Deep learning for the deblending of (high-redshift) galaxies

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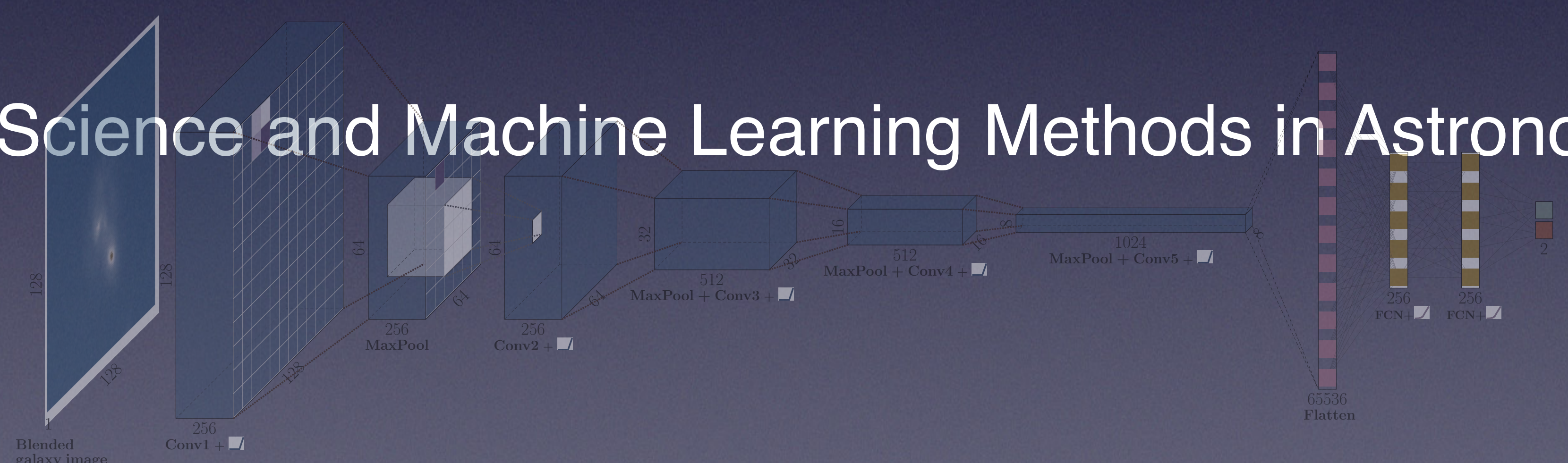
AG2020
Splinter E-Science and Machine Learning Methods in Astronomy



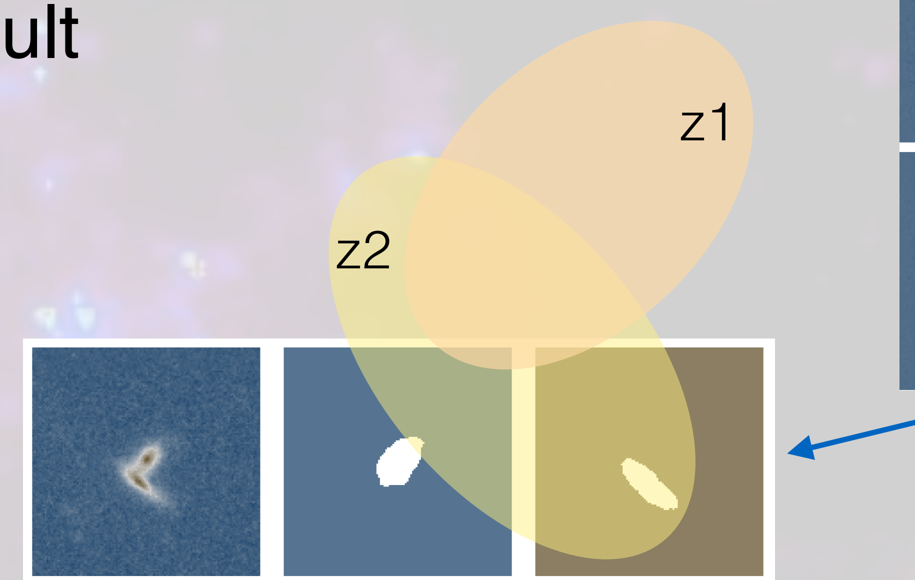
arXiv:1905.01324, the COIN Cosmostatistics Initiative, project #15 (https://cosmostatistics-initiative.org/)
Collaborators: Alexandre Boucaud, Emille Ishida, Rafael S. de Souza & the <u>COIN</u> collaboration

The deblending problem

Goal: ‘Good’ photometry for surveys with high blended fraction (expected), e.g. SDSS, LSST and Euclid

Add-on: Galaxy segmentation and morphology / shape
(also prior for ‘classic’ methods)

Challenge: Galaxies are ‘transparent’, so that separating flux in overlapping regions is difficult

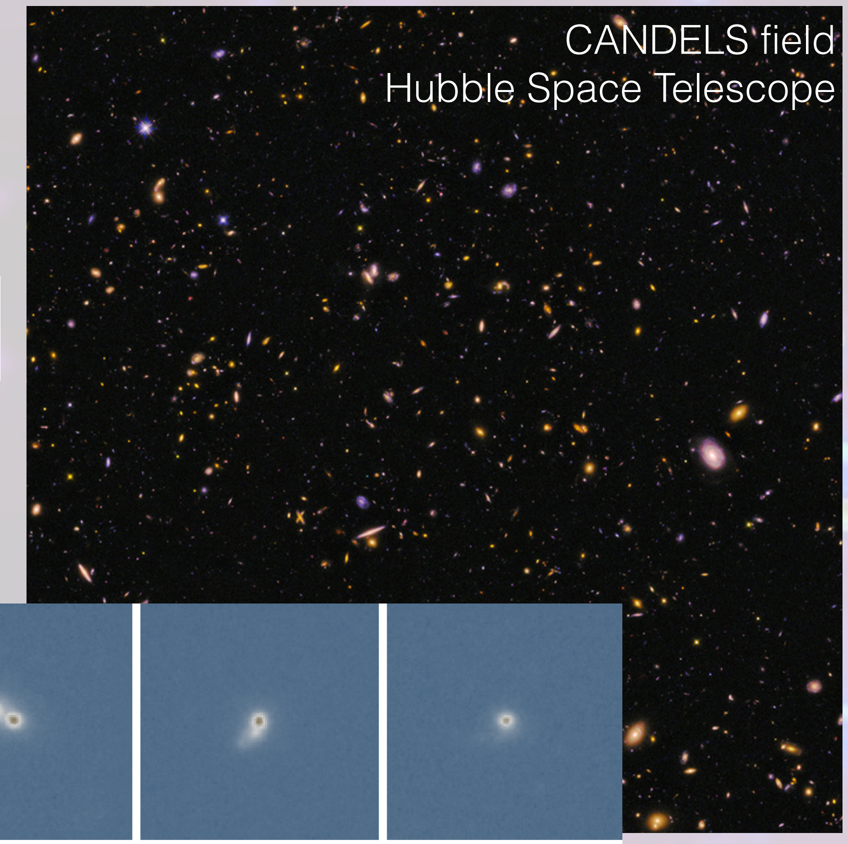


The deblending problem

Goal: ‘Good’ photometry for surveys with high blended fraction (expected), e.g. SDSS, LSST and Euclid - avoid bias!

