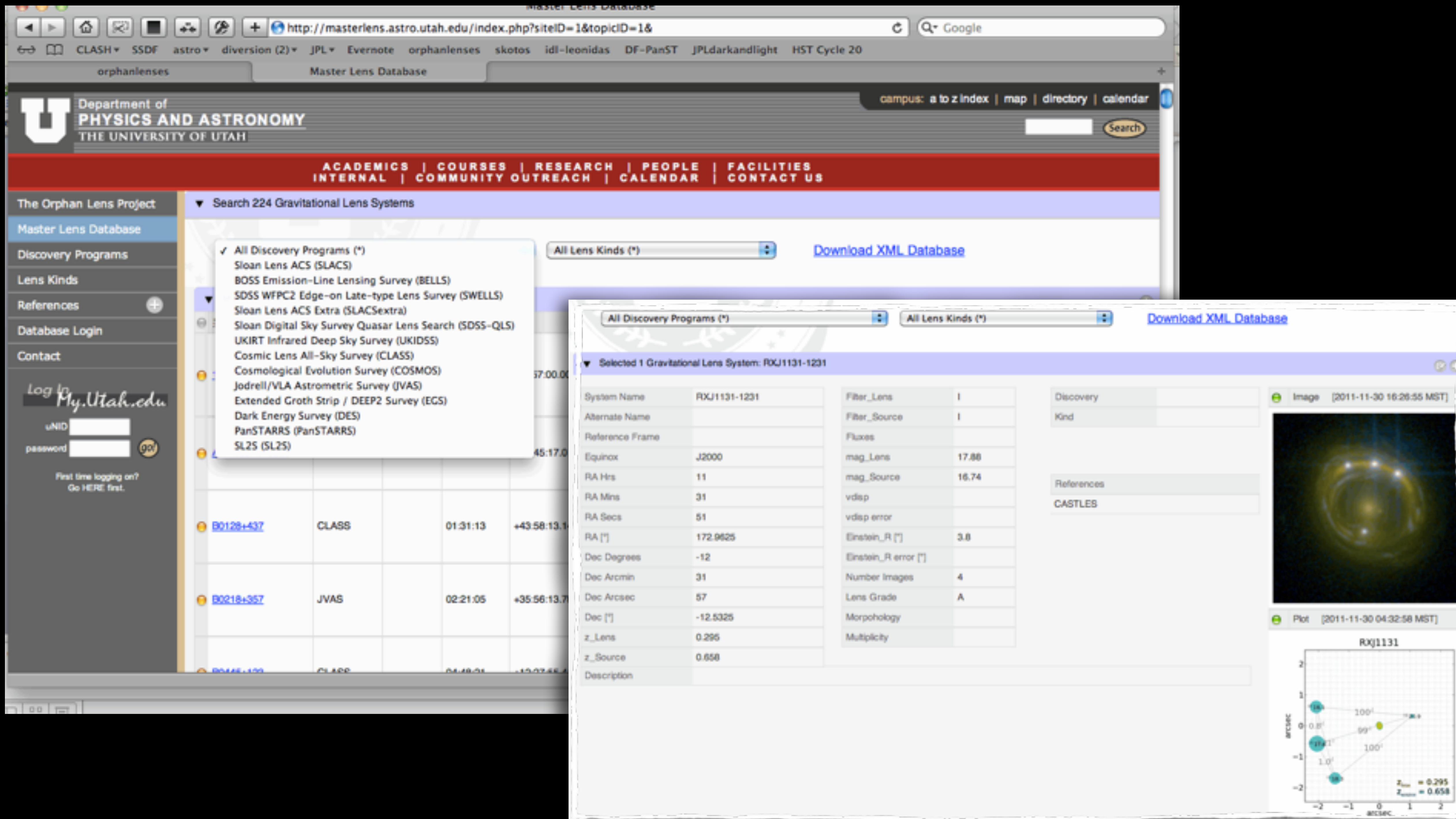
Platform for hosting web-based lens modeling code

Shareable results pages enable collaborative model exploration and optimization



Rafi Kueng PhD Thesis

Community Lens Modeling



http://masterlens.astro.utah.edu/

Finding Lenses:

- Motivation
- Brief history
- Wide field imaging surveys
- Approaches to lens finding

Using Lenses:

- **Hierarchical inference**

Analyzing Strong Lens Ensembles

More lenses means higher precision

Sonnenfeld & Marshall

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More lenses means higher precision

- Requires joint analysis

Sonnenfeld & Marshall

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Sonnenfeld & Marshall

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Extract maximum information from data

Sonnenfeld & Marshall

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Models of ensembles are hierarchical

Extract maximum information from data

Fit for selection function

Sonnenfeld & Marshall

Simple Example: 100 Lensed Quasars

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- Suppose we follow up 100 time delay lenses. We'll want to combine them to infer the Hubble constant

