3rd ASTERICS-OBELICS Workshop

23-25 October 2018, Cambridge, UK.

H2020-Astronomy ESFRI and Research Infrastructure Cluster
(Grant Agreement number: 653477).

Applications of Machine Learning to Deblending in LSST

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LSST Basics

- 8.4 m telescope under construction in Chile
- 10 year survey of the southern sky beginning in 2022
- Will generate ~200 petabytes of data products (~20 billion stars and ~20 billion galaxies)
- Main science areas LSST will address:
  - Understanding Dark Matter and Dark Energy
  - Hazardous Asteroids and the Remote Solar System
  - The Transient Optical Sky
  - The Formation and Structure of the Milky Way

The Basic Problem

Blended Scene

image from HSC-COSMOS Dataset: courtesy Nate Lust

How bad is the problem?

Survey	i-band limiting magnitude	Sources blended with at least 1 neighbor	Source
DES	~24	30%	Samuroff et al (2017)
HSC	~26	58%	Bosch et al (2017)
LSST (predicted)	~27	>63%	Sanchez et al (in Prep)

How bad is the problem?

- Dawson et al. 2016 estimate that 14% of galaxies observed on the ground are actually blends

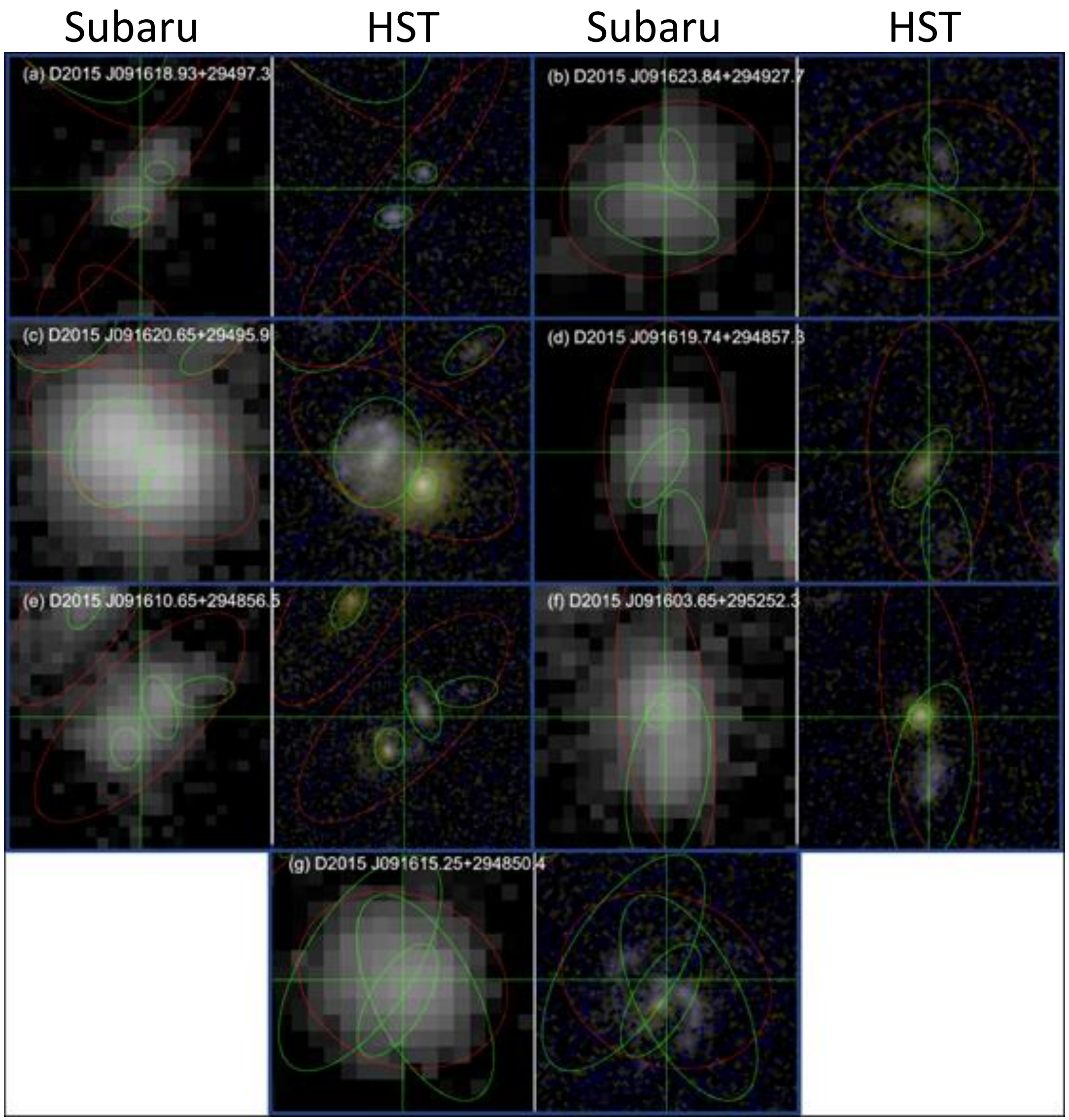
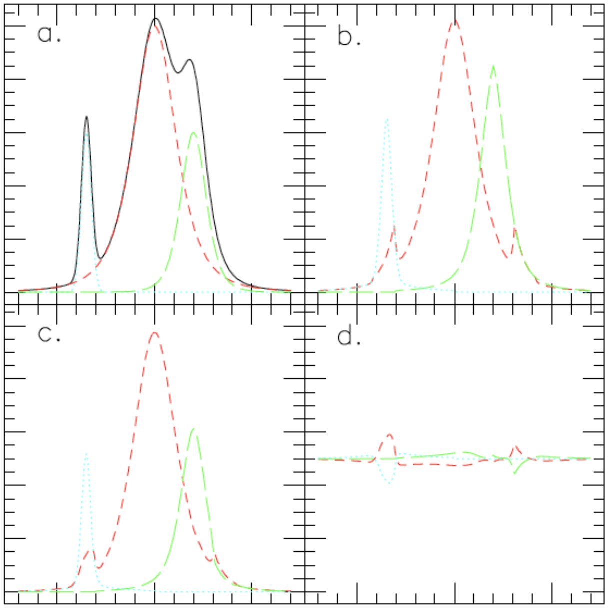


