Weak Lensing Shape Measurement with Machine Learning

Malte Tewes

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Collaborating with

- EPFL:
  - Thibault Kuntzer
  - Frédéric Courbin
- Bonn:
  - Reiko Nakajima
  - Hendrik Hildebrandt

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Argelander-Institut für Astronomie

What is "Weak Lensing Shape Measurement" ?

THE ASTROPHYSICAL JOURNAL SUPPLEMENT SERIES, 212:5 (28pp), 2014 May MANDELBAUM ET AL.

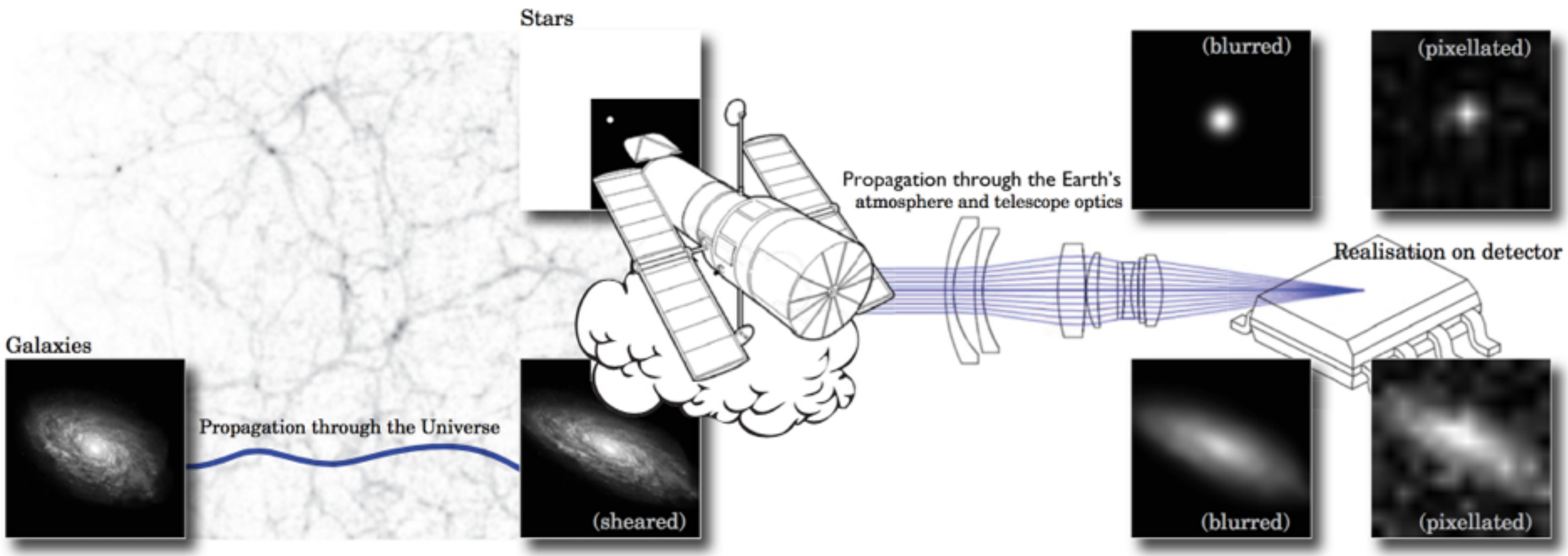
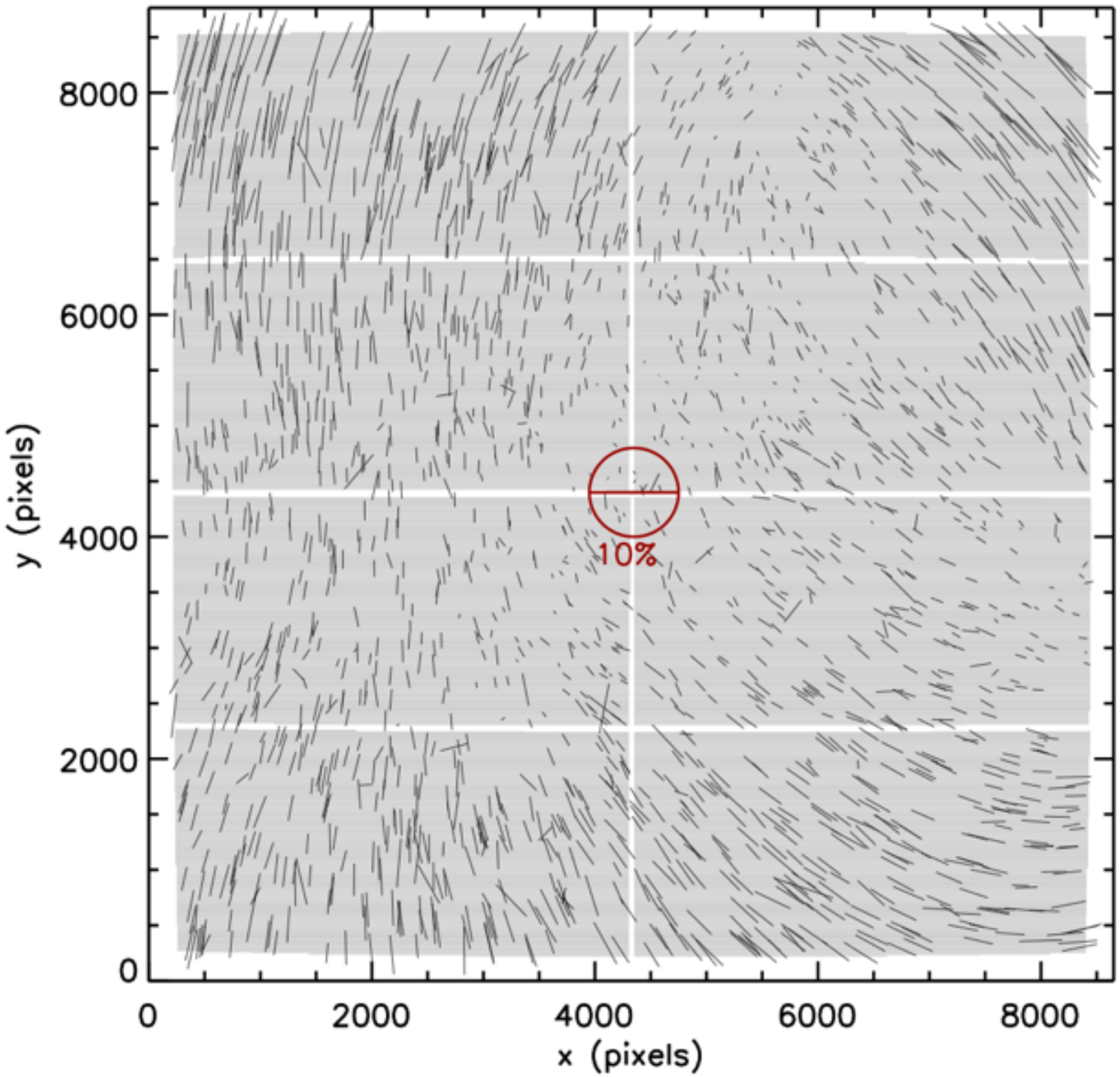


Figure 1. Illustration of the process of gravitational lensing and other effects that change the apparent shapes of galaxies in the astronomical imaging process. (Based on Figure 8 from Kitching et al. 2011).

… now a 20+ year old problem!