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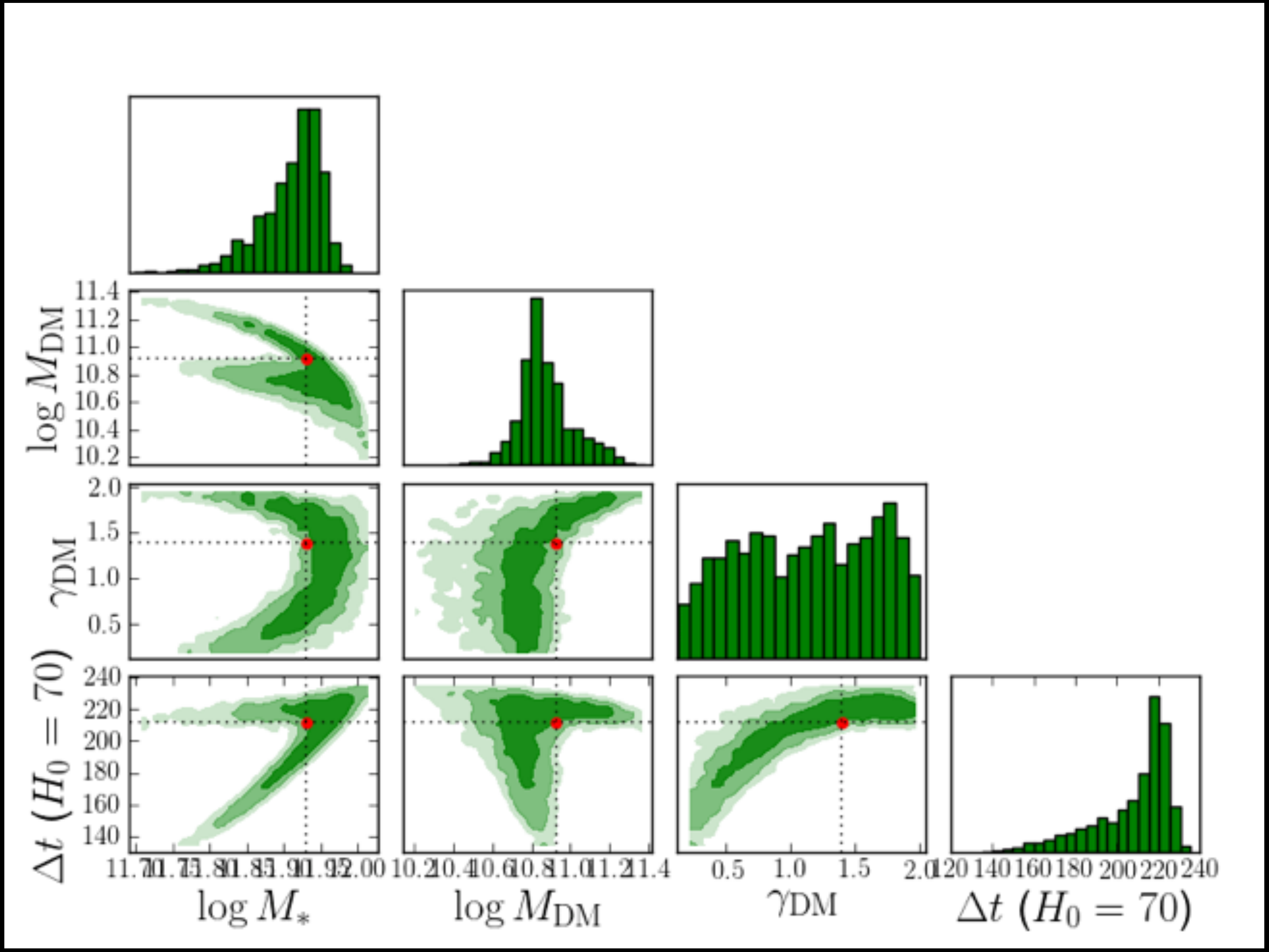
- We don't want to introduce systematic errors by using an over-simplistic density profile - but if we go flexible, the prior will be important