image credit: Dawson et al. 2016

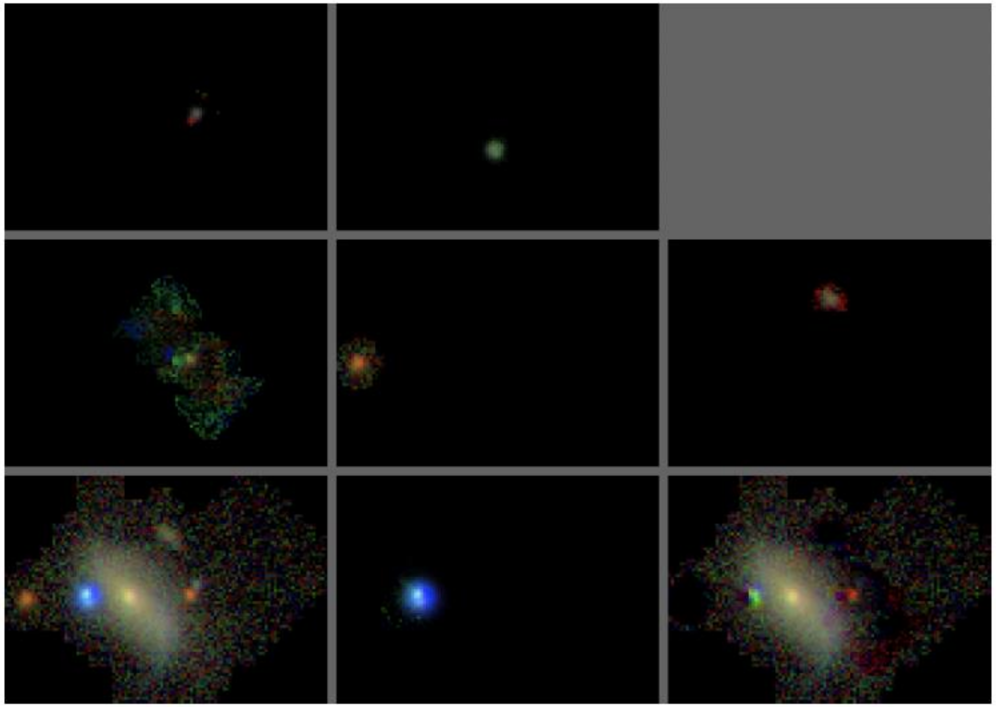
The SDSS Deblender



- Simple algorithm:
  1. Make symmetric templates (b)
  2. Reweight the data (a) with the template (b) to get (c)
- Works well in 2D, since 3 objects in a row is less likely at SDSS depths

SDSS Deblender

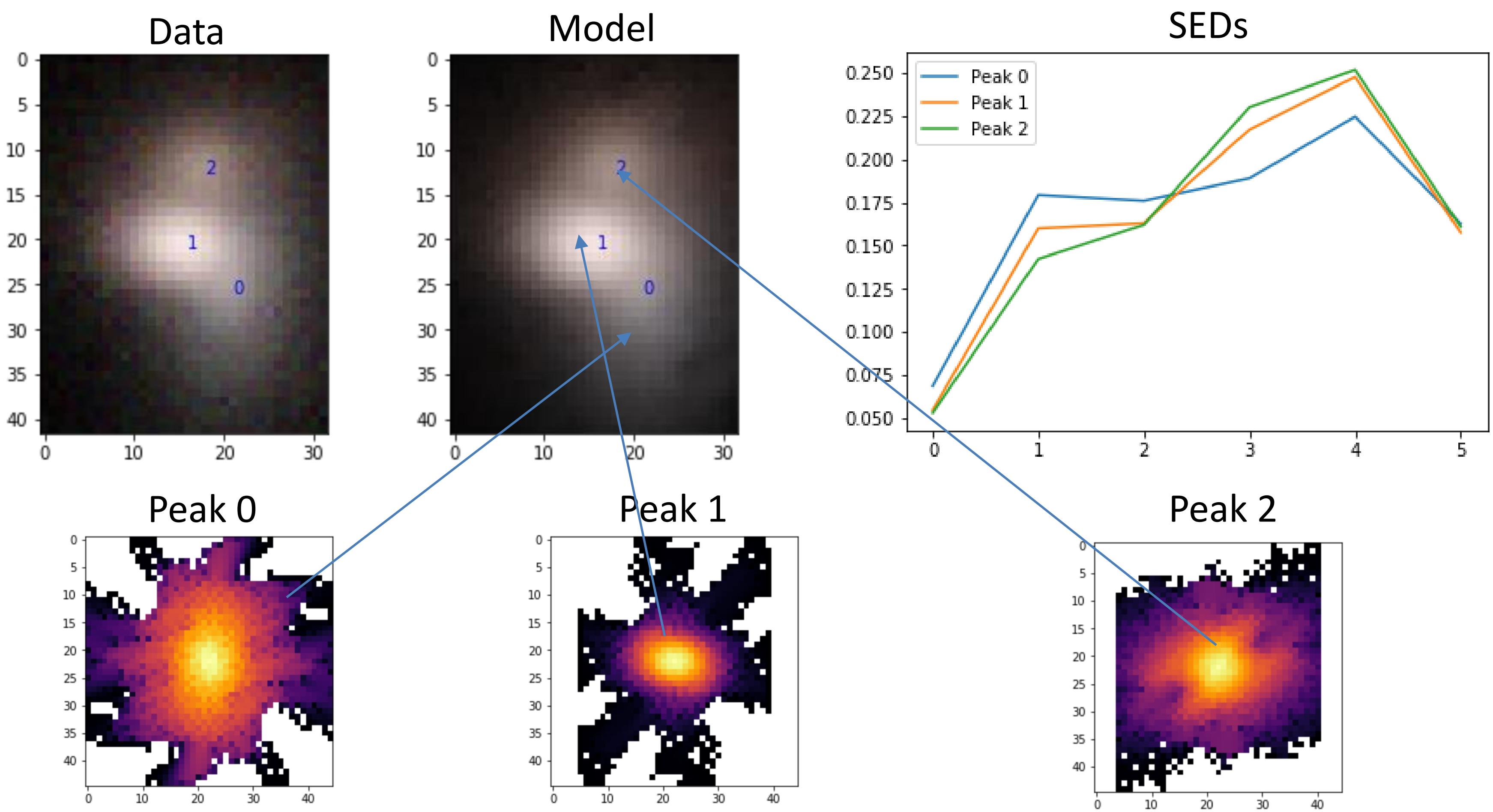
- Performed well for most objects but failed for the 3 in a row sources
- This is a lot more common at HSC and LSST depths, and a new deblender is needed
- Co-developed the new solution with Peter Melchior