Shape measurement systematic number 1 : the PSF



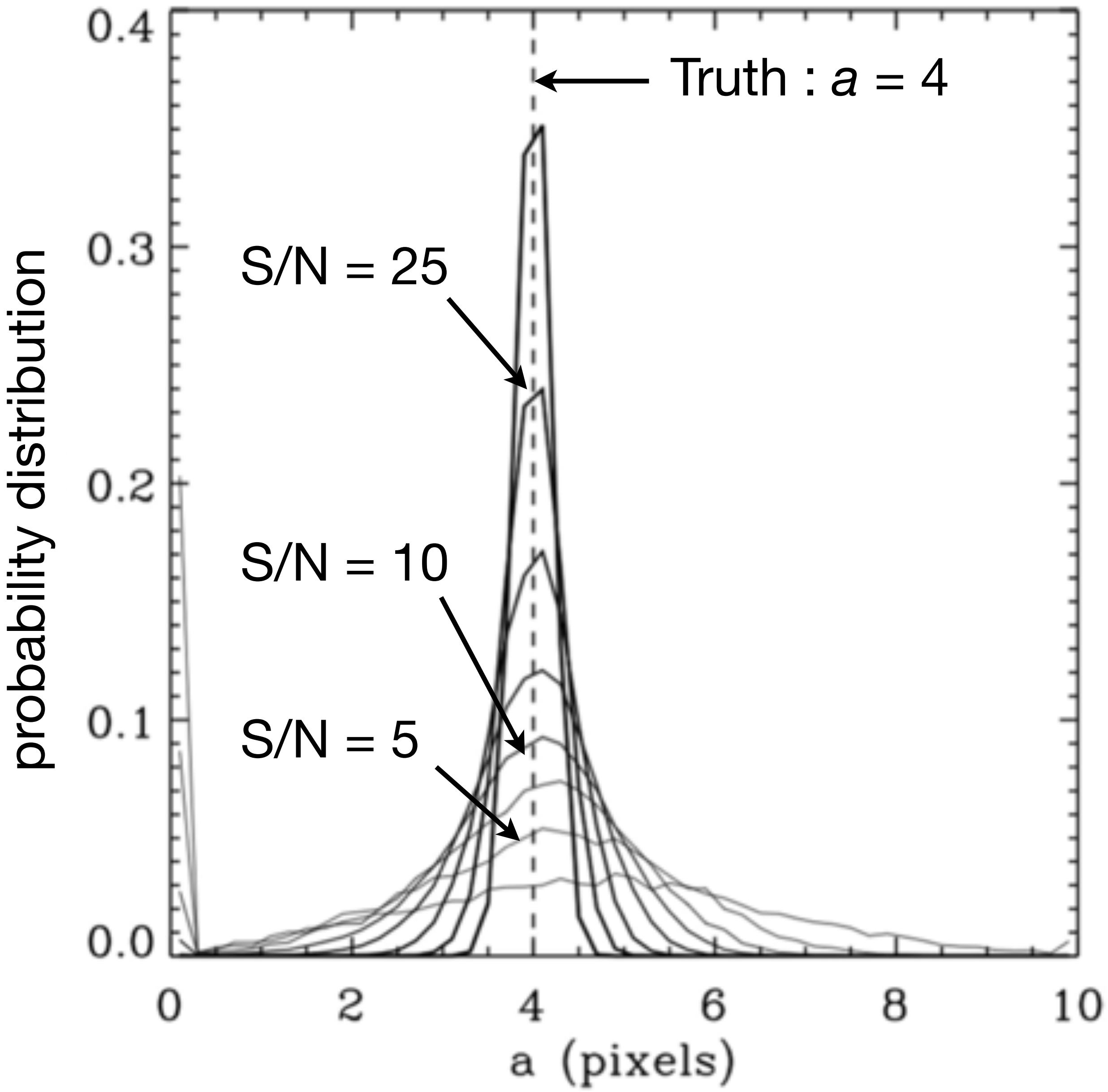
Measured PSF ellipticity
35’ x 35’ field, 900s exposure
Cerro Tololo Blanco Telescope
Deep Lens Survey

Jee et al. (2012)

Ellipticity from cosmic shear :

$\lesssim 1\%$

Shape measurement systematic number 2 : "noise bias"



For example:
Refregier, Kacprzak et al. (2012)

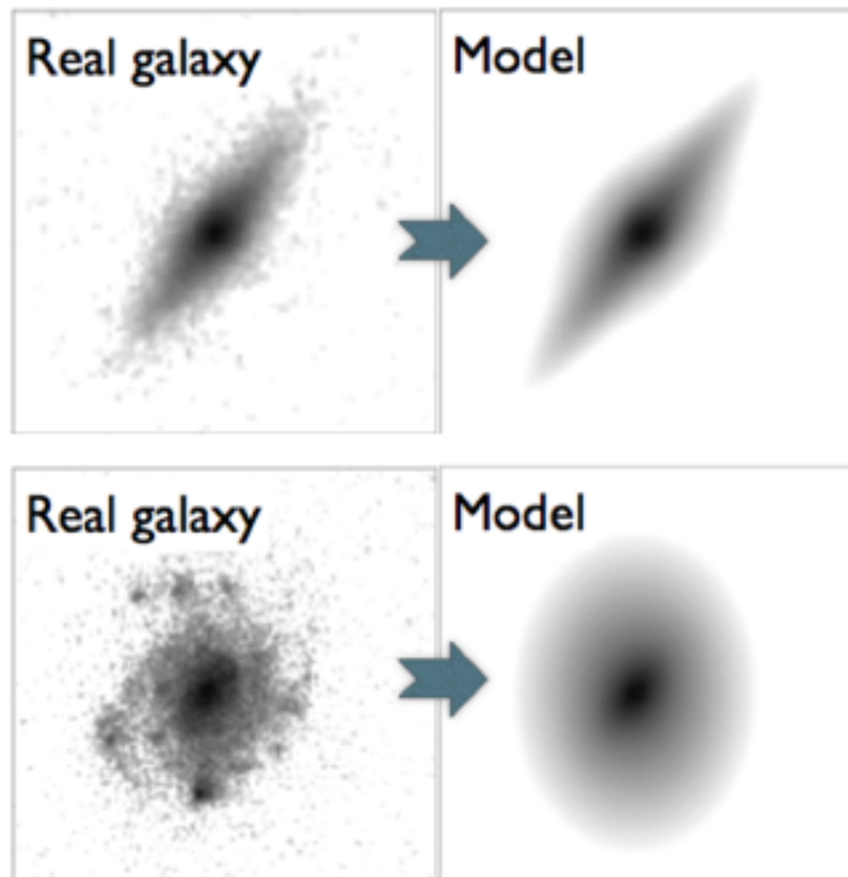
Simple experiment : galaxies drawn and then fitted with a 2D Gaussian (MLE) Galaxy width *a* is the only free parameter; it gets biased by noise!

For the S/N relevant for future surveys, noise bias is comparable with the shear signal, and nearly two orders of magnitude greater than acceptable !

Shape systematic number n… (related to the measurement)

Chromaticity of galaxies and PSF

Morphology of real galaxies, and blended objects



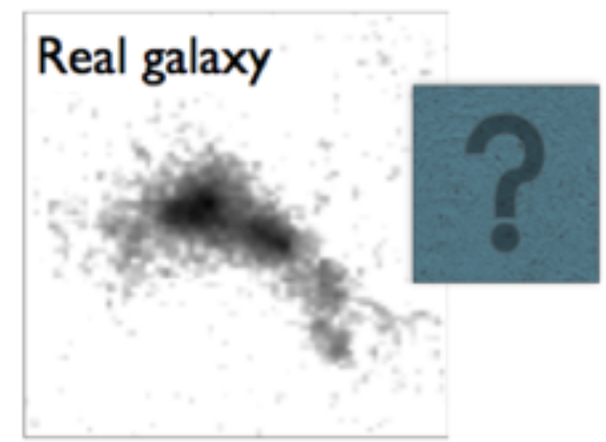


Figure: GREAT3 Handbook (Mandelbaum & Rowe 2013)

“Correlated noise”, due to faint background objects contaminating the source galaxy images

Hoekstra et al. (in prep)