Simple Example: 100 Lensed Quasars

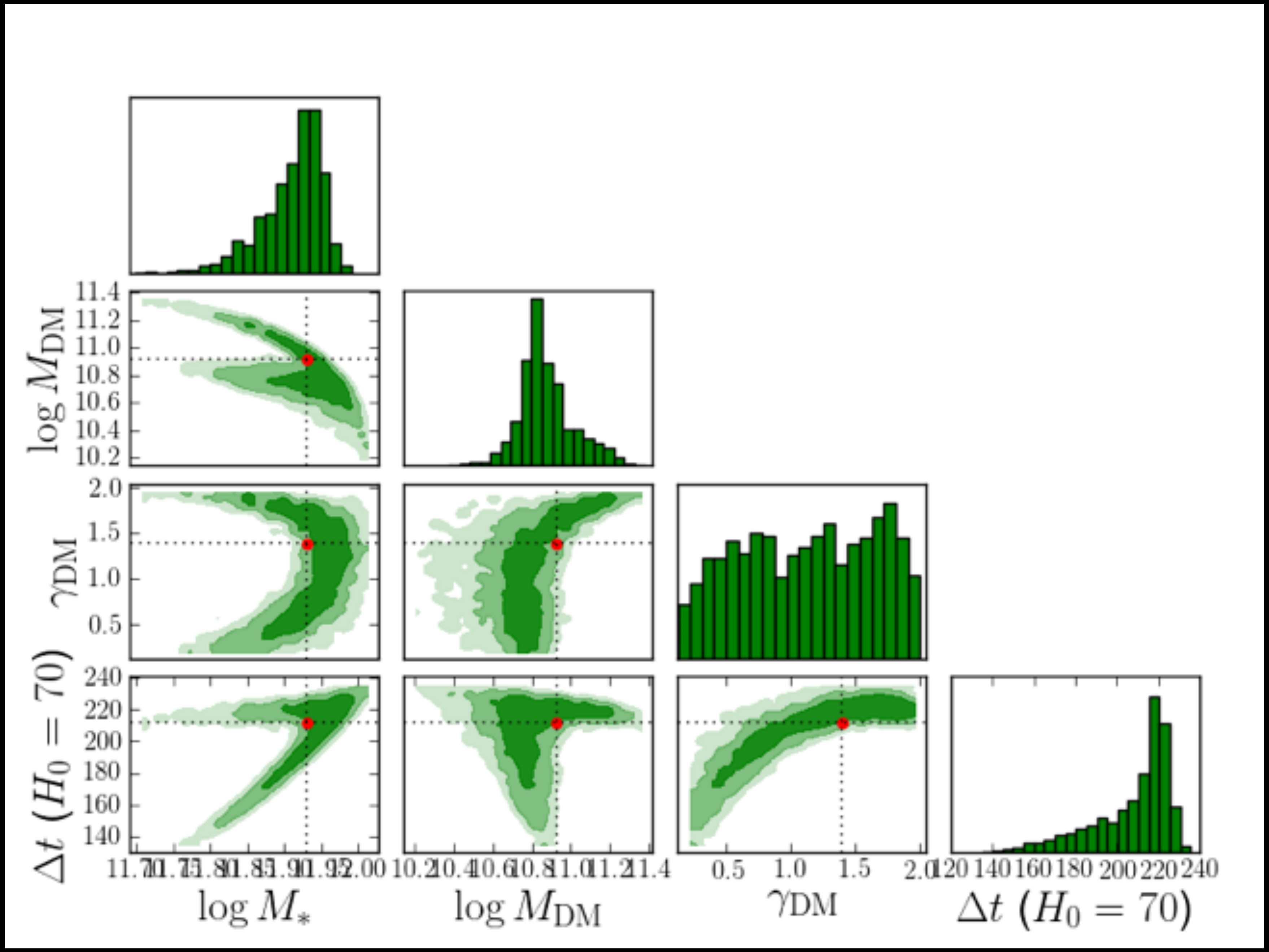
- Suppose we follow up 100 time delay lenses. We'll want to combine them to infer the Hubble constant
- We don't want to introduce systematic errors by using an over-simplistic density profile - but if we go flexible, the prior will be important
- Solution: make weak assumption that massive galaxies are somehow self-similar, and infer this conditional PDF (scaling relation plus scatter) simultaneously with the cosmological parameters

100 Spherical Cows



Double image configuration, spherical symmetry, known QSO positions, stellar mass to 0.1dex, radial magnification ratio (from extended source) to 1.5%