Single Band

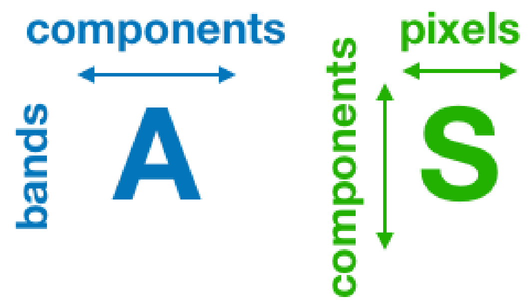
Use colors!

scarlet: Basic Model



Mathematical Model

$$M = A\hat{T}\hat{P}S$$



- A: SED (bands x sources)
- S: Morphology (sources x pixels)
  - Centered on the image
- P: Linear PSF convolution (for now)
- T: Linear Translation
- The algorithm will fit A and S simultaneously

Proximal Operators

$$\mathrm{prox}_{\lambda f}(x) \equiv \underset{v}{\mathrm{argmin}} \left\{ f(v) + \frac{1}{2\lambda} ||x - v||_2^2 \right\}$$

- Proximal operators have many different interpretations, including being a fixed point x* of f
- This allows one to find the x that minimizes f using

$$x^{n+1} \leftarrow \mathrm{prox}_{\lambda g}\left(x^n\right)$$

For more, see Combettes and Pesquet 2010, Parikh and Boyd 2013, Rapin et al. 2013

Forward-Backward Splitting

- We can use proximal operators to minimize constrained variables, for example

$$f = f(x) + g(x)$$

- In this case the proximal algorithm to minimize f(x) with constraint g(x) is

$$x^{n+1} \leftarrow \mathrm{prox}_{\lambda g}\left(x^n - \lambda \nabla f(x^n)\right)$$

scarlet Algorithm

$$\underset{A,S}{\text{minimize}} \; f(A,S) + \sum_{i=1}^{N_A} g_i^A\left(A_i\right) + \sum_{i=1}^{N_S} g_i^S\left(S_i\right)$$

where:

$$f(A,S) = \frac{1}{2}\,||D - A\hat{T}\hat{P}S||_2^2$$

gives the updates for A and S:

$$A_{n+1} = \text{prox}_{\lambda_A g_1^A}\left(\ldots\text{prox}_{\lambda_A g_N^A}\left(A_n - \frac{1}{\lambda_A}\nabla_A\left(A_n\hat{T}\hat{P}S_n - D\right)\right)\right)$$

$$S_{n+1} = \text{prox}_{\lambda_S g_1^S}\left(\ldots\text{prox}_{\lambda_S g_N^S}\left(S_n - \frac{1}{\lambda_S}\nabla_S\left(A_{n+1}\hat{T}\hat{P}S_n - D\right)\right)\right)$$

Constraints

- We wrote the proxmin package to execute proximal gradients in python (https://github.com/pmelchior/proxmin)
- Allows users the flexibility to use custom proximal operators as constraints on each variable
- Several built-in constraints including L0 and L1 norms, non-negativity, smoothness (TV), unit normalization, etc.

SED Constraints

- Non-Negative

$$\text{prox}_+(A) = \begin{cases} A, & A >= 0 \\ 0, & \text{otherwise} \end{cases}$$

