DEEP LEARNING ESTIMATION OF THE BACKGROUND LIGHT ON ASTRONOMICAL IMAGES

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PAU

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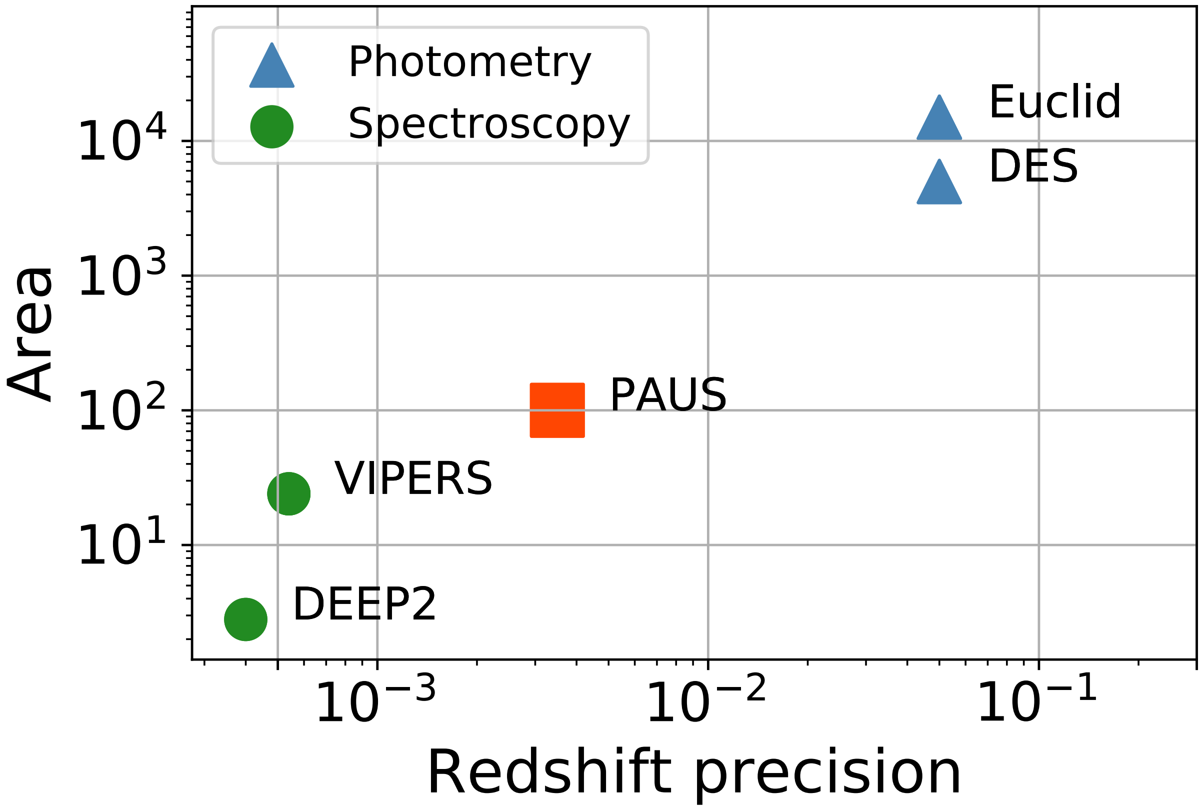
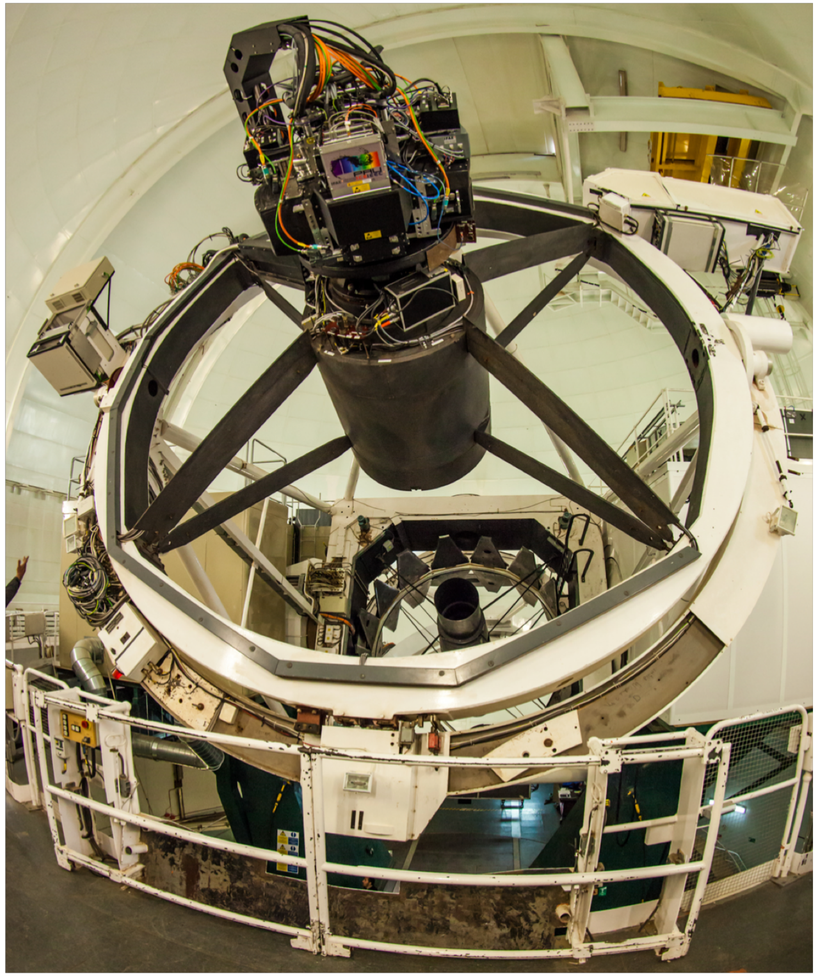
GALAXY SURVEYS