low stellar density (Ross et al. 2012a). The correlation of galaxy density with stellar density is the most significant known bias on measured clustering, likely caused by incomplete deblending of detected objects in crowded fields of the SDSS imaging data. On the other hand, no significant correlation is seen between number density and potential

Dawson et al. 2016



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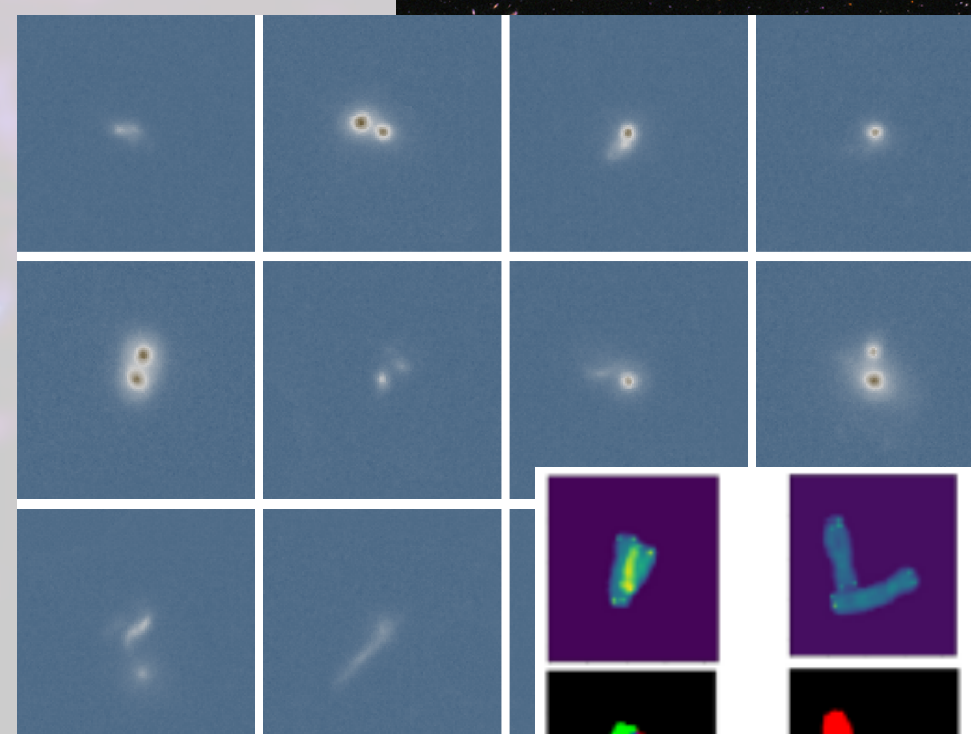
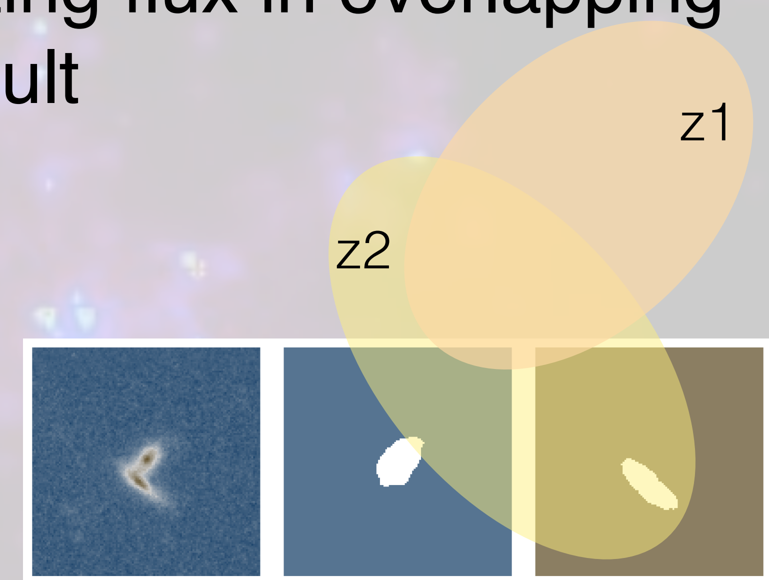


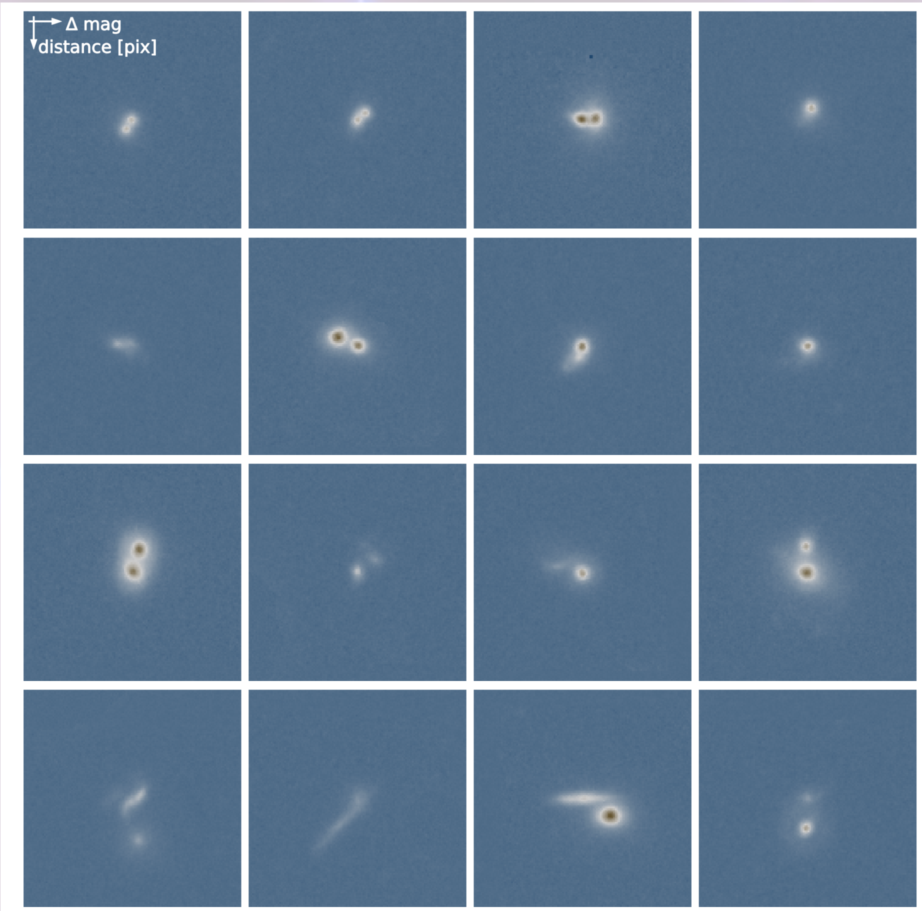
Challenge: Galaxies are ‘transparent’, so that separating flux in overlapping regions is difficult