Shape measurement: context

Two further concerns related to the *size* of present and future surveys:

- CPU cost has to be reduced (a lot) compared to the state-of-the-art
  - Aim at ~ 10 ms per galaxy
- Accuracy requirements get significantly more stringent
  - In plain quantitative terms, but also in *complexity* of systematics
  - Calibration on simulations seems unavoidable

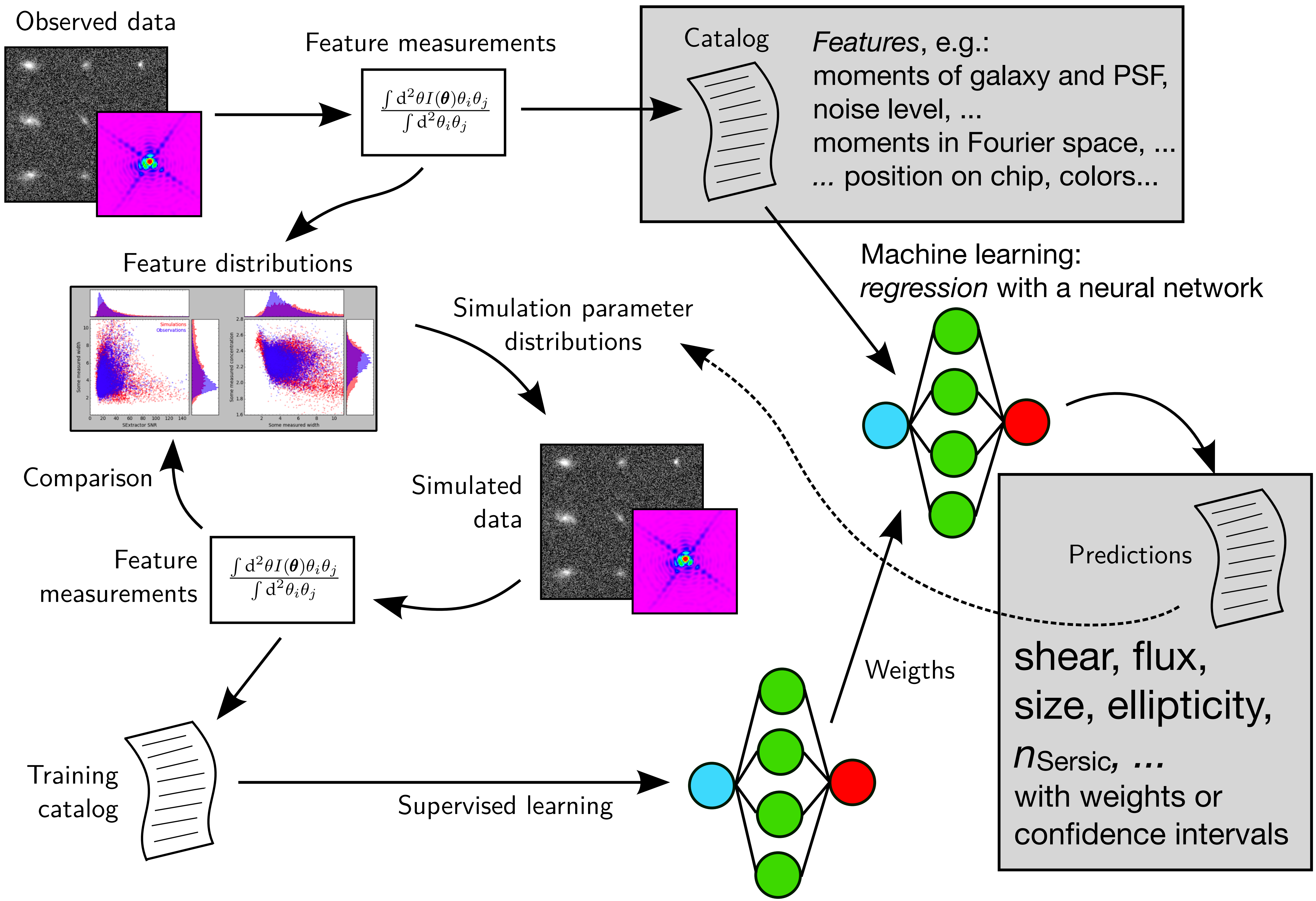
Idea: use supervised ML, trained on *simulated* images, to

- get custom-calibrated lensing estimates for every galaxy,
- thereby avoiding (or reducing the importance of) an overall calibration dependent on ensemble properties

Feasibility demonstrated by Gruen et al. (2010)

We focus here on obtaining "point estimates" (with weights) for shear, magnification, and shape parameters.

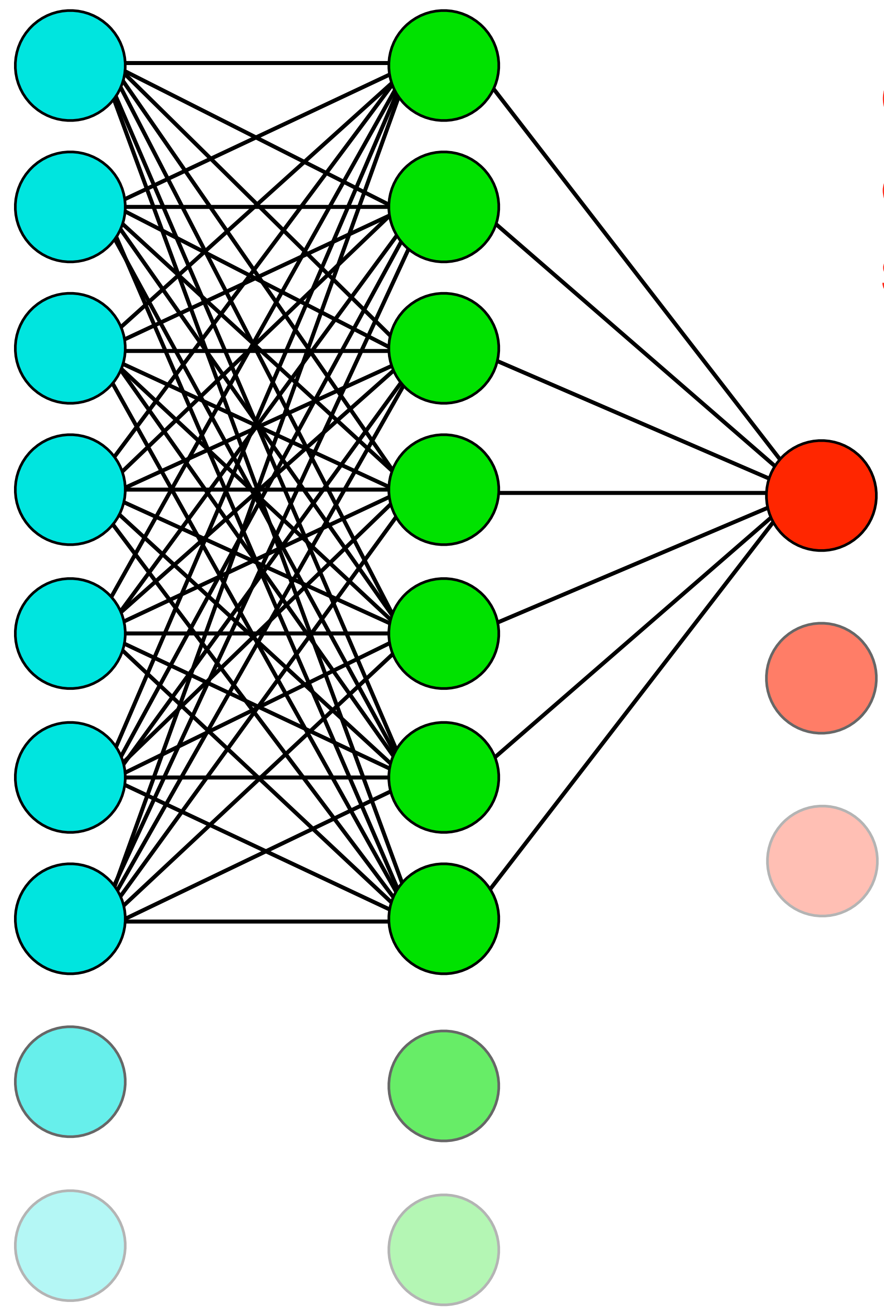
Overview of the supervised learning approach