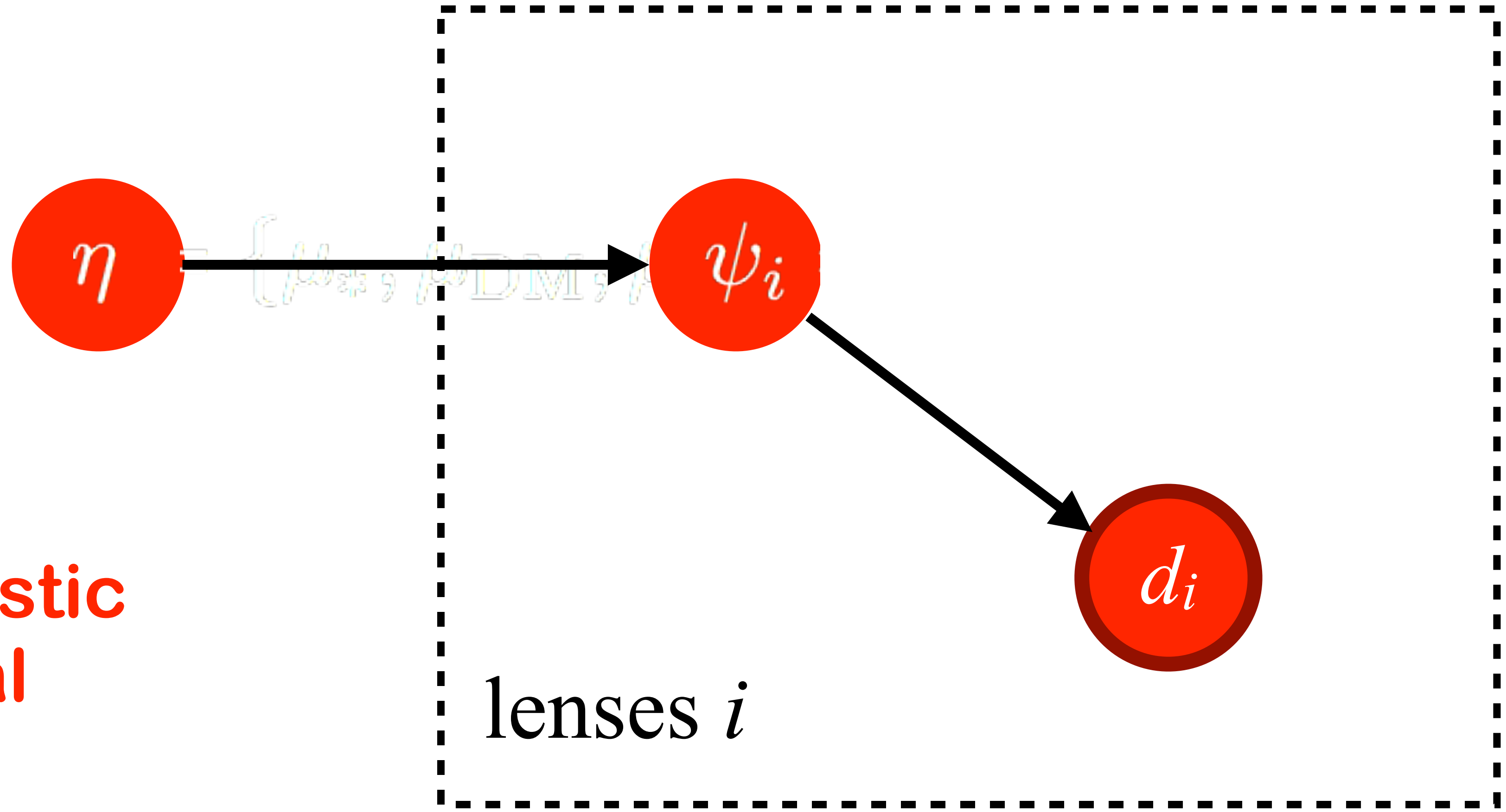
100 Spherical Cows



Double image configuration, spherical symmetry, known QSO positions, stellar mass to 0.1dex, radial magnification ratio (from extended source) to 1.5%

Joint analysis: inferring H_0

$$P(\eta|d) = P(\eta)P(d|\eta) = P(\eta)\prod_i \int d\psi_i P(d|\psi_i)P(\psi_i|\eta)$$



Probabilistic Graphical Model

- **Global hyper-parameters:** $\eta = \{\mu_*, \mu_{\rm DM}, \mu_\gamma, \sigma_*, \sigma_{\rm DM}, \sigma_\gamma, H_0\}$
- **Individual lens parameters:** $\psi_i = \{M_{*,i}, M_{{\rm DM},i}, \gamma_{{\rm DM},i}, R_{{\rm e},i}\}$

Inferring H_0

$$P(\eta|d) = P(\eta)P(d|\eta) = P(\eta)\prod_i \int d\psi_i P(d|\psi_i)P(\psi_i|\eta)$$

Likelihood P(d|n) can be approximated as a sum over samples drawn from interim posterior:

P(d|n) = \int P(d|y) P(y|n)

= \int P(d|y) P(y) [P(y|n) / P(y)]

~ 1/N \sum [P(y|n) / P(y)]k

~ 1/N \sum wk

MCMC sample each lens once, then sum importances in next level of inference

Inferring H_0 (and other hyper-parameters)