Similar challenge:
Overlapping chromosomes

Lily Hu et al. 2017

Application of Deep Neural Networks: Galaxy photometry and deblending, shape measurements

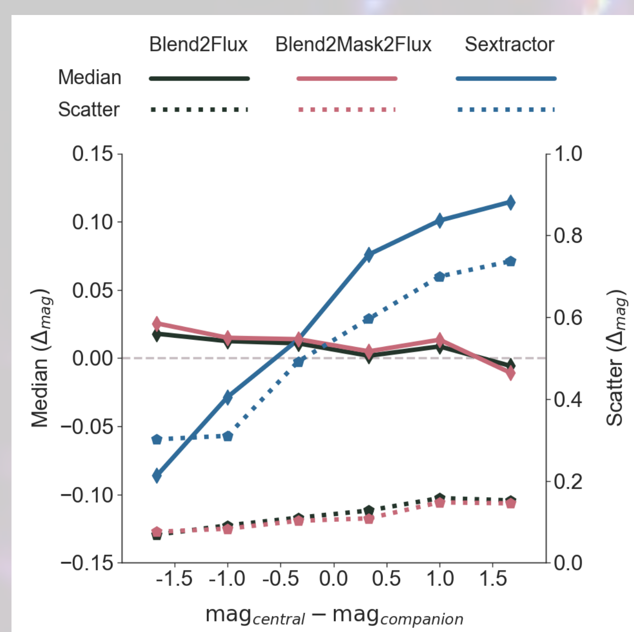


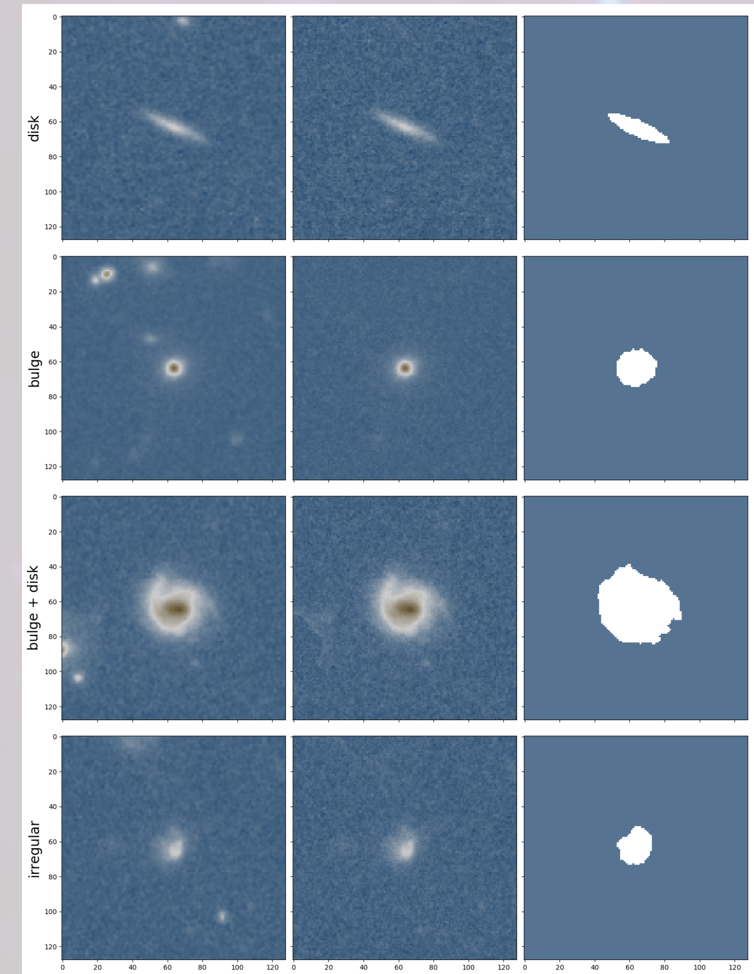
Artificially blended CANDELS data
18 < mag < 24
(https://github.com/aboucaud/candels-blender)

Get photometry of blended galaxies..