Neural network as free-form estimator, minimal example

Input: measurements on noisy galaxy image and information about PSF

By default: based on moments within an adaptive elliptical weighting function
(Hirata & Seljak 2003, Mandelbaum et al. 2006, Rowe et al. 2014)



Output: calibrated estimate of shape or shear or magnification

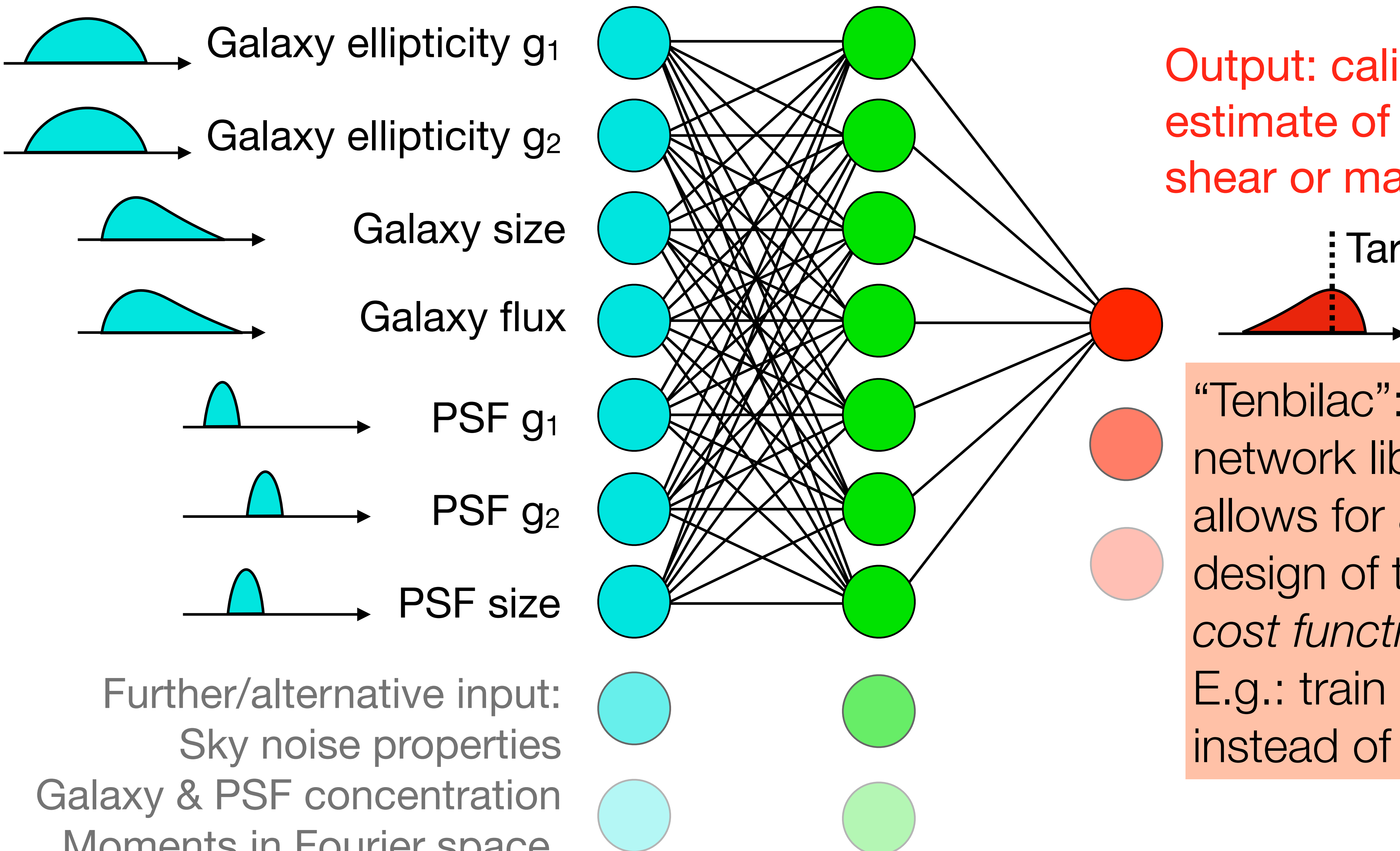
Further output:
Associated weight,
etc…

Further/alternative input:
Sky noise properties
Galaxy & PSF concentration
Moments in Fourier space,
Position on chip, colors,
redshifts, etc…

Internals of the neural network
(e.g., this one would have 64 parameters)

Neural network as free-form estimator, minimal example

Input: biased and **noisy** measurements…
We'll teach the Machine about that noise !



Output: calibrated estimate of shape or shear or magnification

"Tenbilac": neural network library that allows for a flexible design of the *training cost function*.
E.g.: train against ***bias*** instead of ***error***.

Further/alternative input:
Sky noise properties
Galaxy & PSF concentration
Moments in Fourier space,
Position on chip, colors,
redshifts, etc…

Internals of the neural network
(e.g., this one would have 64 parameters)