- Sum to unity

$$\text{prox}_1(x) = \frac{x}{\sum_i x_i}$$

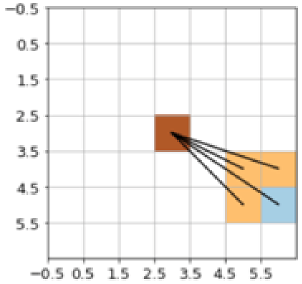
Morphology Constraints

- Non-Negative
- Soft Symmetry

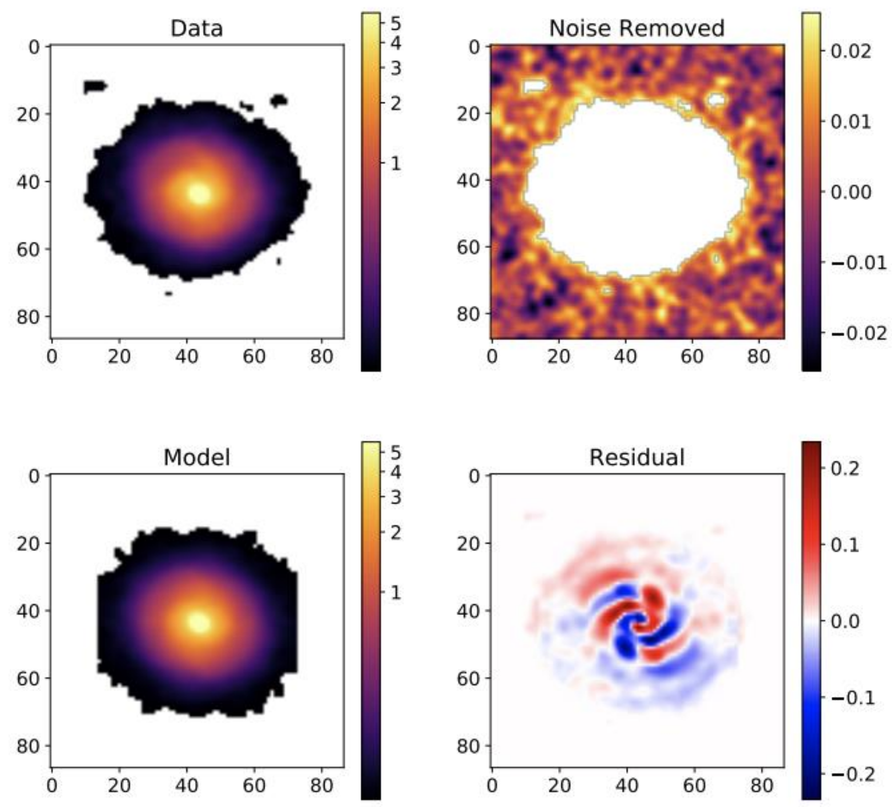
$S^{\dagger}_{k,n} \equiv$ Symmetric $S_{k,n}$

$$S_{k,n} = (1-\sigma)\, S_{k,n-1} + \frac{\sigma}{2}\left(S_{k,n-1} + S^{\dagger}_{k,n-1}\right)$$

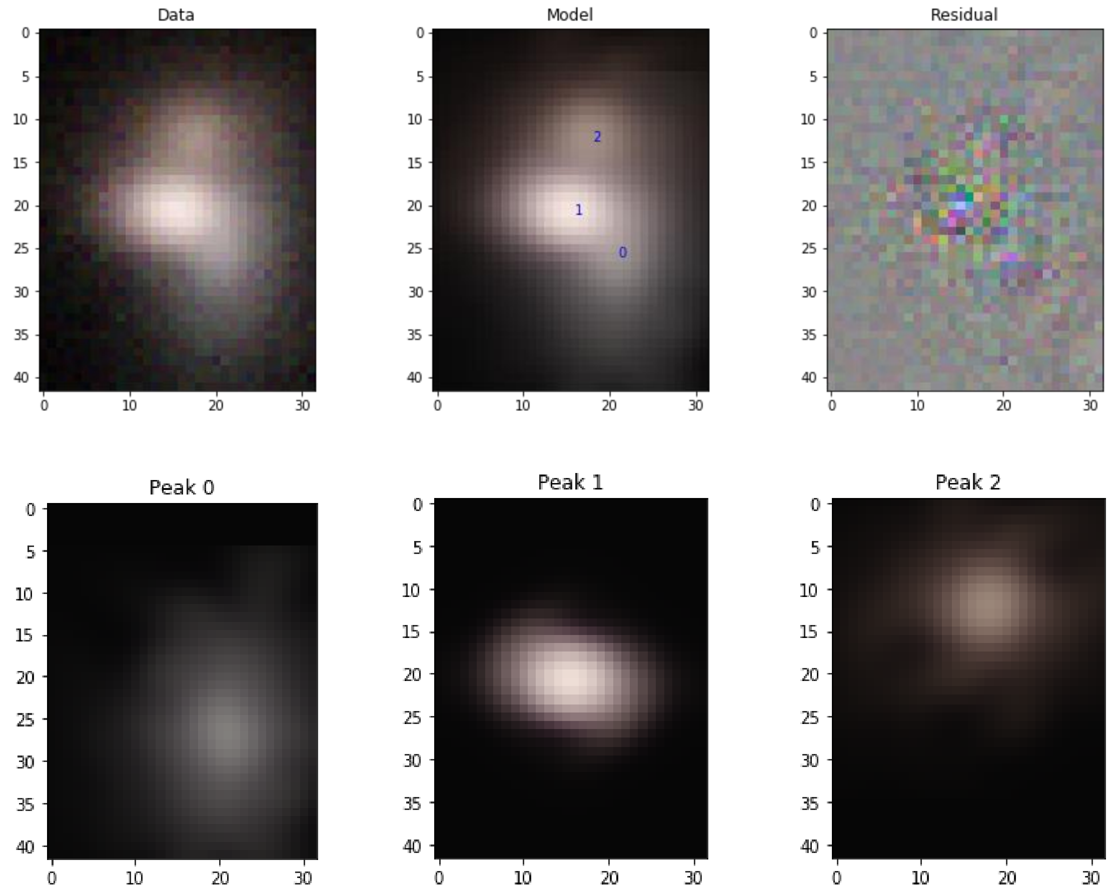
- Monotonic
  - Not a true proximal operator (saves CPU cycles)
  - Each pixel must be less than or equal to the sum of its reference pixels