Goals for our deep NNs

..do so bias-free



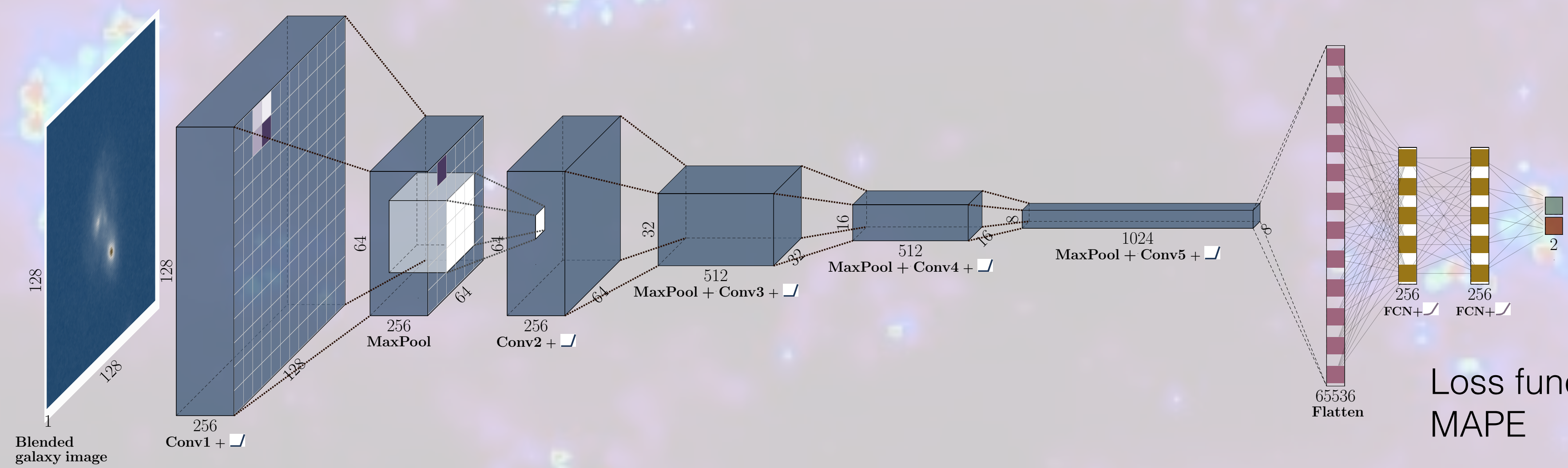


..Derive galaxy masks (shape measurements)

Boucaud et al.,
COIN collaboration
MNRAS 491,2 (2020)

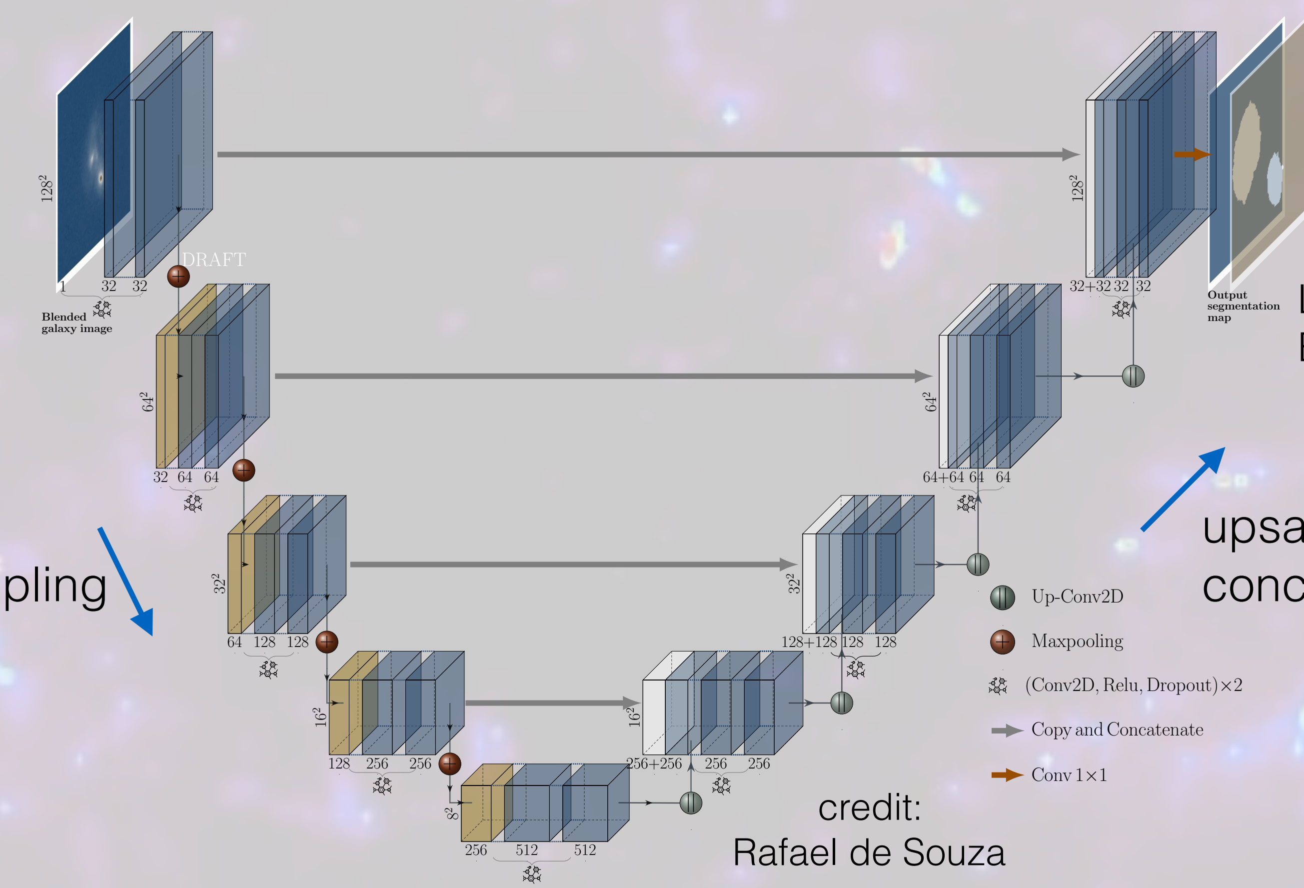
Application of Deep Neural Networks: Galaxy photometry and deblending, shape measurements

1) *blend2flux*
a CNN for photometry



Loss function:
MAPE

2) *blend2mask2flux*
photometry + masks



+ a CNN type *blend2flux*
(but 3-channel input)

Loss function:
Binary cross-entropy

downsampling

upsampling
concatenation

credit:
Rafael de Souza

Boucaud et al.,
MNRAS 491,2 (2020)