Spectroscopic surveys vs photometric surveys.



THE PAU SURVEY

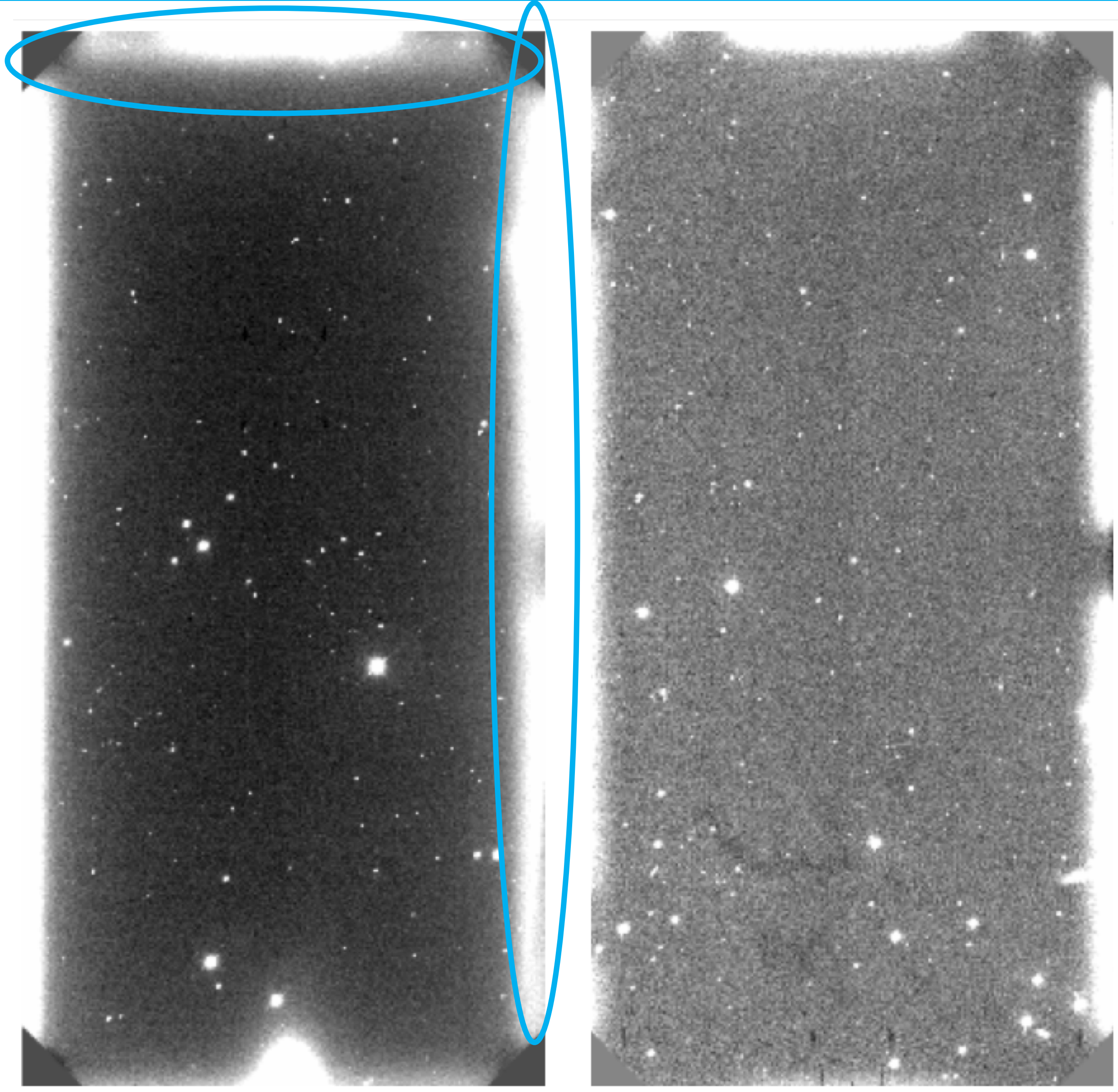
- Imaging survey with a 40 narrow band photometric filters camera (PAUCam) (Padilla et al 2019).
- The camera is installed in the 4.2m - William Herschel Telescope, in La Palma.
- It covers a wavelength range from 450nm to 850nm.
- It effectively measures high resolution photometric spectra (R $\sim$ 50).
- Capable of measuring photo-z with a precisión $\sigma \sim 0.0035(1+z)$ to faint magnitudes (i < 22.5) covering large areas of sky (Eriksen et al. 2018)
- It has also 6 ugrizY broad band filters installed.