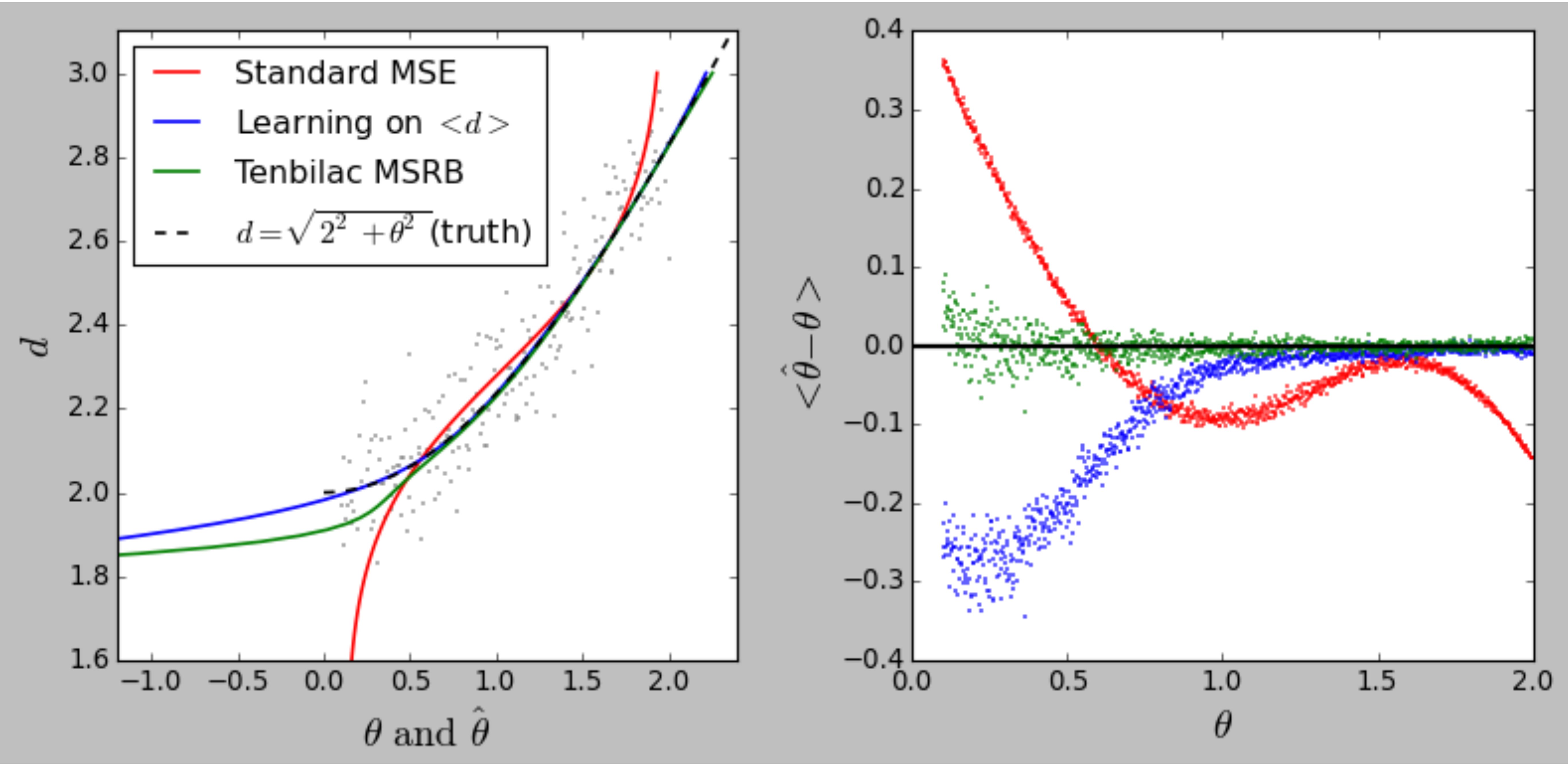
One-dimensional numerical experiment

$$d = \sqrt{2^2 + \theta^2} + \mathcal{N}(0, 0.1)$$

Aim: get an unbiased estimator $\hat{\theta}(d)$

Training data structured in several ***cases*** (ensemble of simulations that have the same “truth” θ), and each case has several ***realizations*** (differing here only in their noise).

Dealing with noise: 1D example of an “inverse regression”



Mean Square Error (MSE): minimize $\langle(\hat{\theta}-\theta)^2\rangle_{\mathrm{all}}$

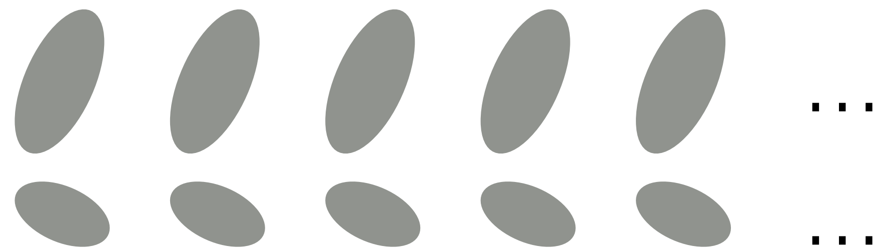
Mean Square Bias (MSRB): minimize ~ $\langle(\langle\hat{\theta}\rangle_{\mathrm{realizations}}-\theta)^2\rangle_{\mathrm{cases}}$

github.com/mtewes/tenbilac, NN library for MegaLUT

Example: directly obtaining a *shear* estimator

Training for ellipticity: the training data is *not* subject to lensing.

- Case 1:
- Case 2:
- …

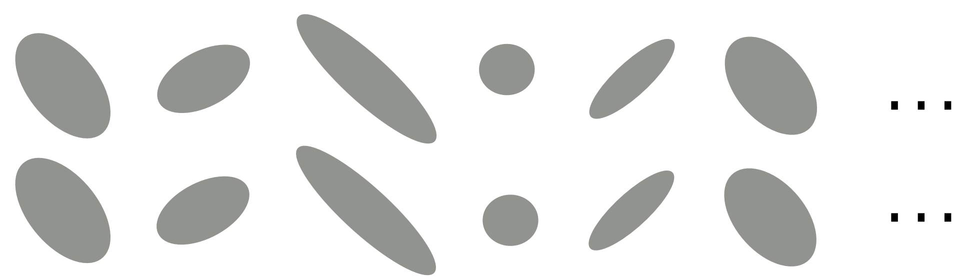


Realizations differ only in *noise*.

Training for shear: the training data *has lensing*.

Approach 1

- Case 1:
- Case 2:
- …

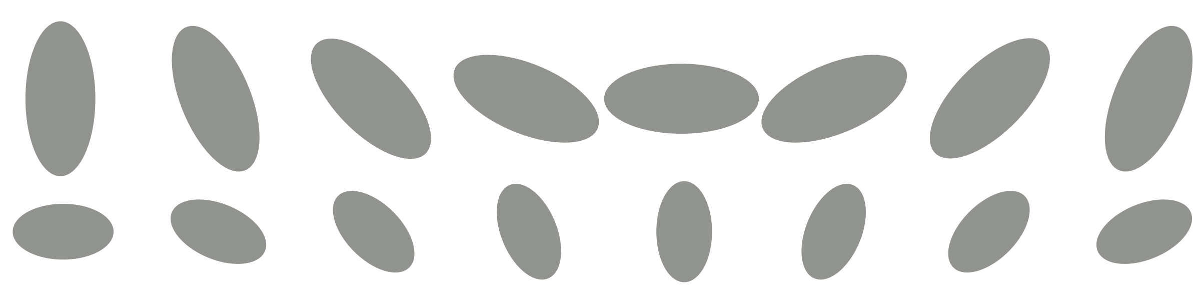


Cases have different shears. Realizations are drawn from distributions of real galaxies.

Works well… *if you know these distributions!* This is almost an “ensemble calibration” :-(

Approach 2 (work in progress…)

- Case 1:
- Case 2:
- …



Cases have different shears.
Realizations differ only in noise and orientation.

Yields shear estimates as unbiased as possible for any galaxy ellipticity, size, SNR, …
Then train a network to predicts *weights* to minimize bias in Approach 1.

Example application:

Galaxy size measurements on CFHTLenS

CFHTLenS: image simulations and machine learning setup

- Measuring and simulating the *coadded* images (i band)
- Using the same PSF reconstruction as lensfit
- Pure Sérsic profiles, without lensing, clean stamps
- Parameter distributions iteratively adjusted to roughly match observations