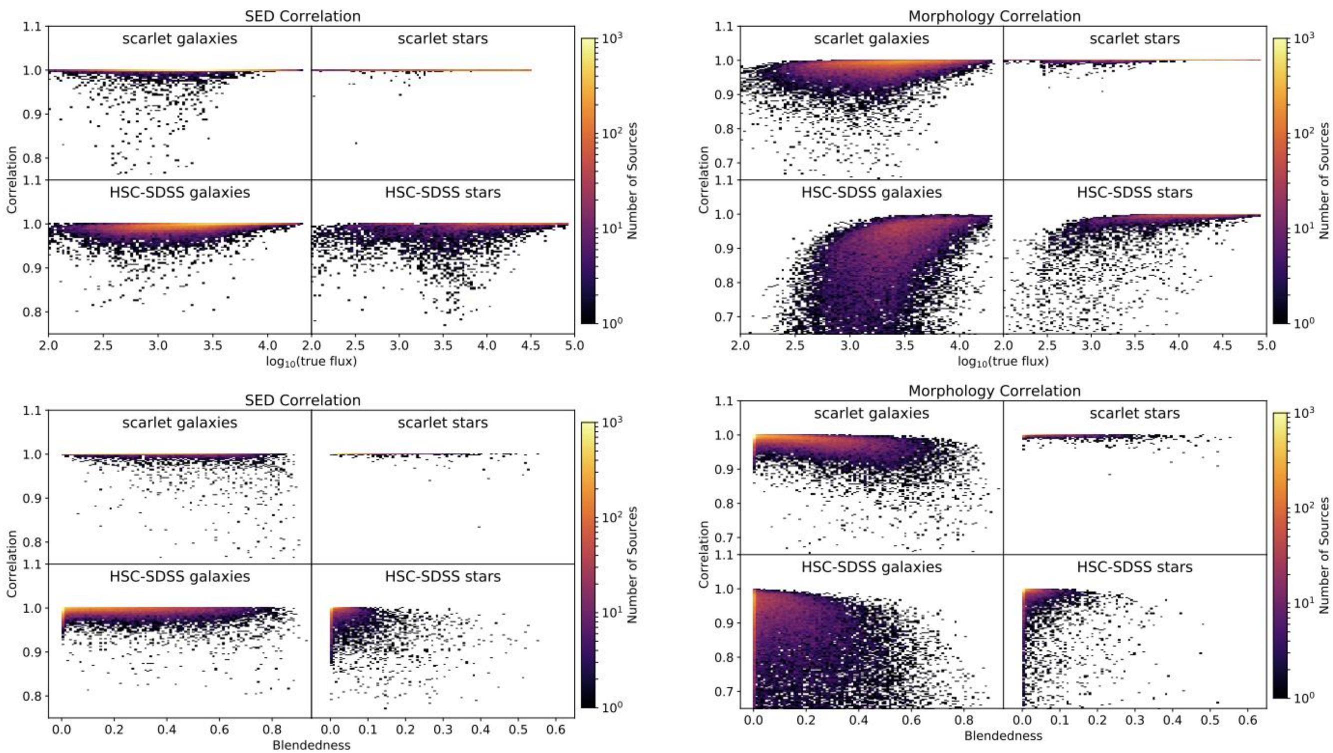
How close are resolved spirals to the constraints?