SCATTERED LIGHT: HOW TO MODEL IT

- PAUS images suffer from **scattered light,** an optical effect where light appears where it is not intended to be.
- The camera was intervened in 2015 to mitigate the scattered light issue.
- 8% of PAUS data in the COSMOS field is flagged as scattered light affected.
- The photoz have a 18% of outliers, some of them might come from scattered light.

- Scattered light is **not random**: There is a **spatial scattered light dependence.**
- It appears on the **edges of the CCD** following a pattern.
- It is **band dependent**.
- It depends on the background level.



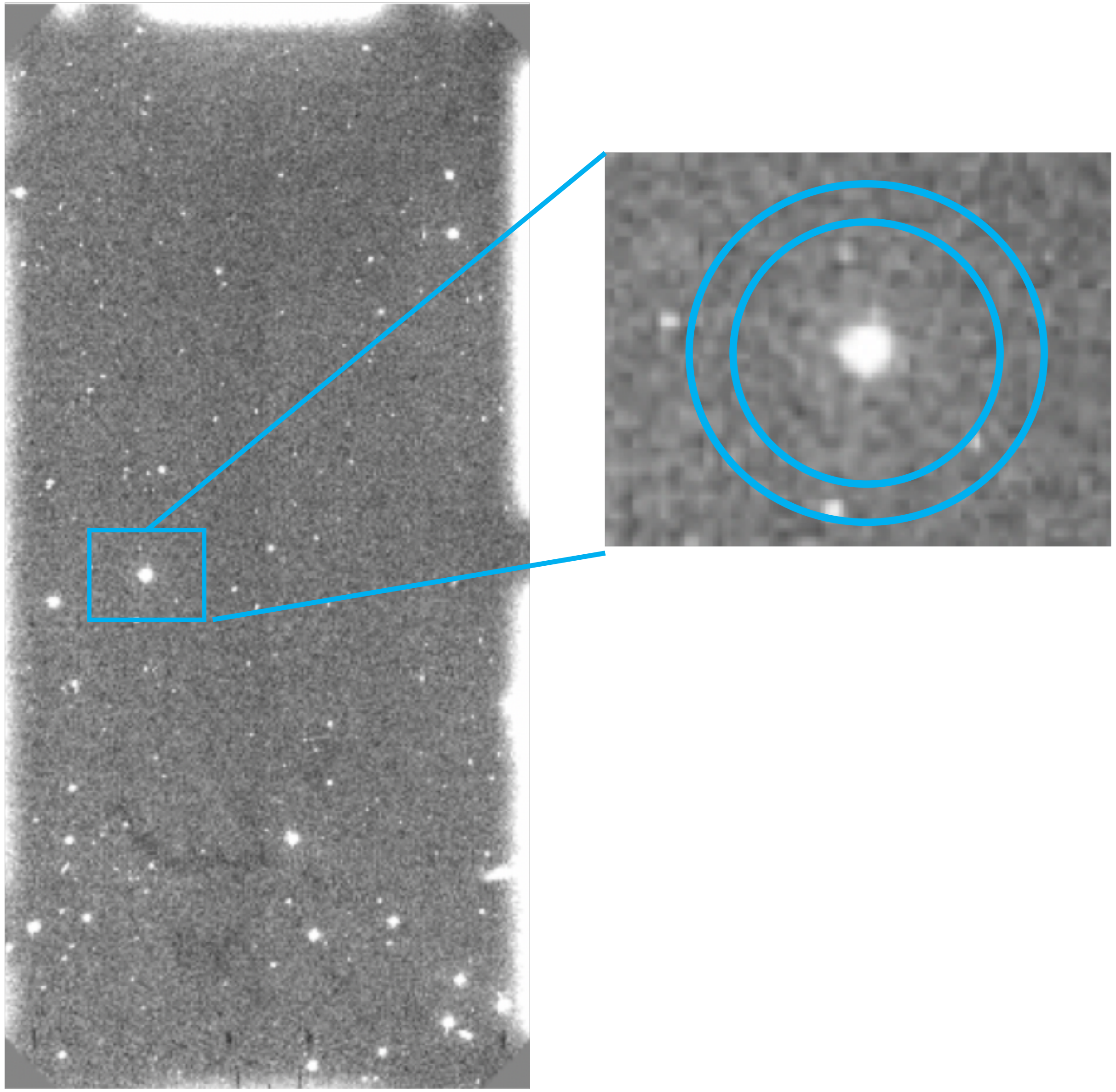
DEEP LEARNING TO PREDICT THE BACKGROUND: MOTIVATION

The background behind the galaxy is estimated as the **median of the pixels inside the annulus**.