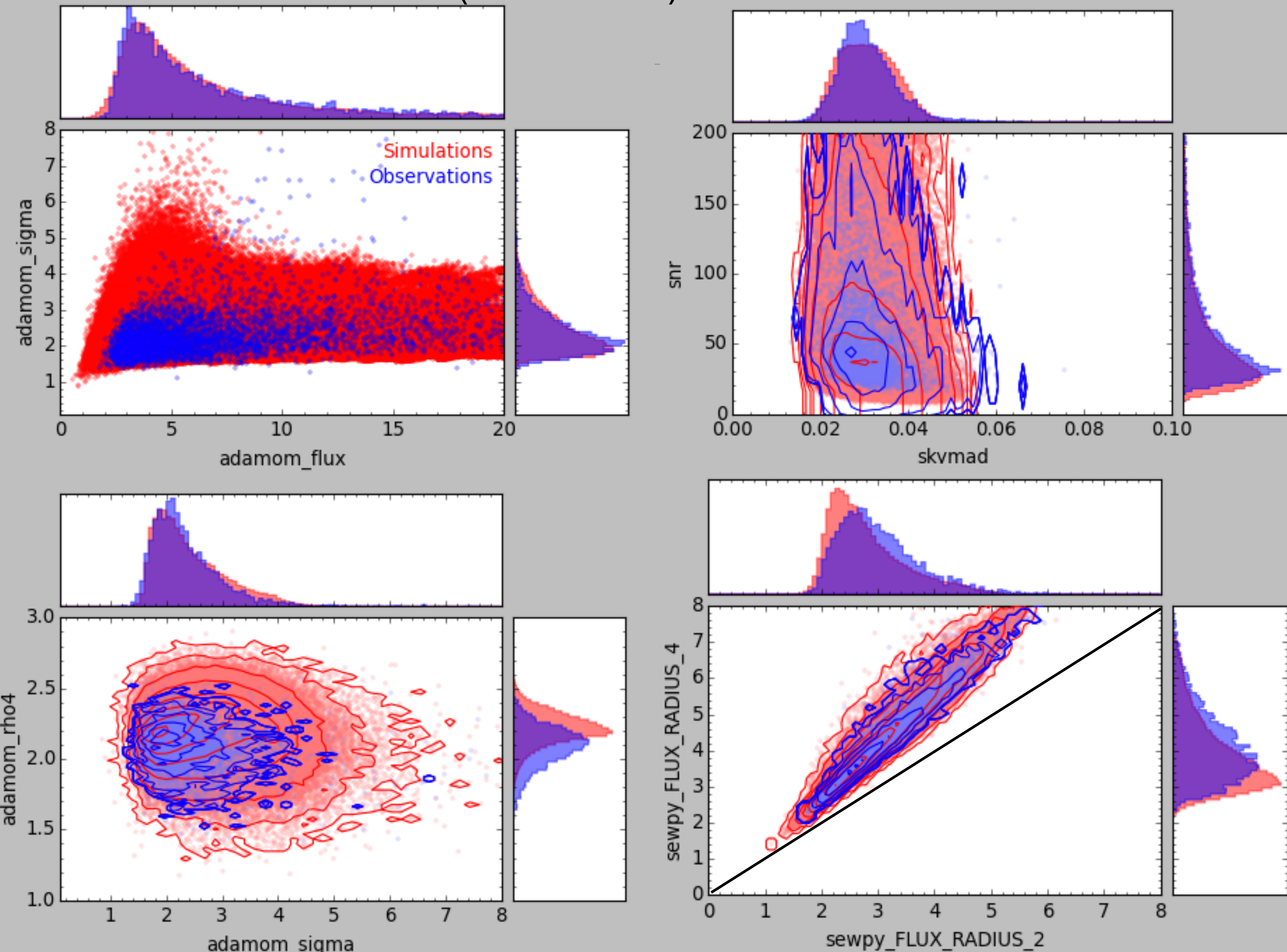
- 16 input features, from HSM adaptive moments and SExtractor:

  PSF: g1, g2, size, concentration
  Galaxy: g1, g2, concentration, flux,
  background noise, 7 sizes with different contained flux

- Single neural networks for the whole survey, predicting:

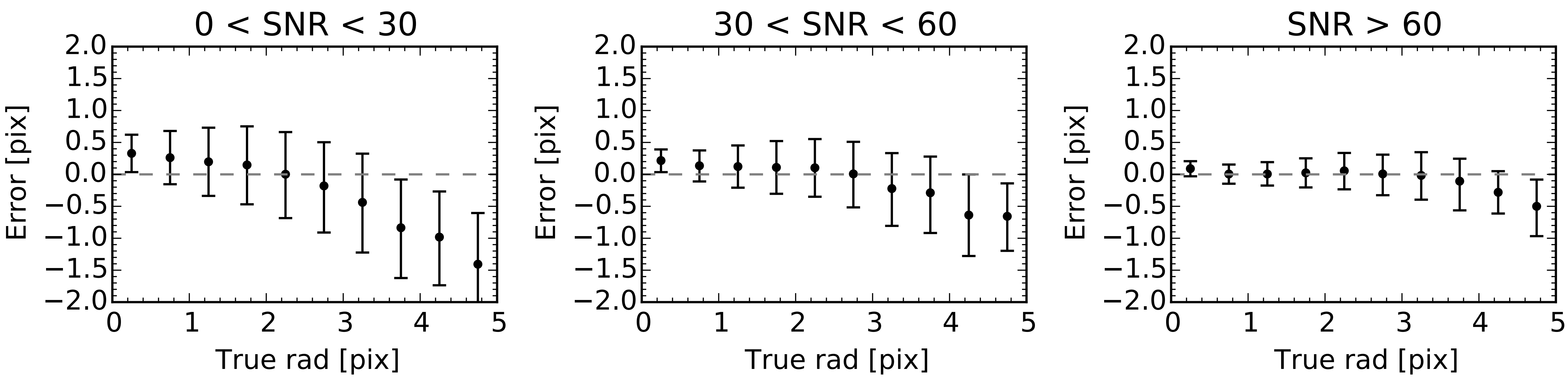
  Size ("pre_rad"),
  Sérsic index ("pre_sersicn"),
  and associated uncertainty estimates

For round (e < 0.02) and small PSFs:

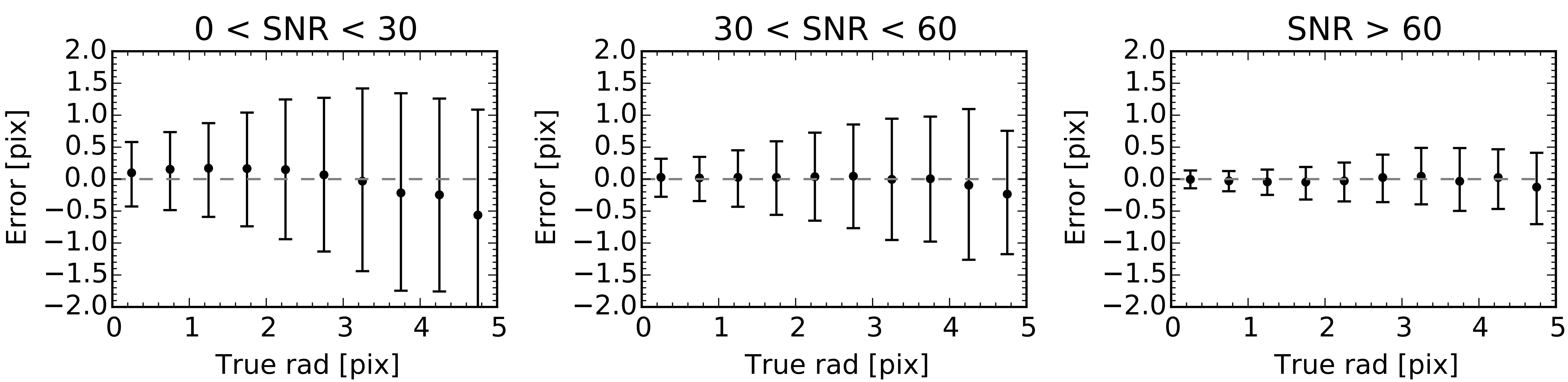


Size measurements, CFHTLenS image simulations

MSE: trained to minimize the mean square error



MSB: trained to minimize the mean square bias



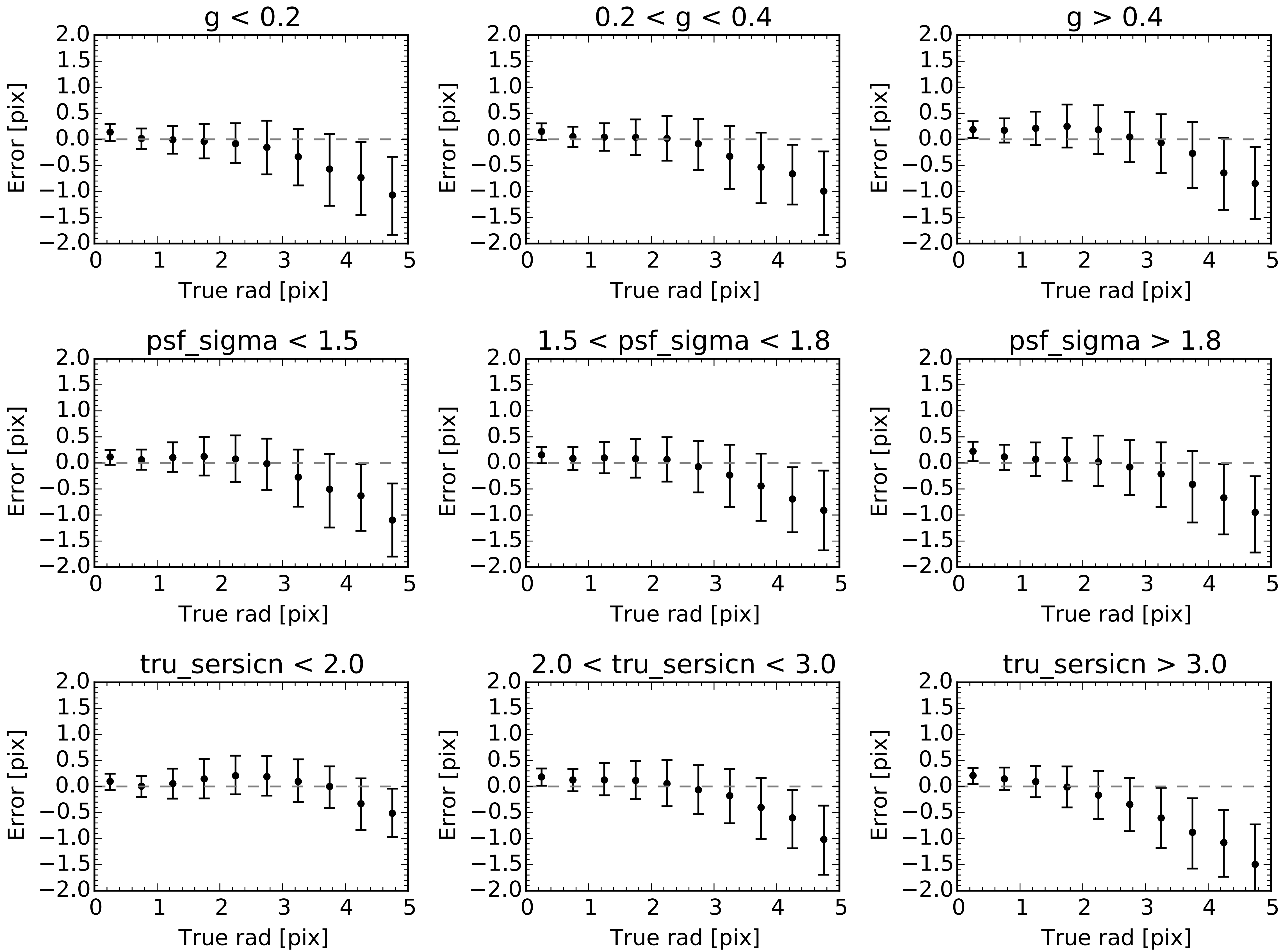
Size measurements, CFHTLenS, averages over **all SNR**

MSE

for varying galaxy ellipticity

for varying PSF size

for varying galaxy Sérsic ind.



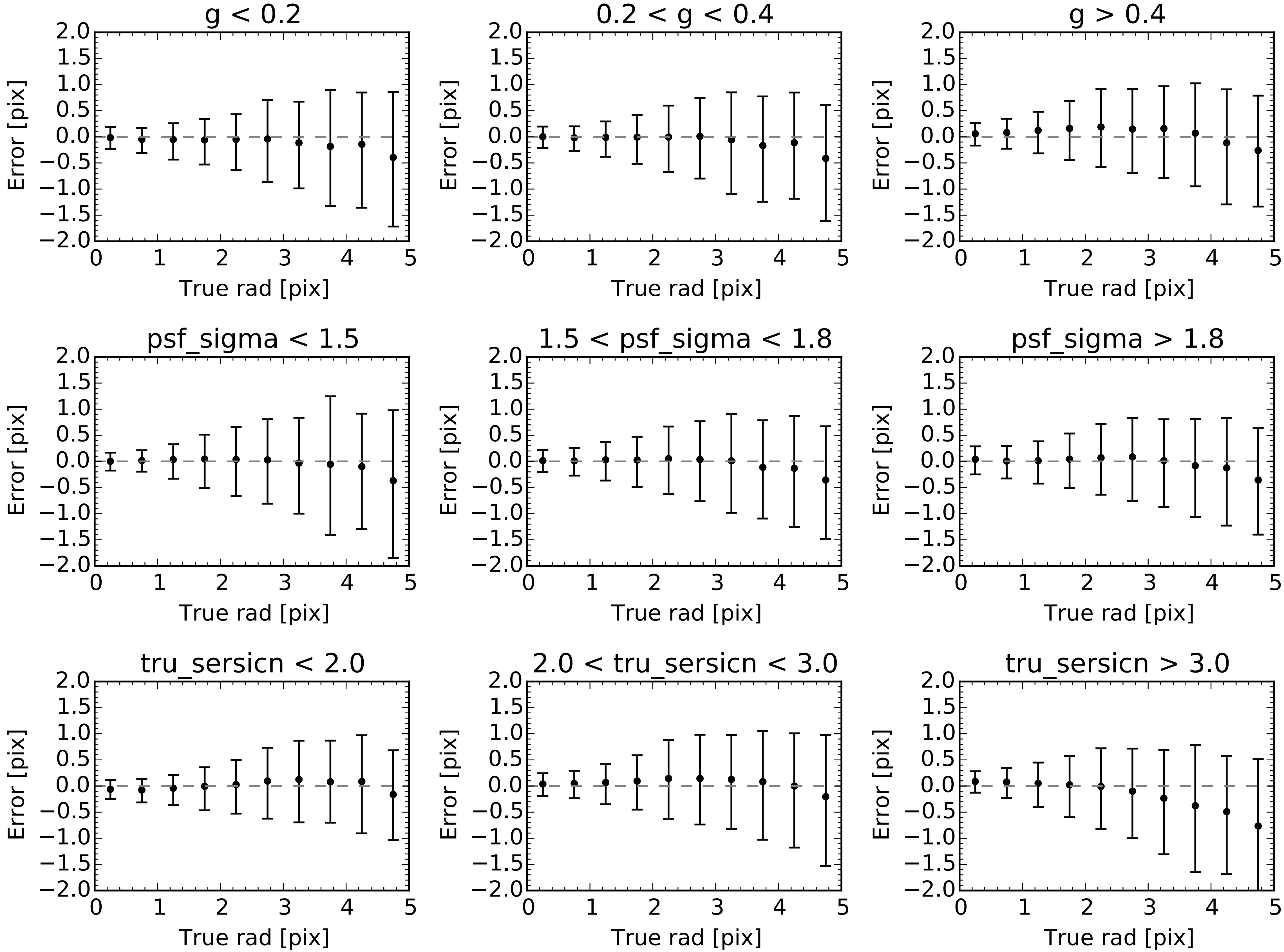
Size measurements, CFHTLenS, averages over **all SNR**

MSB

for varying galaxy ellipticity

for varying PSF size

for varying galaxy Sérsic ind.