Simulated Blends

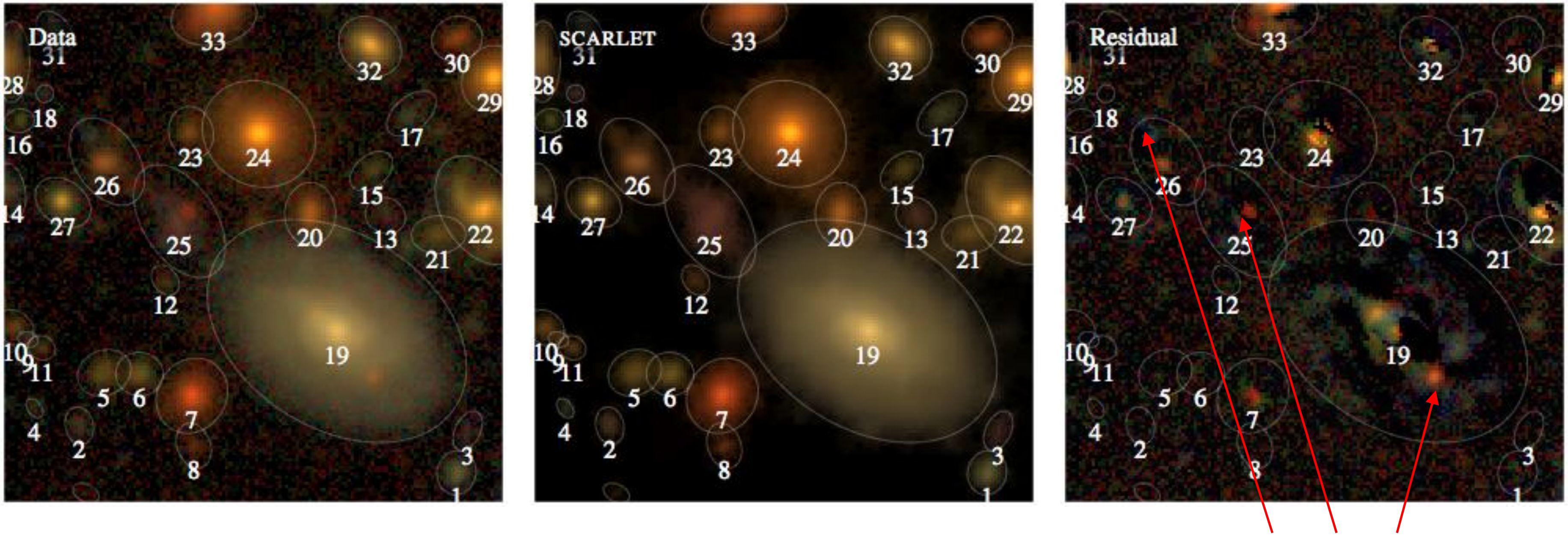


Comparison with SDSS



$$\beta = 1 - \frac{S_k \cdot S_k}{\sum_i S_i \cdot S_k}$$

HSC-COSMOS



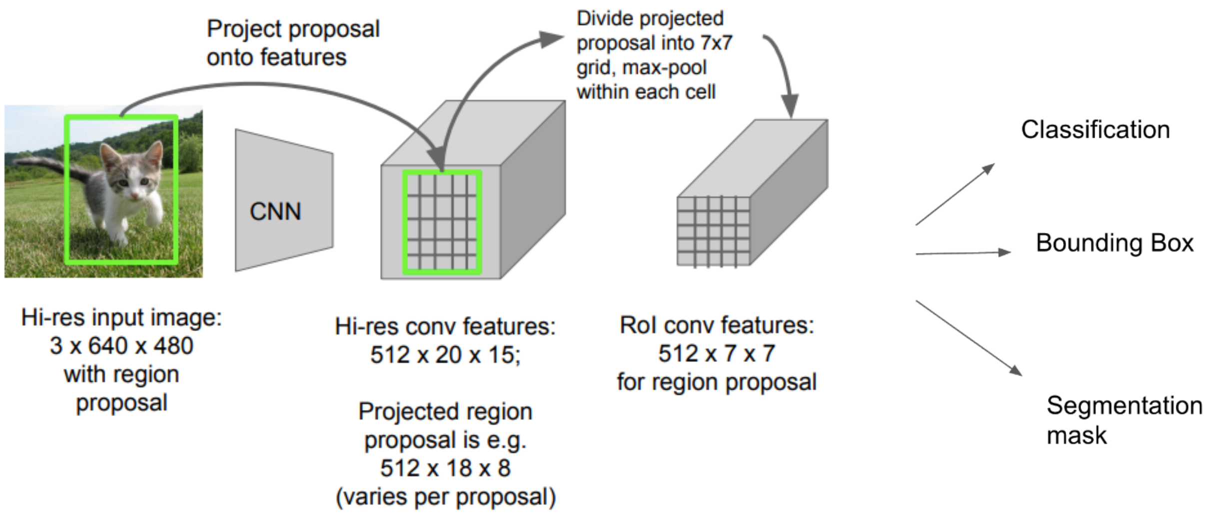
- Detection clearly missed some objects
- Some objects need to be modeled with multiple components
- Color residuals clearly show where new sources are needed

undetected sources

Attempts at using Neural Network

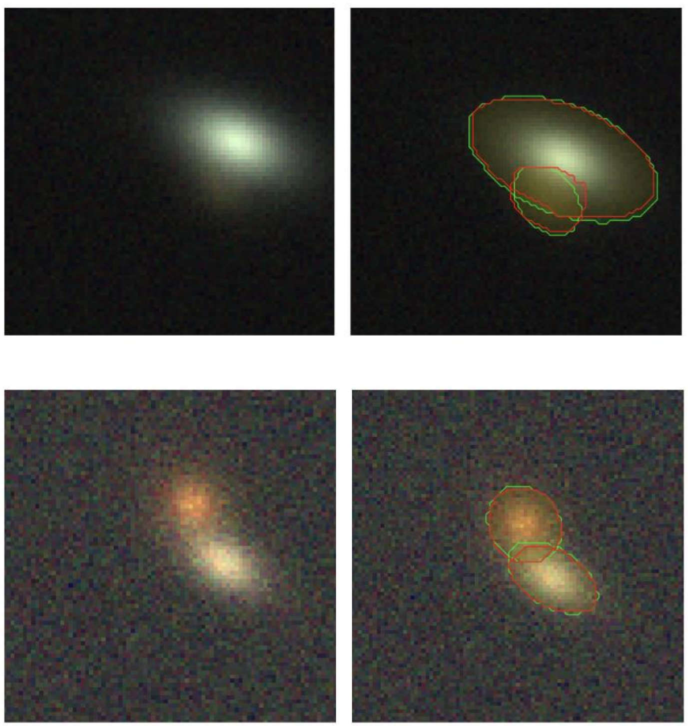
- Work of Sowmya Kamath (grad student at Stanford)

Mask-R CNN

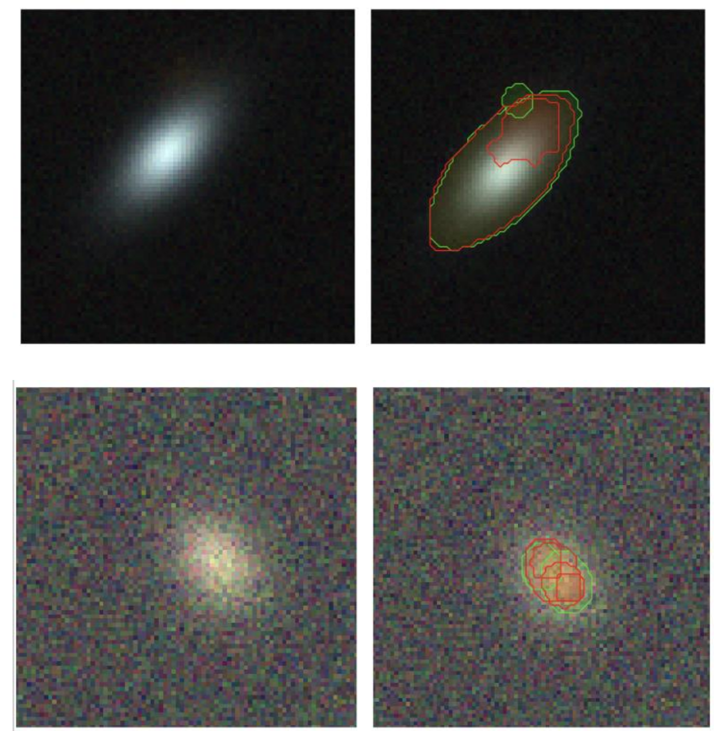

Project proposal onto features
Divide projected proposal into 7x7 grid, max-pool within each cell
CNN
Classification
Bounding Box
Segmentation mask
Hi-res input image: 3 x 640 x 480 with region proposal
Hi-res conv features: 512 x 20 x 15;
Projected region proposal is e.g. 512 x 18 x 8 (varies per proposal)
RoI conv features: 512 x 7 x 7 for region proposal