The error per pixel is the standard deviation inside the annulus.

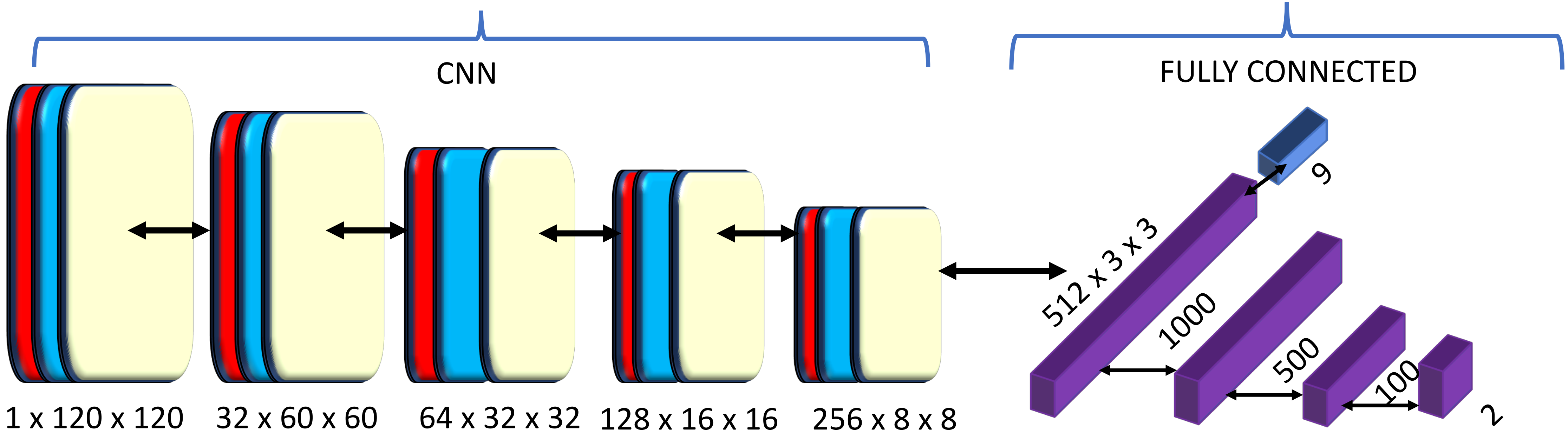
This method is not optimal when:

- The background is tilted (like in scattered light affected regions)
- There are other objects falling inside the annulus



BKGnet: A CNN TO PREDICT THE BACKGROUND

We propose **BKGnet**: a supervised deep learning network to predict the background behind a given target galaxy accounting for scattered light and other undesired effects.

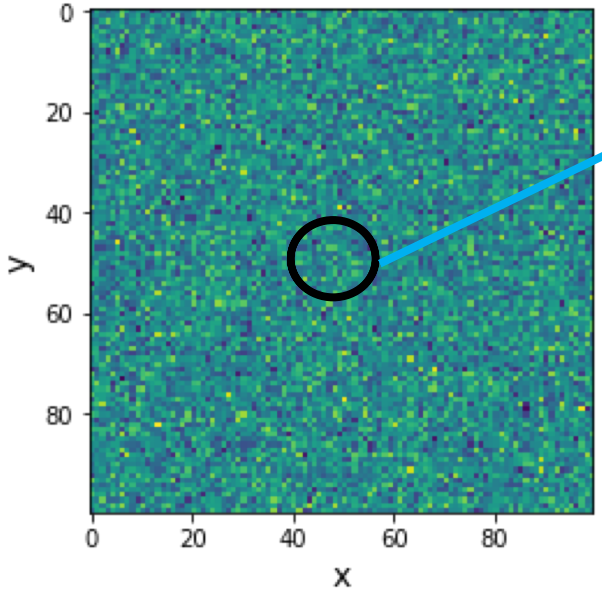


$$\text{Loss} = \left(\frac{(Bkg - true\_bkg)}{\sigma_{bkg}}\right)^2 + 2\log(\sigma_{bkg})$$