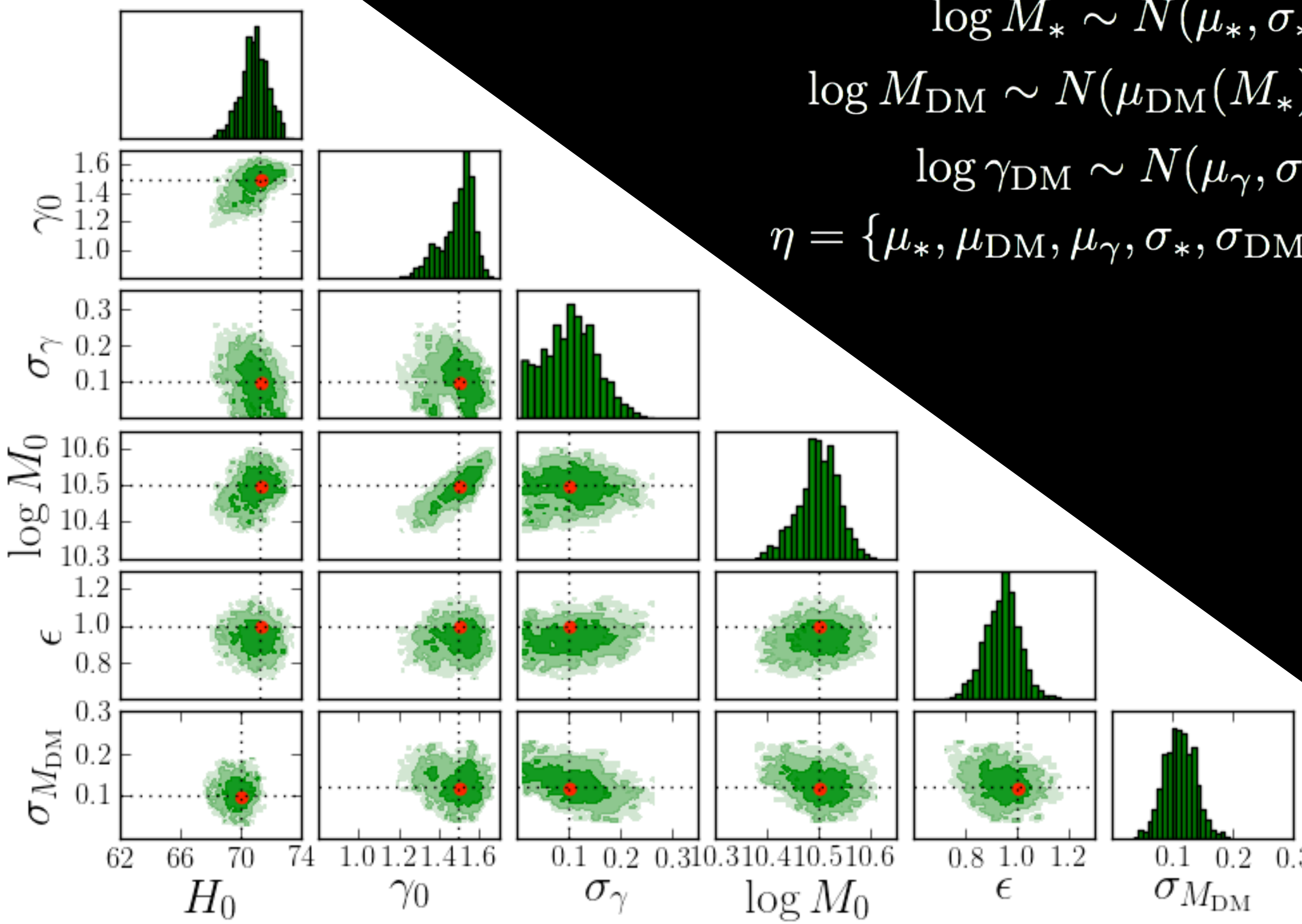
$$\psi_i = \{M_{*,i}, M_{\mathrm{DM},i}, \gamma_{\mathrm{DM},i}, R_{\mathrm{e},i}\}$$

$$\log M_* \sim N(\mu_*, \sigma_*)$$

$$\log M_{\mathrm{DM}} \sim N(\mu_{\mathrm{DM}}(M_*), \sigma_{\mathrm{DM}})$$

$$\log \gamma_{\mathrm{DM}} \sim N(\mu_\gamma, \sigma_\gamma)$$

$$\eta = \{\mu_*, \mu_{\mathrm{DM}}, \mu_\gamma, \sigma_*, \sigma_{\mathrm{DM}}, \sigma_\gamma, H_0\}$$