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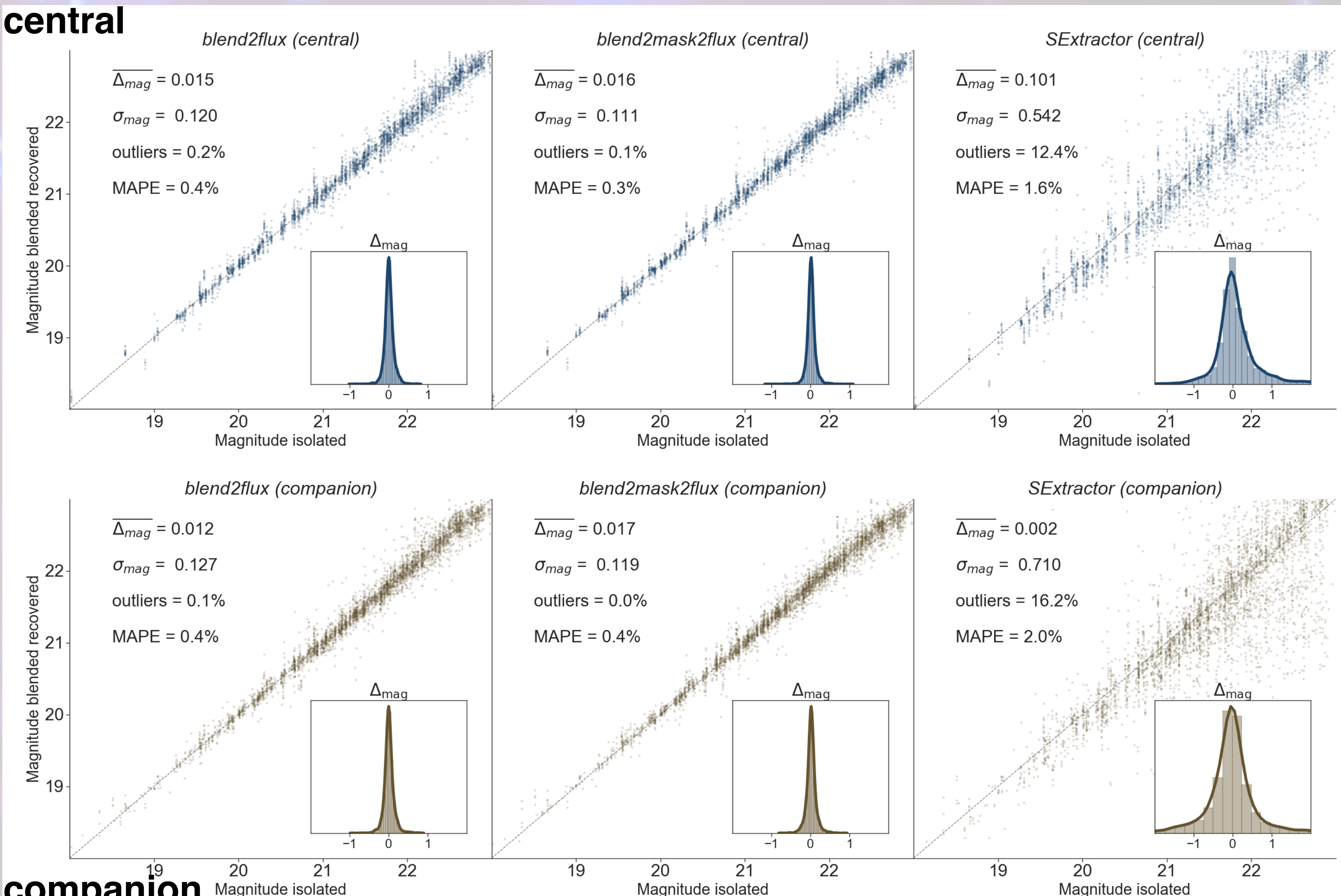
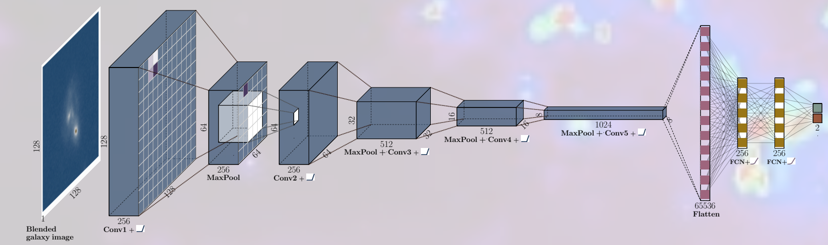
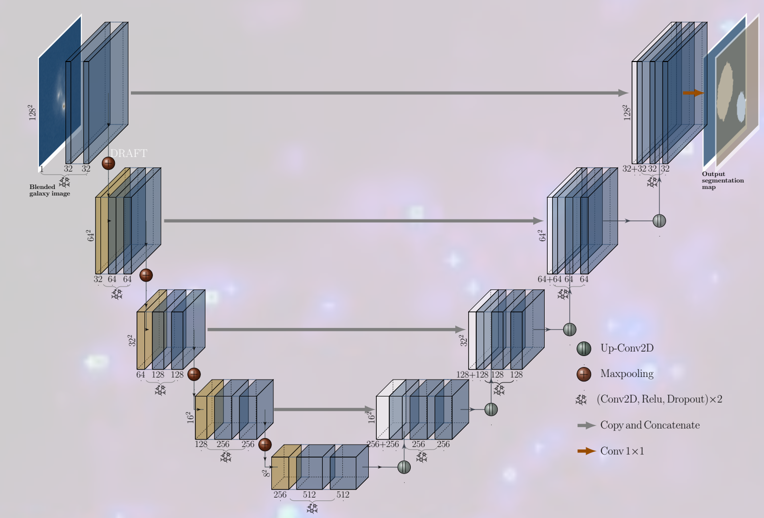
Histograms of photometric errors