Kendall et al. 2017

BKGnet: TRAINING THE NETWORK

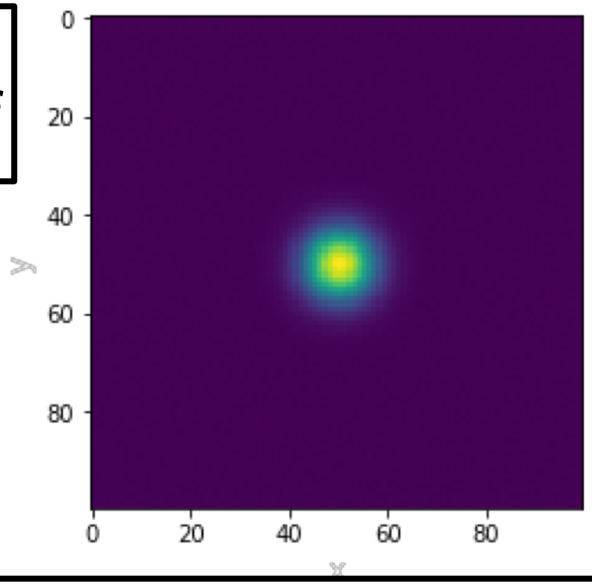
1. Measure the true background



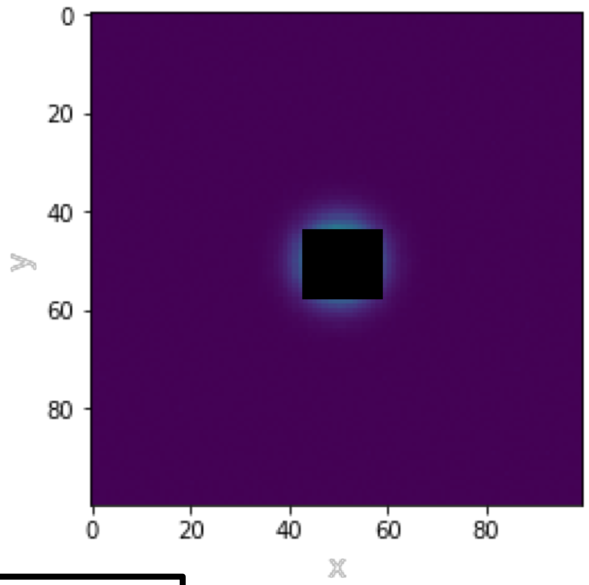
$$BKG_{true} = \frac{1}{N} \sum_{aperture} Pixels$$

120x120 pixel stamps

2. Simulate a galaxy



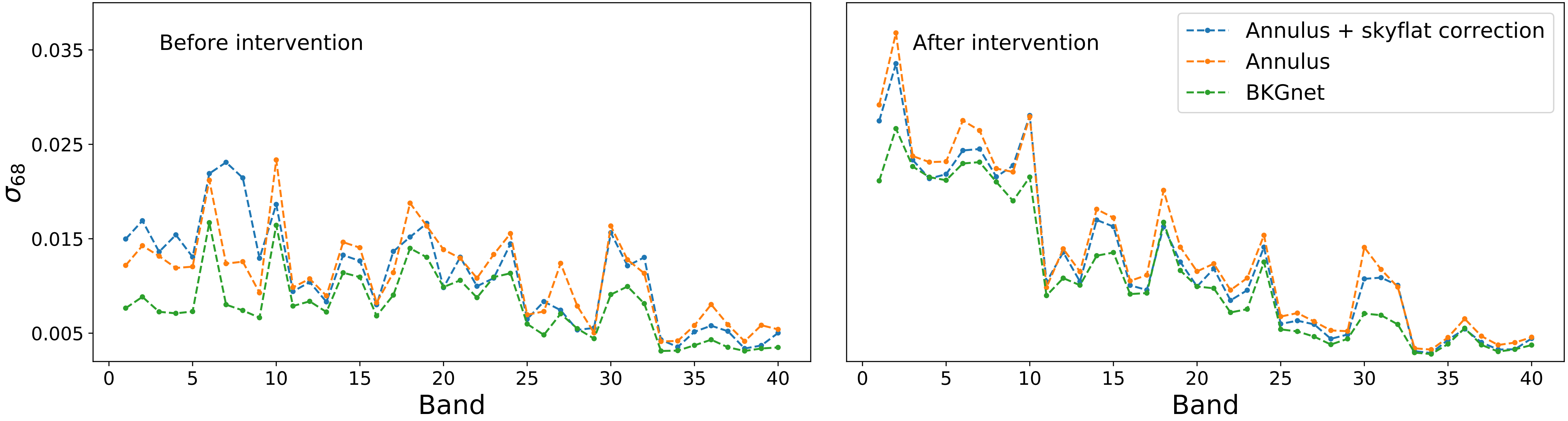
3. Mask the galaxy



EXTRA INFORMATION FOR THE NEWORK:

- Galaxy coordinates in the image (pixel coordinates)
- The narrow band filter.
- I_auto and r50 of the simulated (real) galaxy.
- A camera intervention flag (before/after)