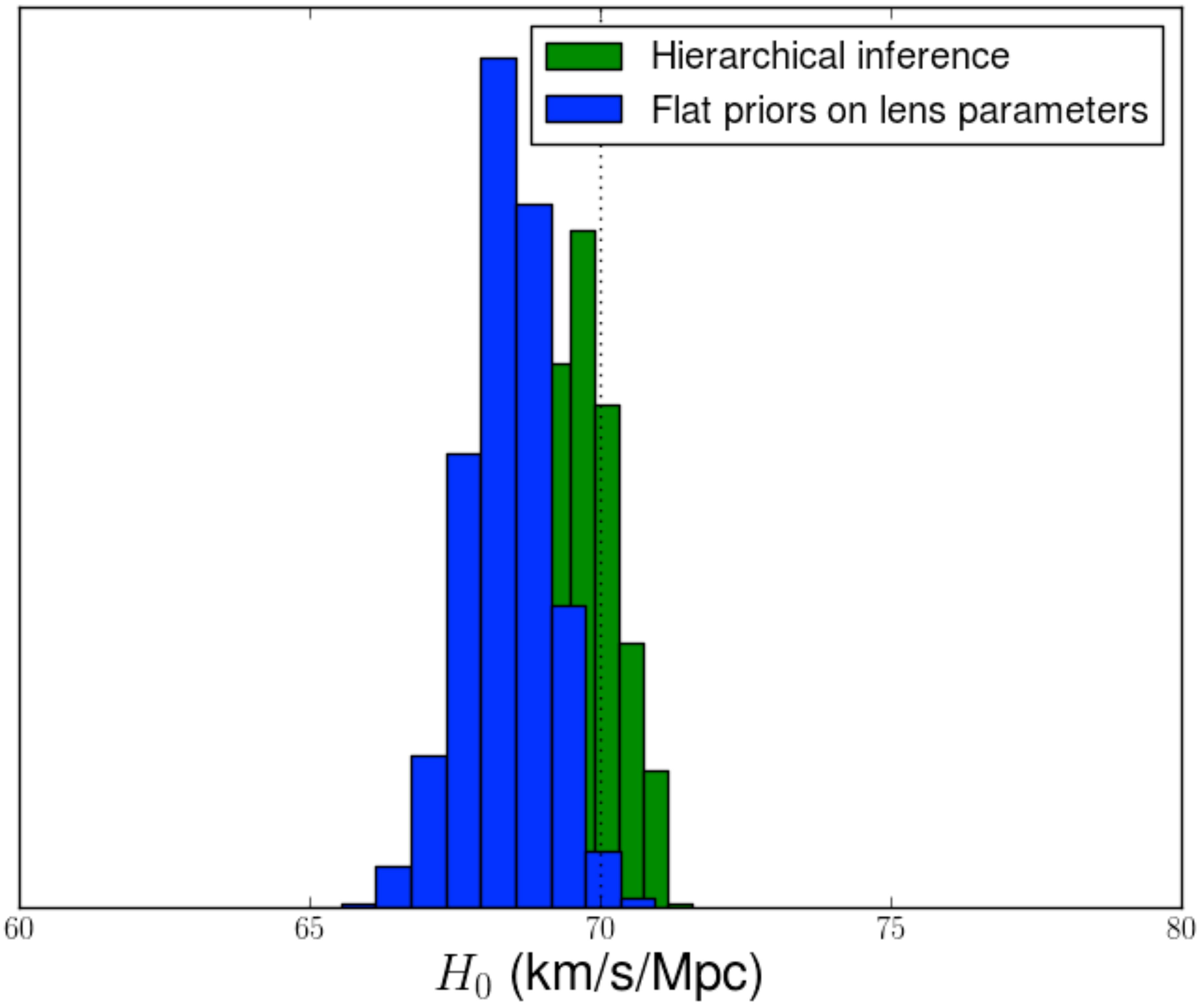


Inferring H_0

Uninformative priors on individual object parameters **lead to bias** if the objects are not unrelated

In this simple case the cosmological **hierarchical inference is unbiased**

Added 6 nuisance parameters to describe lens galaxy population, incurred **no loss of cosmographic precision**



More Hierarchical Inference Examples

- Disk and bulges in SWELLS (Brewer et al)
- Dark halo M-c in CASSOWARY (Auger et al)
- Subhalo populations (Vegetti et al)
- ETG density profiles (Sonnenfeld et al)

Dark and stellar matter in ETGs

THE SL2S GALAXY-SCALE LENS SAMPLE. V. DARK MATTER HALOS AND STELLAR IMF OF MASSIVE ETGS OUT TO REDSHIFT 0.8

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Draft version October 6, 2014