1) *blend2flux*
a CNN for photometry



2) *blend2mask2flux*
photometry + masks

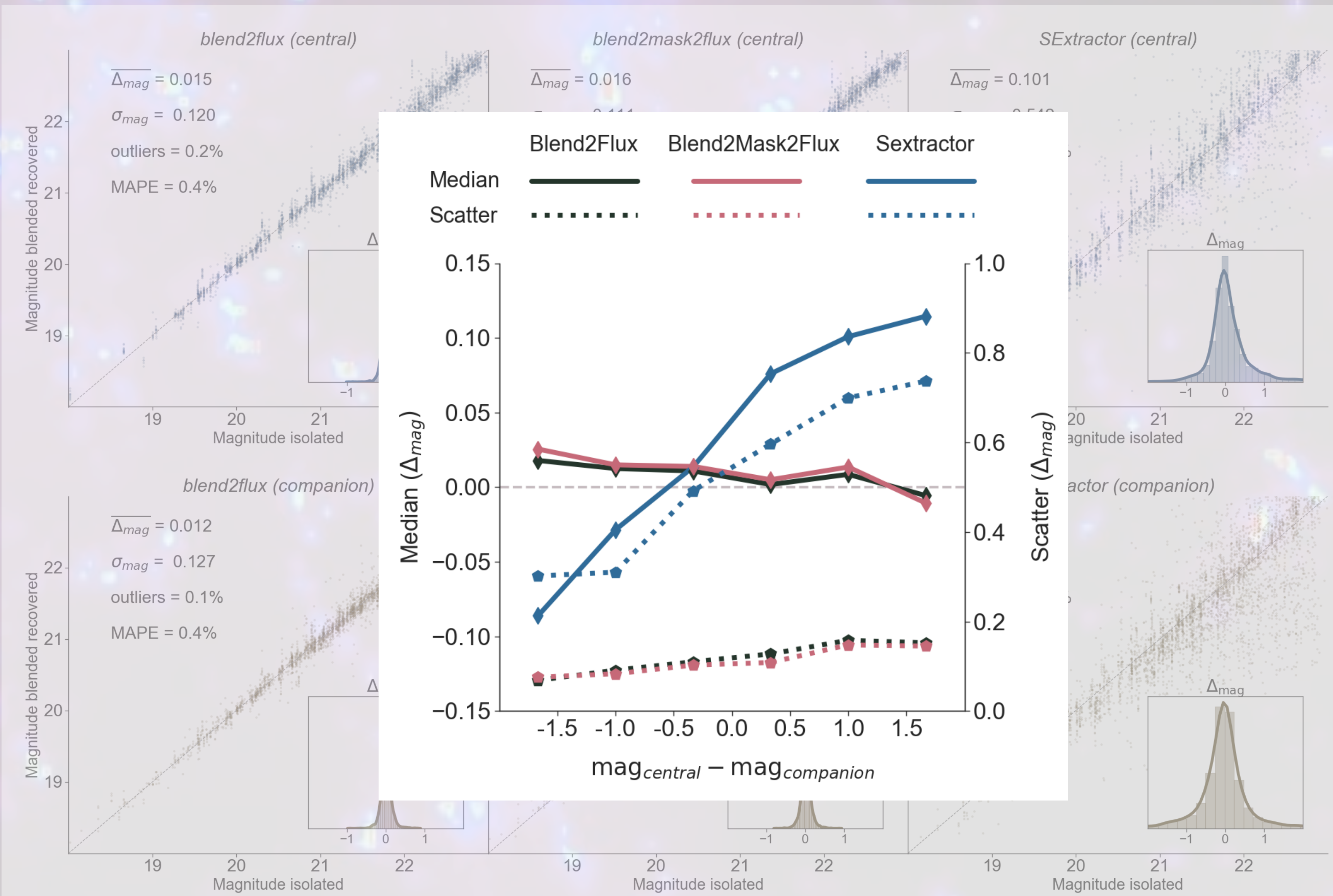


→ similar photometry for both nets, typical scatter 0.1 mag

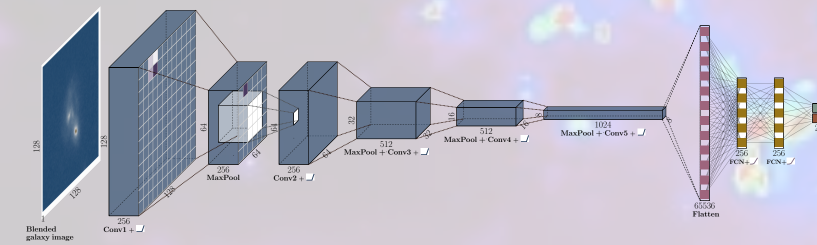
Boucaud et al., MNRAS 491,2 (2020)

Application of Deep Neural Networks:
Galaxy photometry and deblending, shape measurements

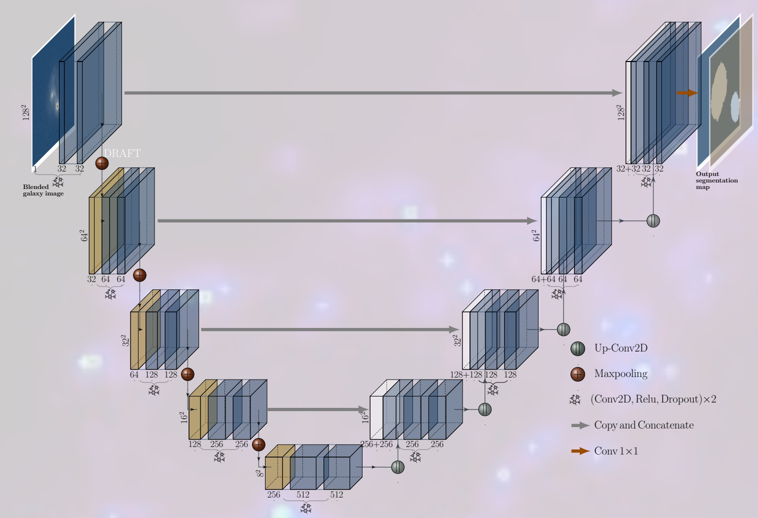
Photometric bias and scatter - magnitude difference



1) *blend2flux*
a CNN for photometry



2) *blend2mask2flux*
photometry + masks



→ small bias and scatter

Boucaud et al.,
MNRAS 491,2 (2020)