BKGnet: BACKGROUND PREDICTIONS ON EMPTY POSITIONS

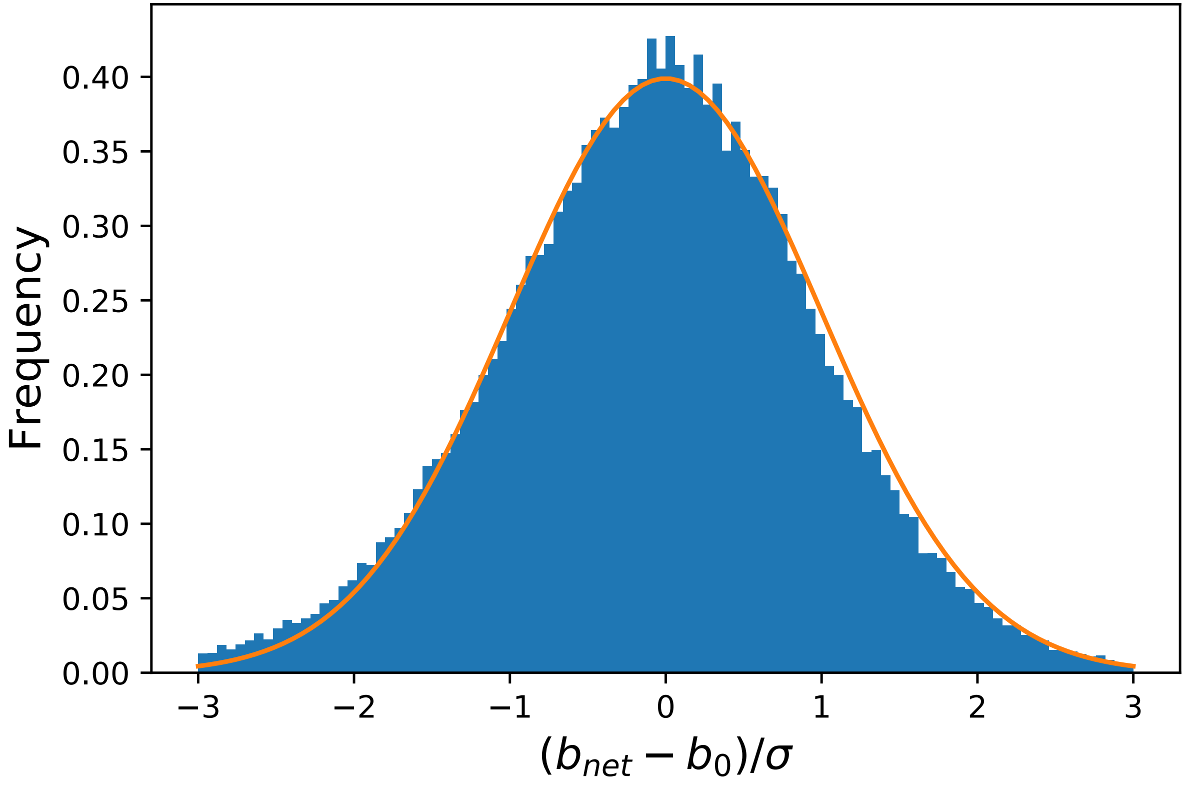


- BKGnet improves upon correcting scattered light with a skyflat by a 37%. (58% in the first filter tray)
- The sky flat becomes less accurate when the amount of scattered light increases.
- The amount of scattered light is smaller here.
- On average, after the intervention we improve the sky flat predictions by a 18%.