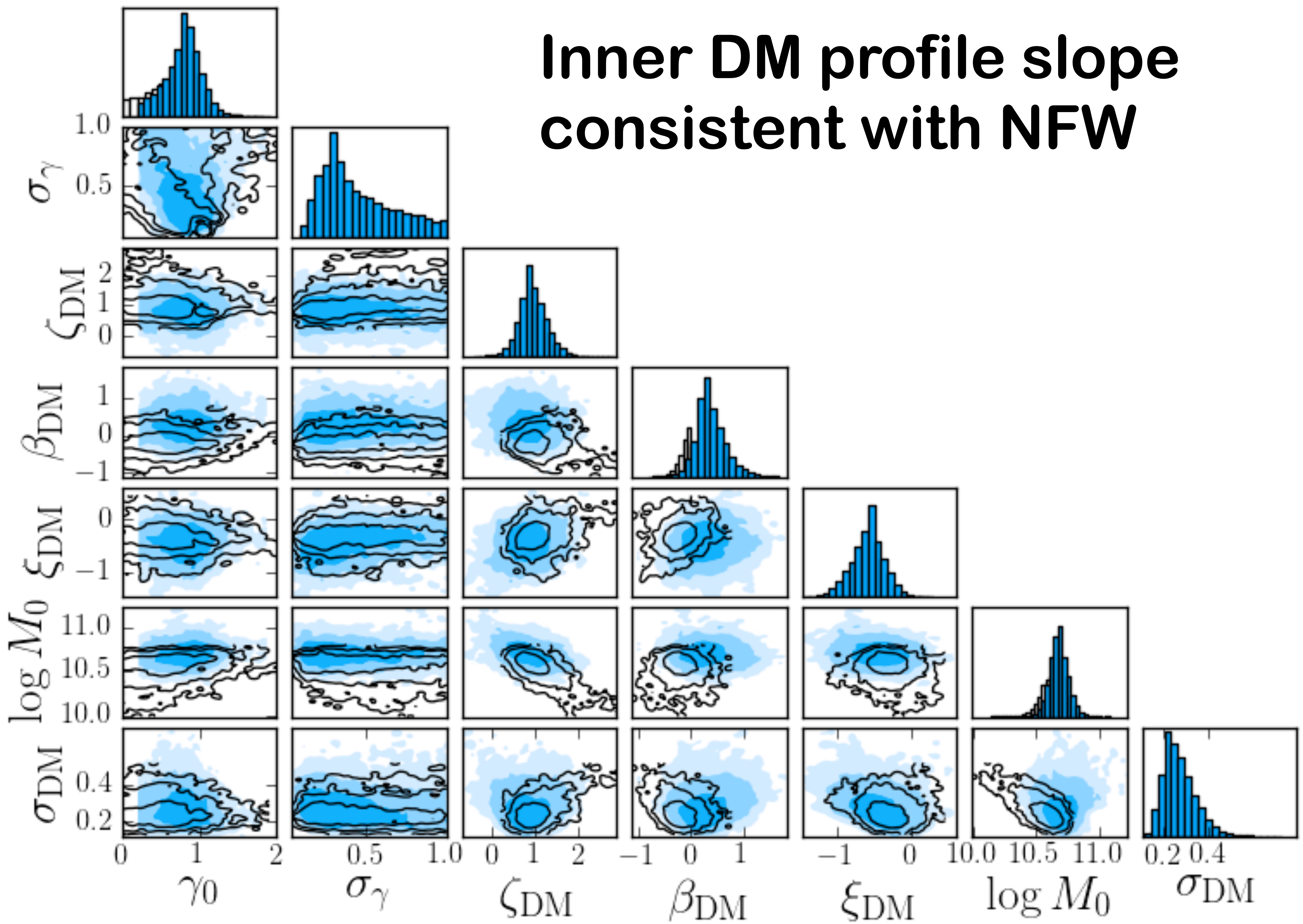
ABSTRACT

We investigate the cosmic evolution of the internal structure of massive early-type galaxies over half of the age of the Universe. We perform a joint lensing and stellar dynamics analysis of a sample of 81 strong lenses from the SL2S and SLACS surveys and combine the results with a hierarchical Bayesian inference method to measure the distribution of dark matter mass and stellar IMF across the population of massive early-type galaxies. Lensing selection effects are taken into account. We find that the dark matter mass projected within the inner 5 kpc increases for increasing redshift, decreases for increasing stellar mass density, but is roughly constant along the evolutionary tracks of early-type galaxies. The average dark matter slope is consistent with that of an NFW profile, but is not well constrained. The stellar IMF normalization is close to a Salpeter IMF at $\log M_* = 11.5$ and scales strongly with increasing stellar mass. No dependence of the IMF on redshift or stellar mass density are detected. The anti-correlation between dark matter mass and stellar mass density supports the idea of mergers being more frequent in larger dark matter halos.