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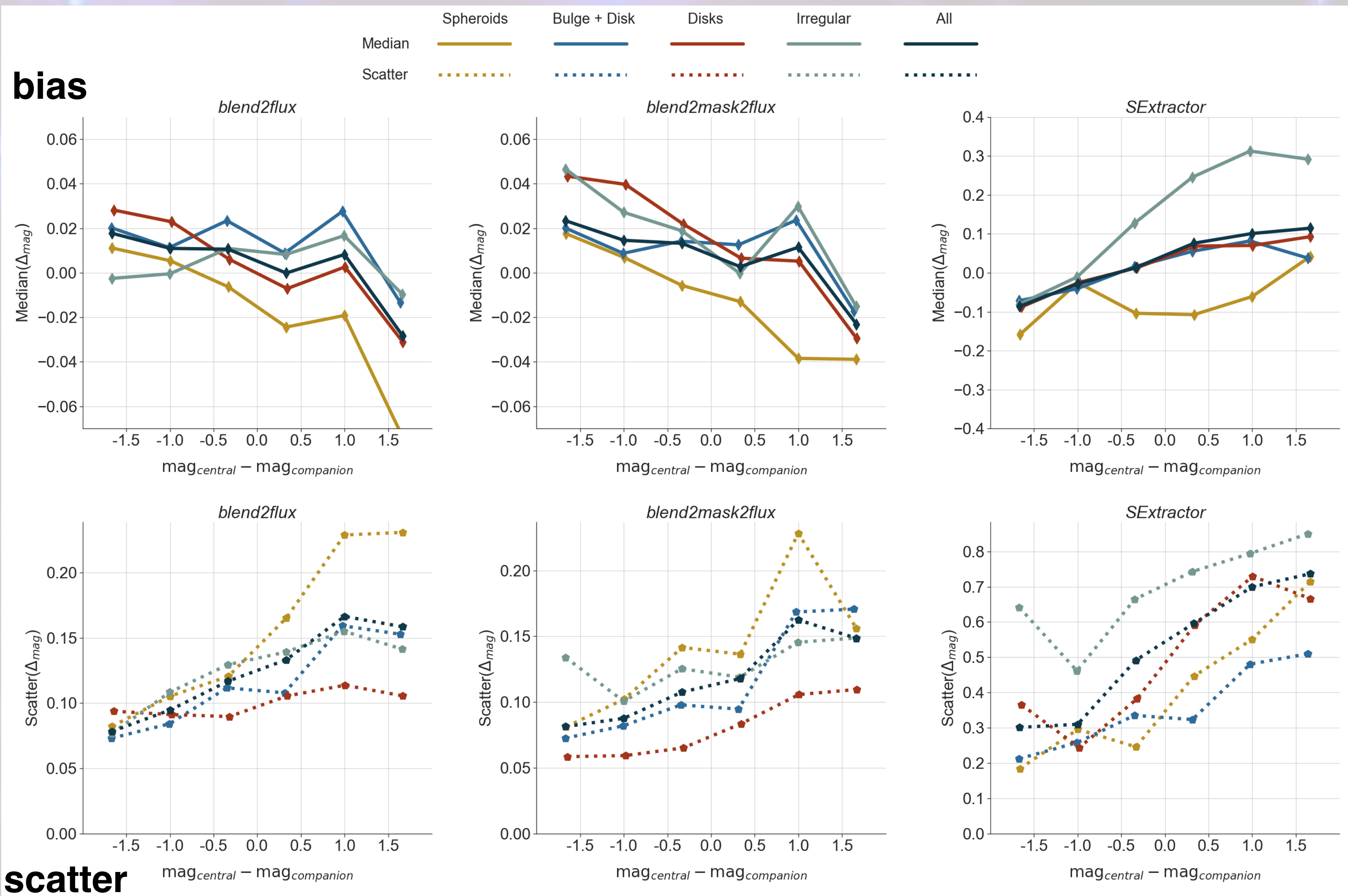
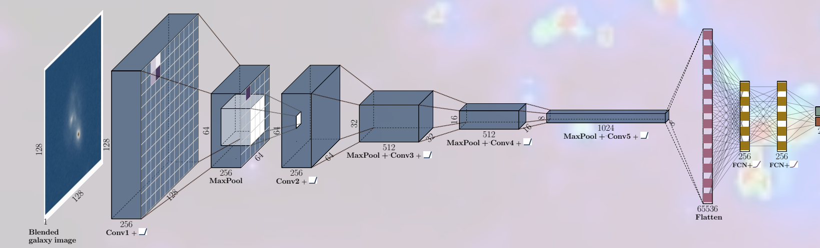
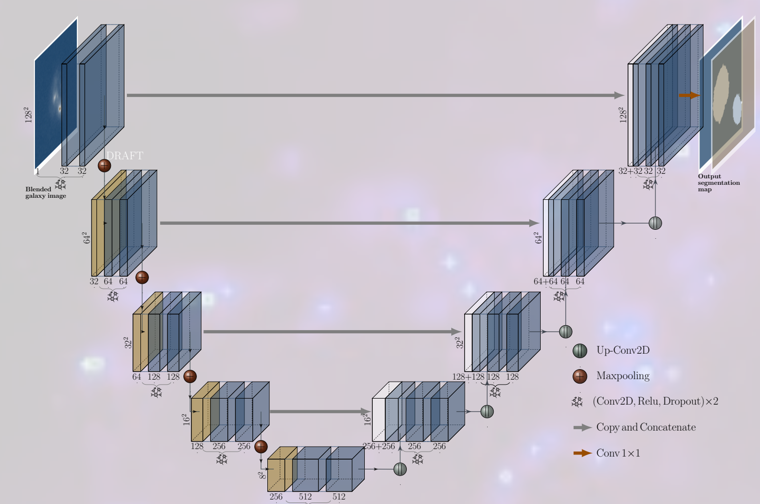
Photometric bias and scatter - galaxy type