BKGnet: ERROR PREDICTIONS ON EMPTY POSITIONS

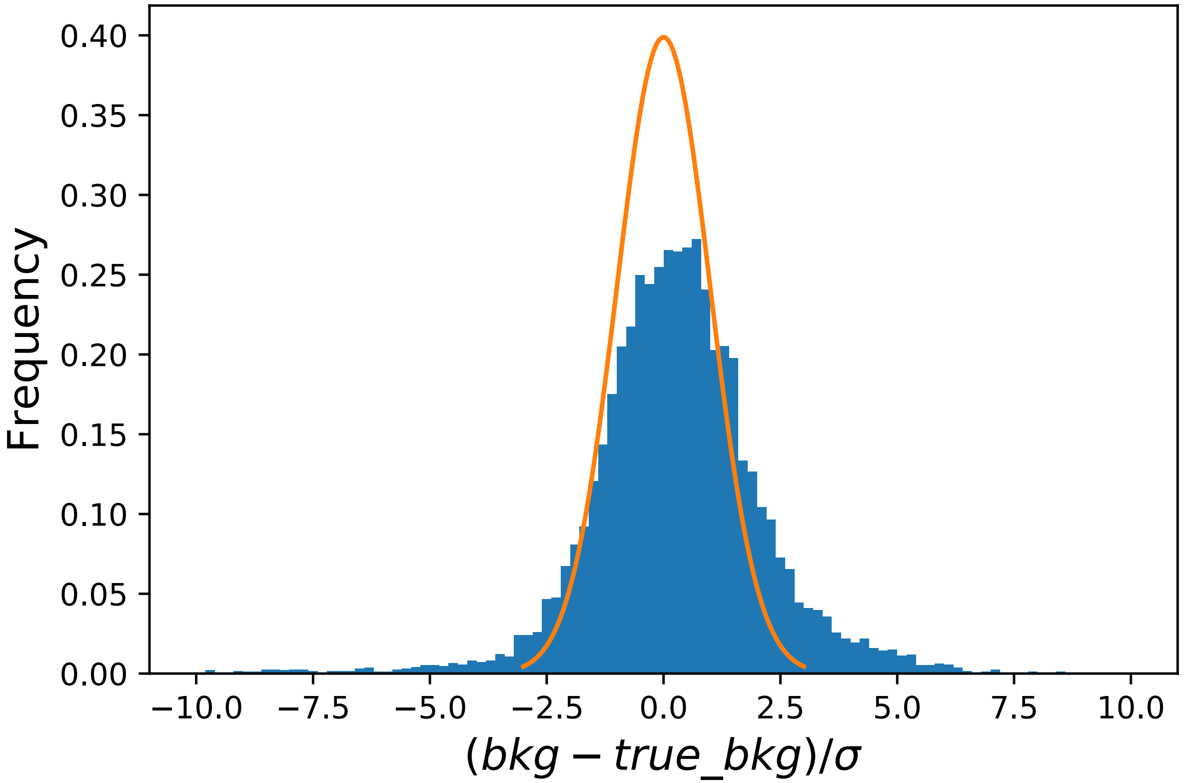
BKGnet

- σ is the error provided by the network.



Annulus

- With the annulus, errors are underestimated by a 47%



PAUS CATALOG WITH BKGnet PREDICTIONS

BKGnet → **PAUdm**

$bkg = BKGnet\ prediction$ → $bkg = median(annulus\ pixels)$

$\sigma_{bkg} = \sqrt{\sigma^2_{bkgnet} - \sigma^2_{label}}$ → $\sigma_{bkg} = std(annulus\ pixels)$

$Flux = raw\ flux - area \cdot bkg$ → $Flux = raw\ flux - area \cdot bkg$

$\sigma^2_{flux} = (S - N_a \cdot bkg) + N_a \cdot bkg + N_a^2 \cdot \sigma^2_{bkg} + N_a \cdot RO^2$ → $\sigma^2_{flux} = (S - N_a \cdot bkg) + N_a \cdot \sigma^2_{bkg} + \frac{N_a^2}{N_b} \cdot \frac{\pi}{2} \cdot \sigma^2_{bkg}$

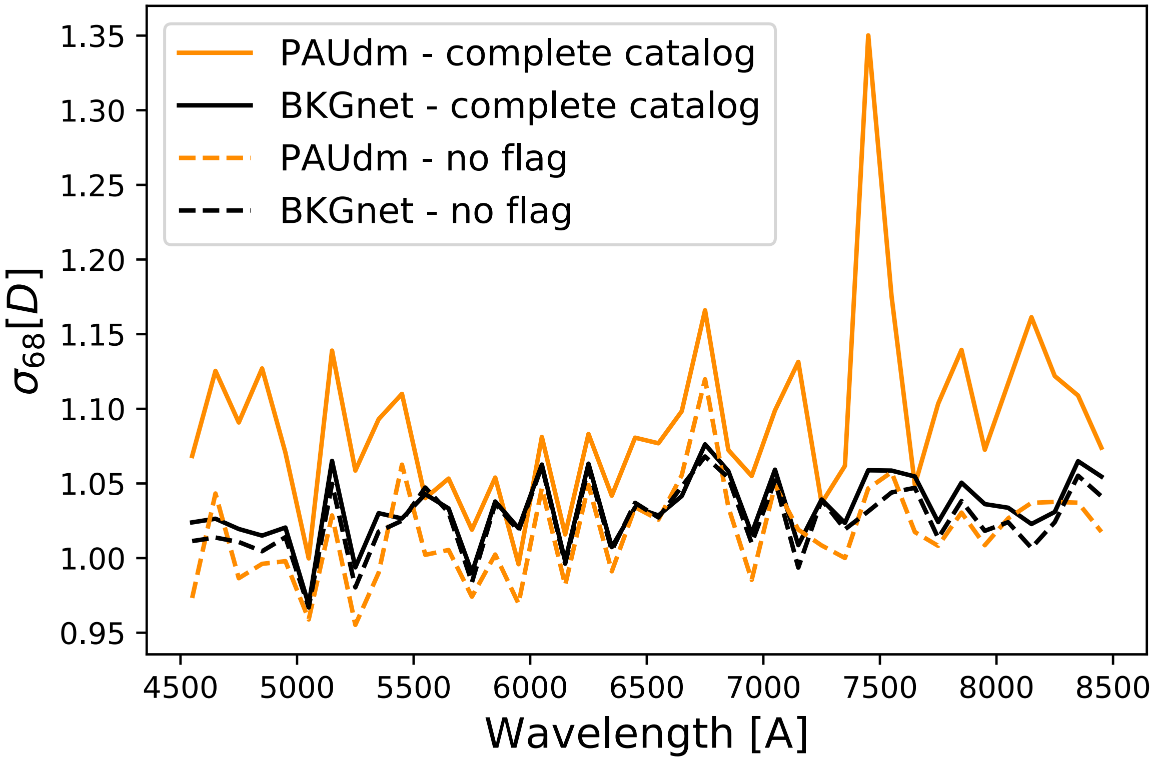
FLUX MEASUREMENT: < 1% difference.

ERROR ON THE FLUX MEASUREMENT: 7 % difference in errors.