Results

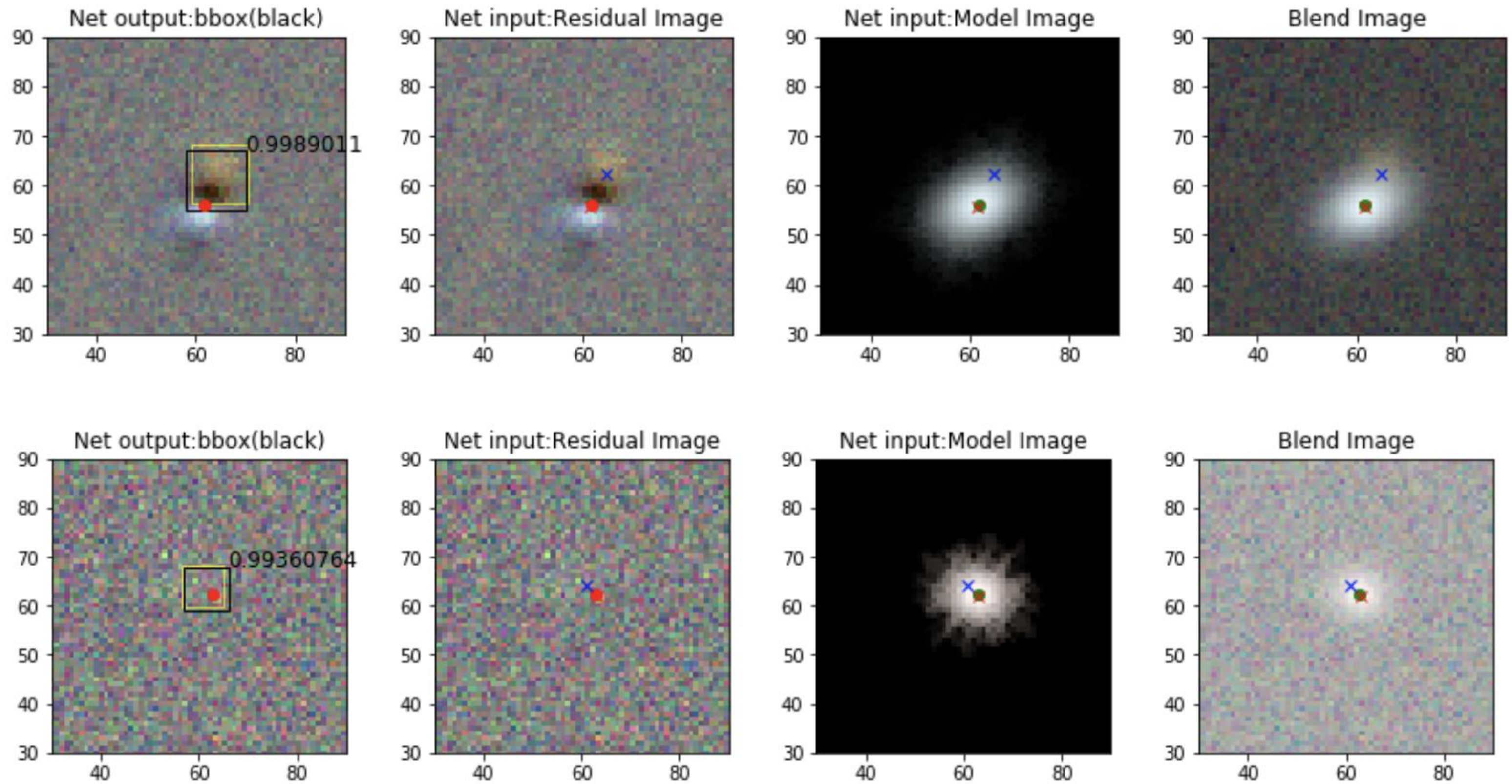
Sometimes it works…



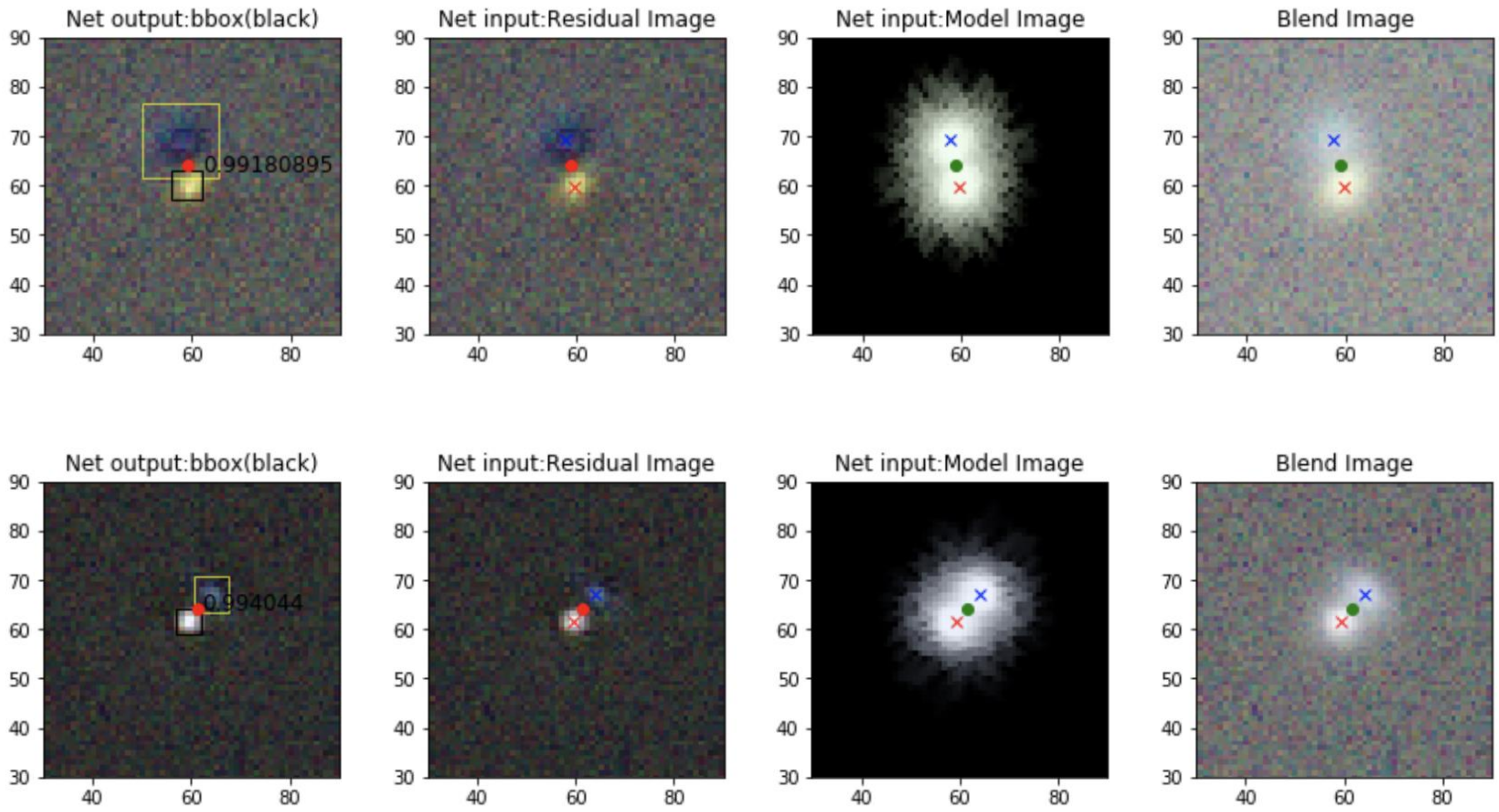
Sometimes it doesn’t



More success using CNN for object detection



But not always…



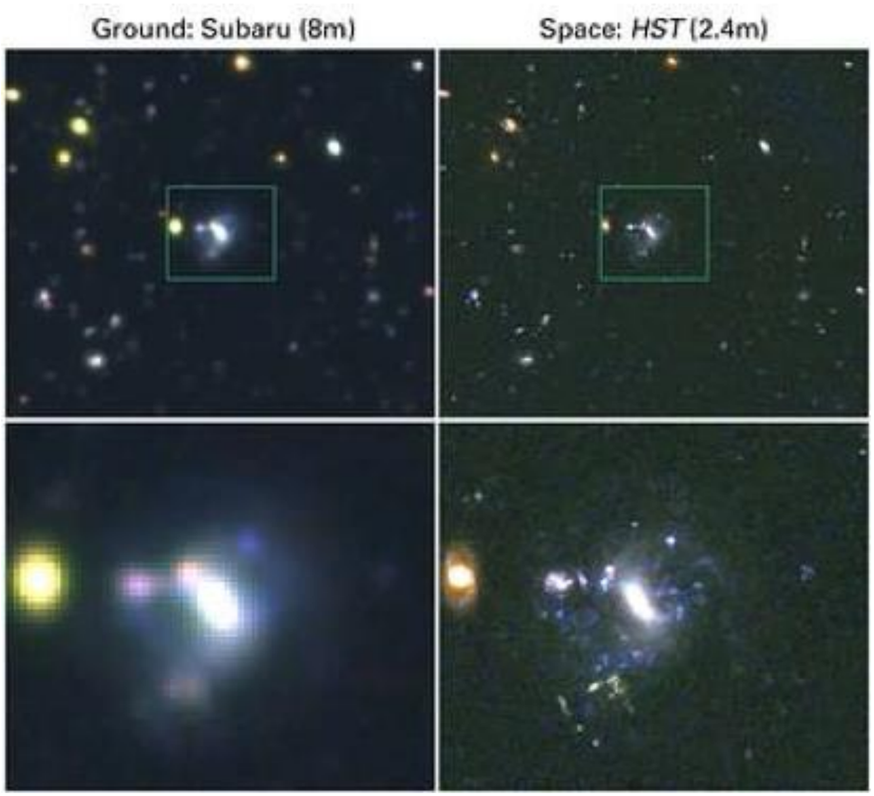
Shear Bias

- Lorena Mezini single band deblending of 2 objects separated by 9 pixels (FWHM 1.7 and 3.4 pixels)
- Showed that a significant bias is introduced due to the translations and PSF convolutions

PSF Model	Shear Bias
Full PSF Deconvolution	-0.152367
Partial PSF Deconvolution	-0.0151375
No PSF Matching	0.00263424

Future Work

- Use analytic (non-linear) PSF deconvolutions and translations
- Allows for multi-survey deblending (eg. LSST and WFIRST)
- Deblend an entire CCD



credit: Australian Telescope National Facility

Future Work

- Full CCD deblending
- Testing on HSC data before going into production
- Simultaneous deblending of ground, space, and GRISM data
- Neural networks? CNN? GQN?
  - No one has had luck so far, but it would remove the use of the inexact symmetry and monotonicity constraints

Acknowledgement

- H2020-Astronomy ESFRI and Research Infrastructure Cluster (Grant Agreement number: 653477).