1) *blend2flux*
a CNN for photometry



2) *blend2mask2flux*
photometry + masks



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Boucaud et al.,
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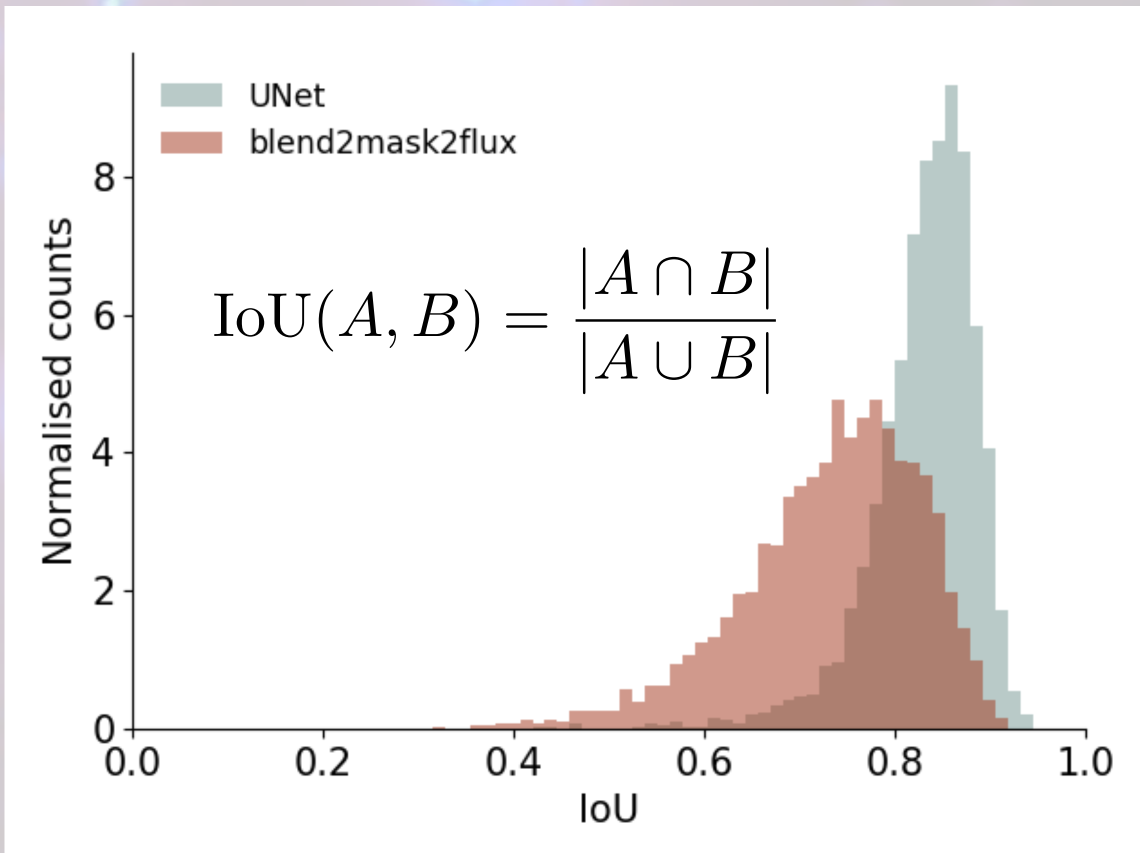
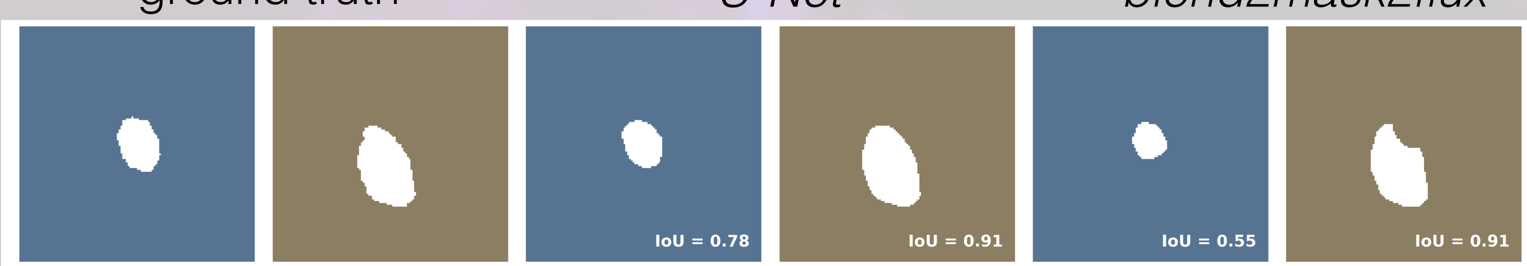
Histogram of IoU (Intersection over Union - Jaccard index)

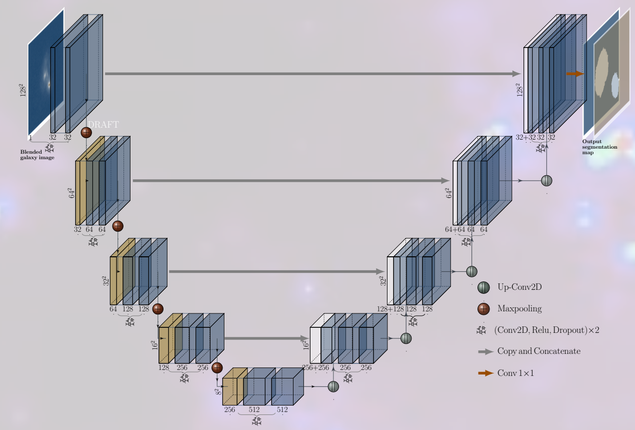


ground truth | *U-Net* | *blend2mask2flux*

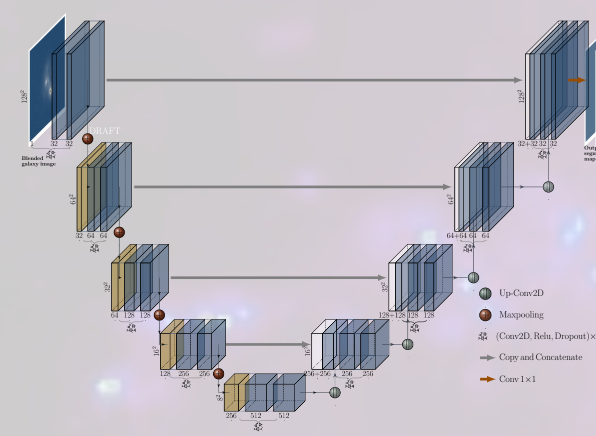


→ Dispersion broadens when optimised for photometry

2 a) *U-net*
masks, no photometry



2 b) *blend2mask2flux*
photometry + masks



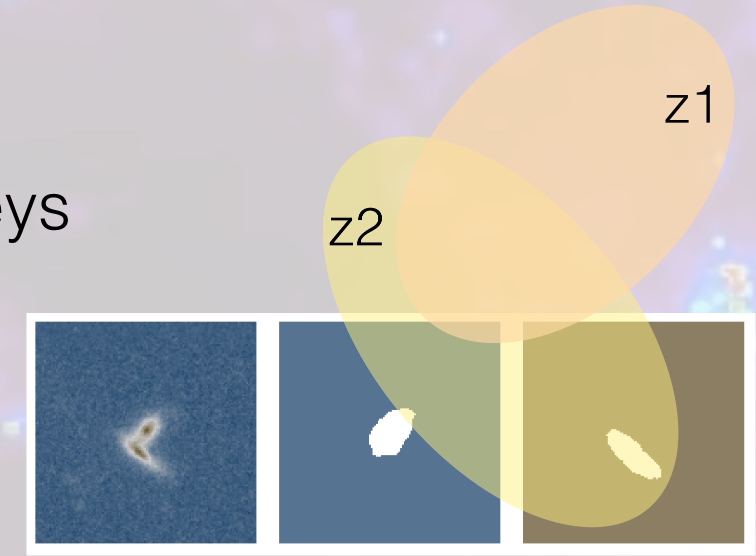
+ a CNN type *blend2flux*

Boucaud et al., MNRAS 491,2 (2020)

Galaxy deblending with DNNs: Take-aways

The deblending problem

- Large fraction of blends for deep photometric surveys
- Non-trivial to disentangle single galaxies
- Causes bias



Photometry

- DNNs recover flux: low bias and high precision
- A 'simple' CNN *blend2flux* performs well
- Slight improvement when simultaneously constraining masks

Mask Segmentation

- *U-Net* architecture suitable to recover shapes
- Pitfall: Train photometry + shapes end-to-end

Limitations - Idealisations

- Pre-detected sources
- Centering
- Restricted to pairs
- Single-channel

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