CATALOG VALIDATION: DUPLICATES TEST

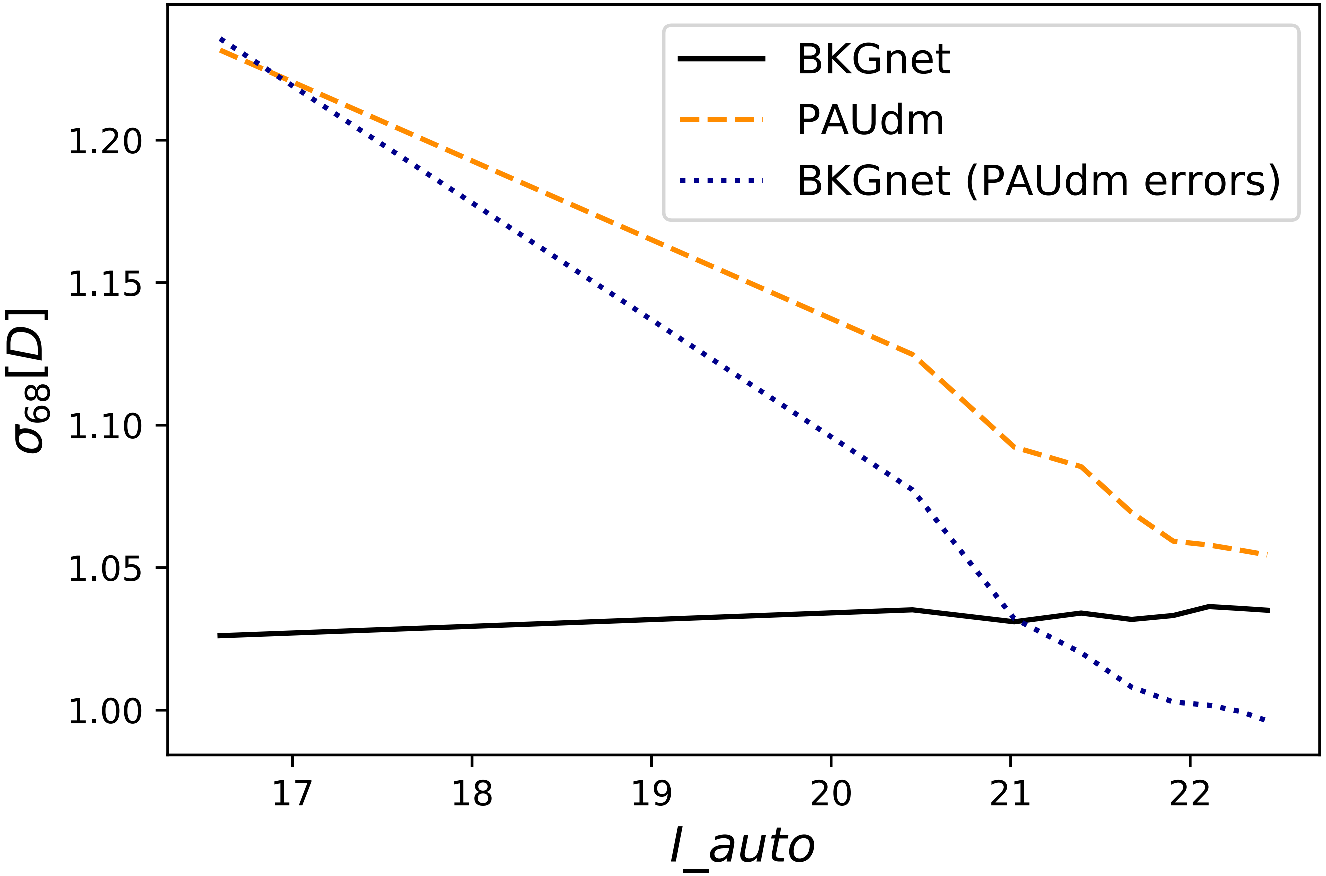
Duplicates test: Compare different exposures of the same galaxy in the same narrow band filter.

$$D = \frac{(exposure_1 - exposure_2)}{\sqrt{\sigma^2_{exposure_1} + \sigma^2_{exposure_2}}}$$



- For the comeplete catalog, BKGnet does much better than the annulus.
- Dropping all objects flagged by PAUdm, the result is very similar for both methods.
- BKGnet finds little difference between dropping flagged objects or not.
- The huge peak around 7500 A disappears.

CATALOG VALIDATION: DUPLICATES TEST



- There is a trend with magnitude with the PAUdm errors.
- The trend disappears with BKGnet errors.
- There is an improvement with the BKGnet background measurements .

CONCLUSIONS

1. We have developed BKGnet, a Deep Learning method to predict the background light.

2. This method is more robust towards scattered light, sources, cosmic rays, absortion, while being statistically accurate.

3. It removes a systematic trend in the we find in the current PAUS catalog.

4. It would allow using observations that currently are discarted.

5. BKGnet is a building block. The aim is to provide an end to end Deep Learning pipeline removing the background, predicting the flux and estimating the photometric redshift.


THANK YOU FOR YOUR ATTENTION
Questions?