Subject headings: galaxies: fundamental parameters — gravitational lensing —

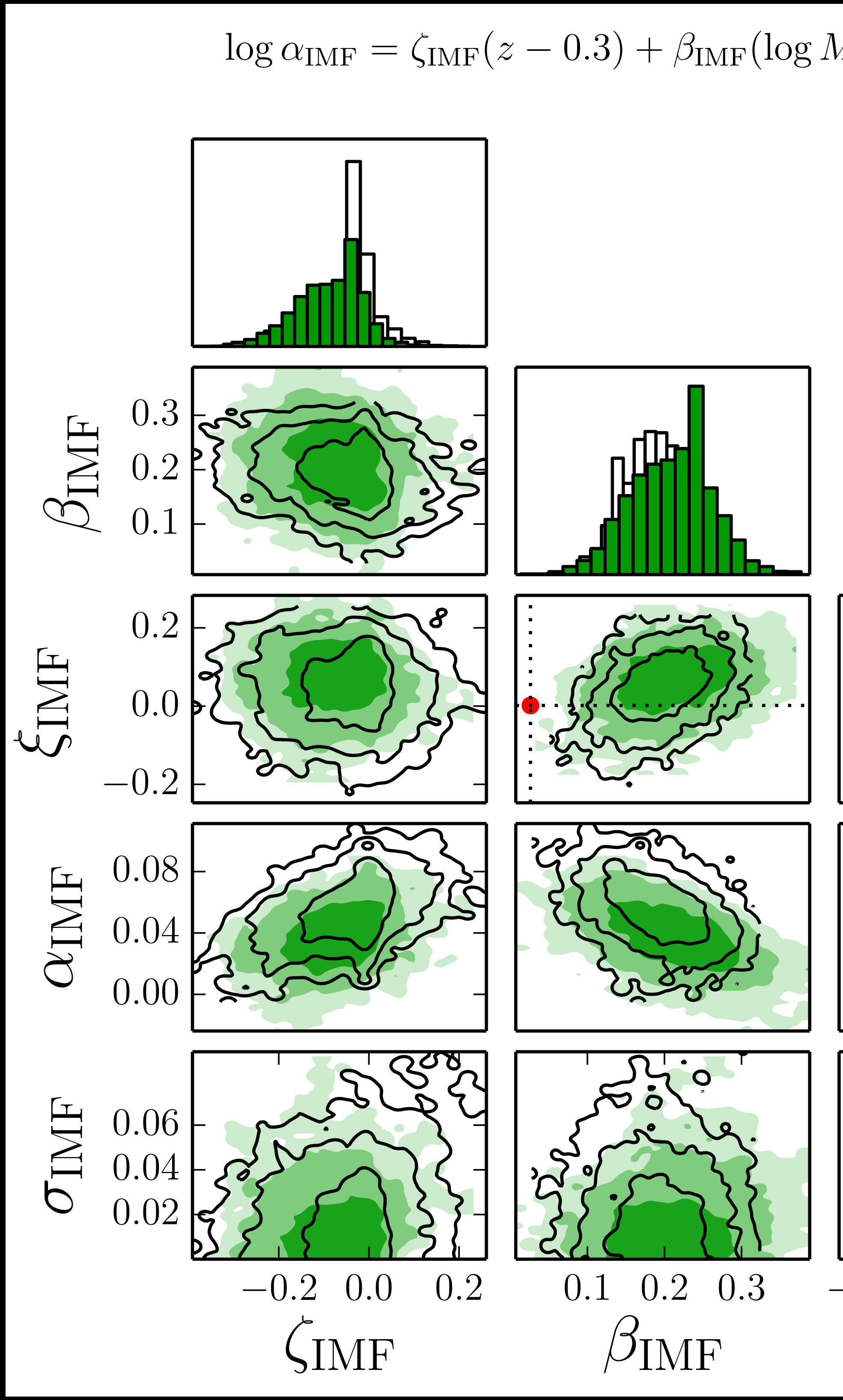
Dark and stellar matter in ETGs

$$\gamma_{\rm DM} = \gamma_0 + N(0, \sigma_\gamma) \quad ; \quad \log M_{\rm DM} = \zeta_{\rm DM}(z - 0.3) + \beta_{\rm DM}(\log M_* - 11.5) + \xi_{\rm DM} \log \Sigma_*/\Sigma_0 + \log M_0 + N(0, \sigma_{M_{\rm DM}})$$



Inner DM profile slope consistent with NFW

Dark and stellar matter in ETGs



IMF non-universal, normalization increases with galaxy mass

Conclusions

- Wide field imaging surveys will contain 10-1000 times more lenses than we currently have
- Pure samples are enabled by high image quality and depth, but we'll need good software instrumentation for catalog and image mining, and significant amounts of human quality control
- Lens candidacy requires a model: explicit, implicit or mental. Each approach has pros and cons
- Accuracy: large samples have great potential for accurate galaxy evolution, dark matter and dark energy studies
- Discovery: large samples will contain novel and exotic systems with new applications