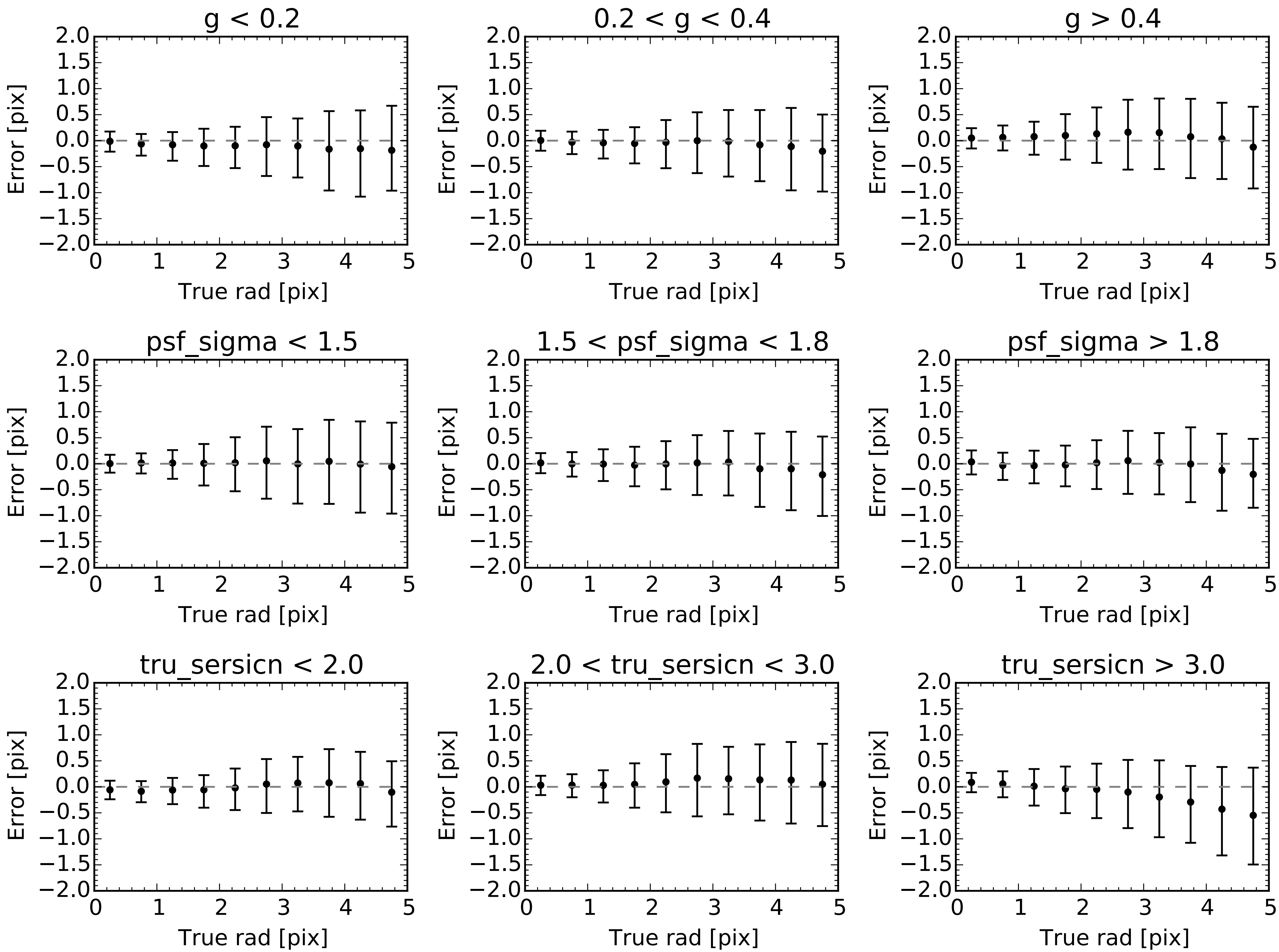
Size measurements, CFHTLenS, averages over **SNR > 30**

MSB

for varying galaxy ellipticity

for varying PSF size

for varying galaxy Sérsic ind.



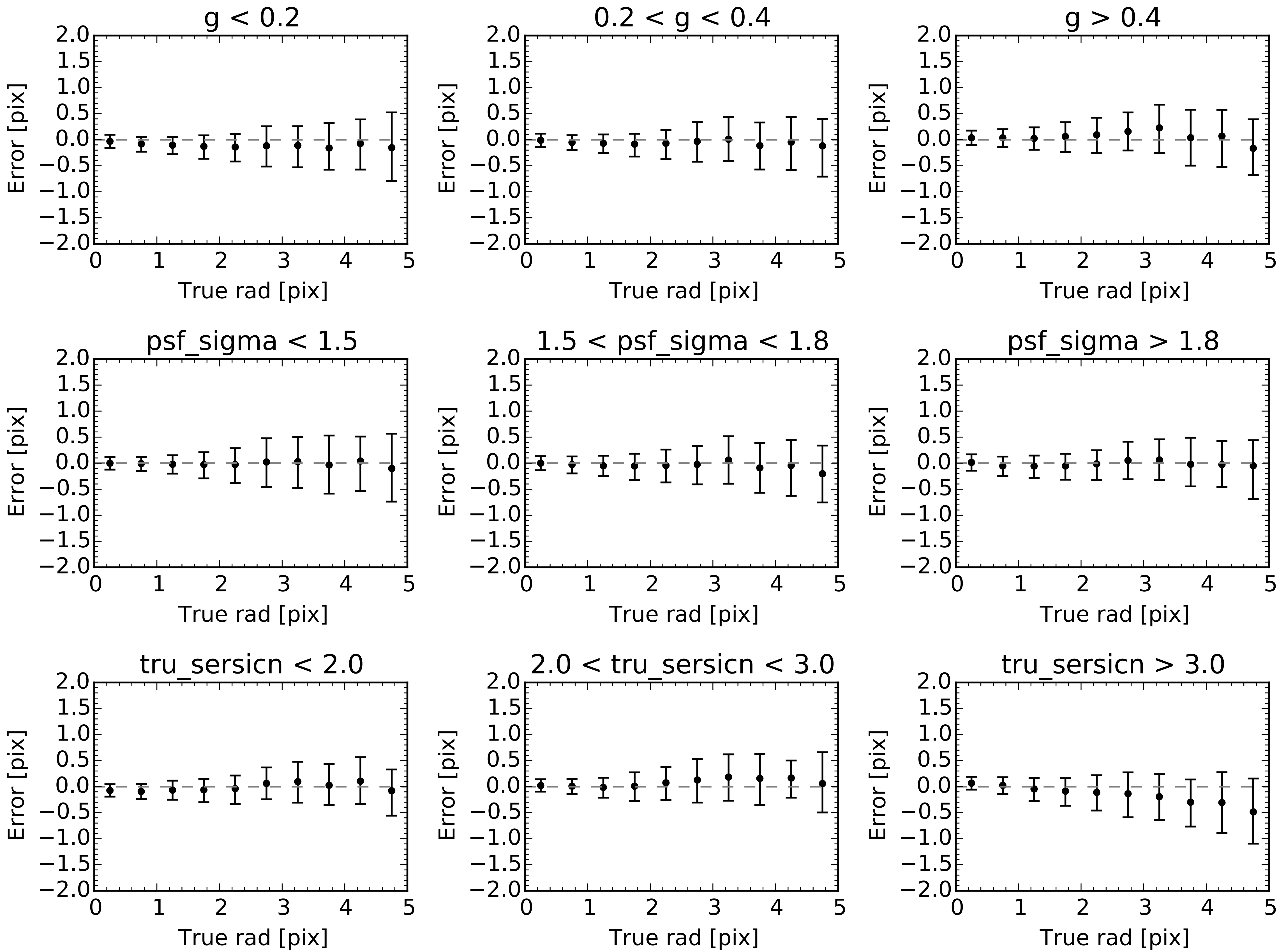
Size measurements, CFHTLenS, averages over **SNR > 60**

MSB

for varying galaxy ellipticity

for varying PSF size

for varying galaxy Sérsic ind.



Summary

- Simple neural networks might be an interesting tool to obtain (or calibrate) estimators for weak gravitational lensing.
- They allow for:
  - a very fast approach
  - an empirical correction for difficult-to-model systematics
  - and, by design, “flatness”, i.e., keeping the dependence on the distribution of source properties small
- Although experimental, Tenbilac allows to propagate noise through a neural network, design custom cost functions for shear or for shapes, and still train on ~10 Million galaxies in a few hours.