

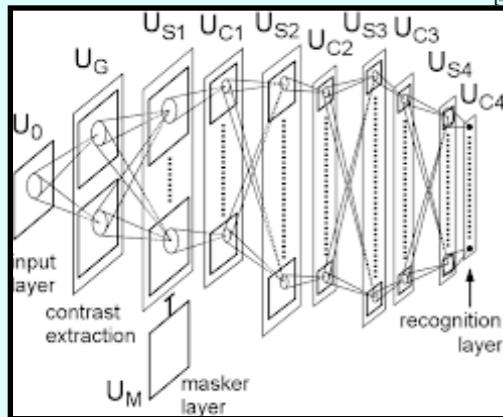
# *Deep learning for Galaxy Morphology*

Diego Tuccillo

Marc Huertas- Company

Sorrento, 20-24 October 2016

# Historical introduction in deep learning

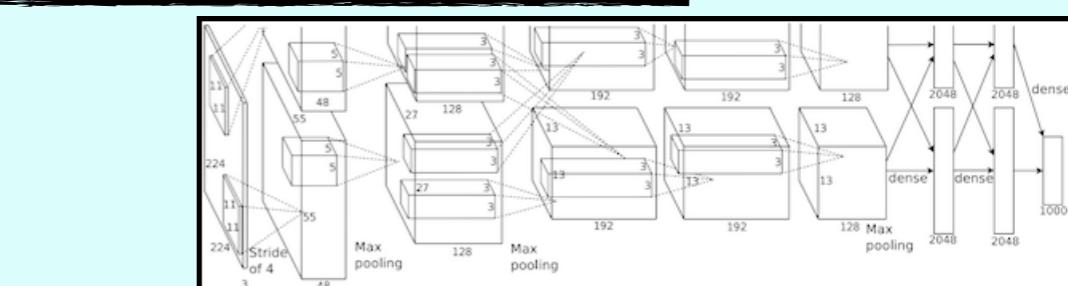
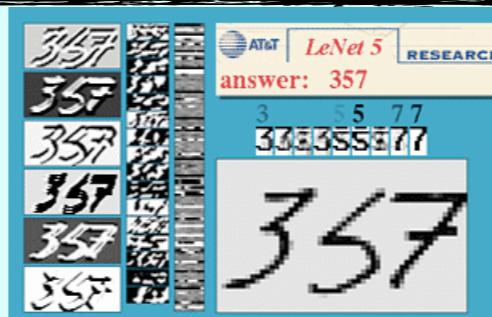


Fukushima  
Neocognitron

1980's

LeCun  
LaNet 5

1990's



Krizhevsky 2012  
AlexNet

cited  
> 6,200 times!

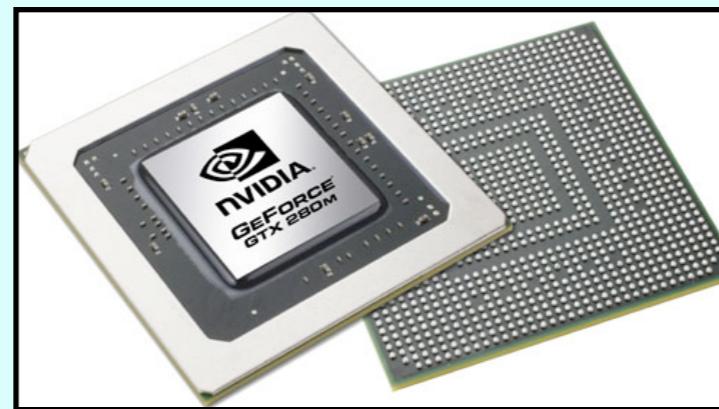
2000's

2010's

**Big come back of ANNs in the last years**



Tons of data

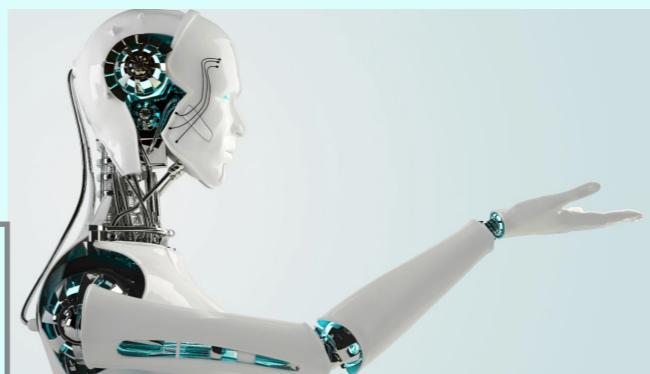


cheap and fast GPUs

deep learning shine  
when there is lot of data  
and complex problems

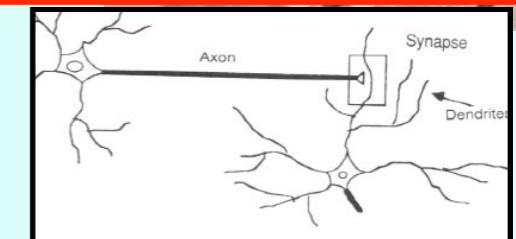
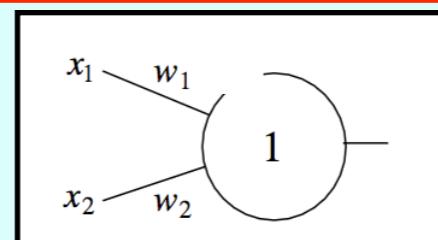
Computer vision  
speech recognition  
machine translation

\*) Machine learning born from the ambitious goal of ***Artificial intelligence***

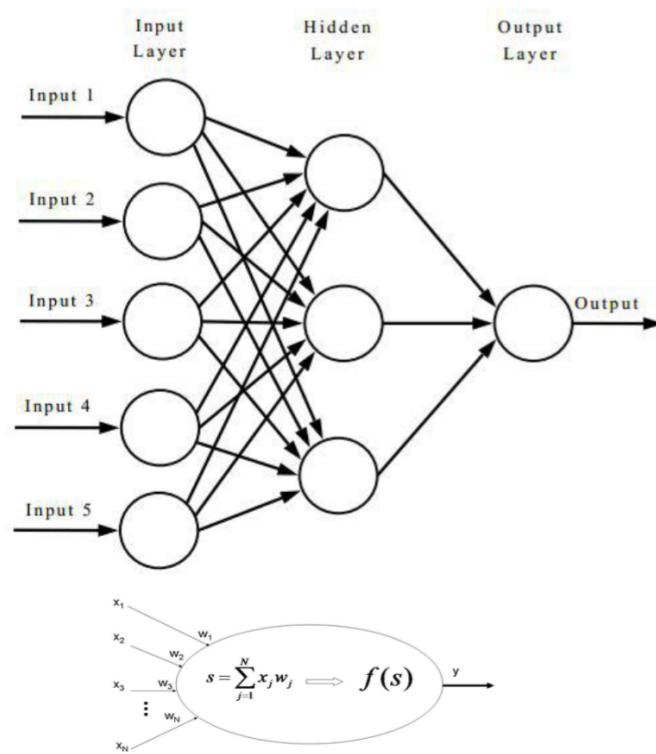


\*) Artificial Neural Network founding project:  
The **Perceptron** (Frank Rosenblatt **1957**)

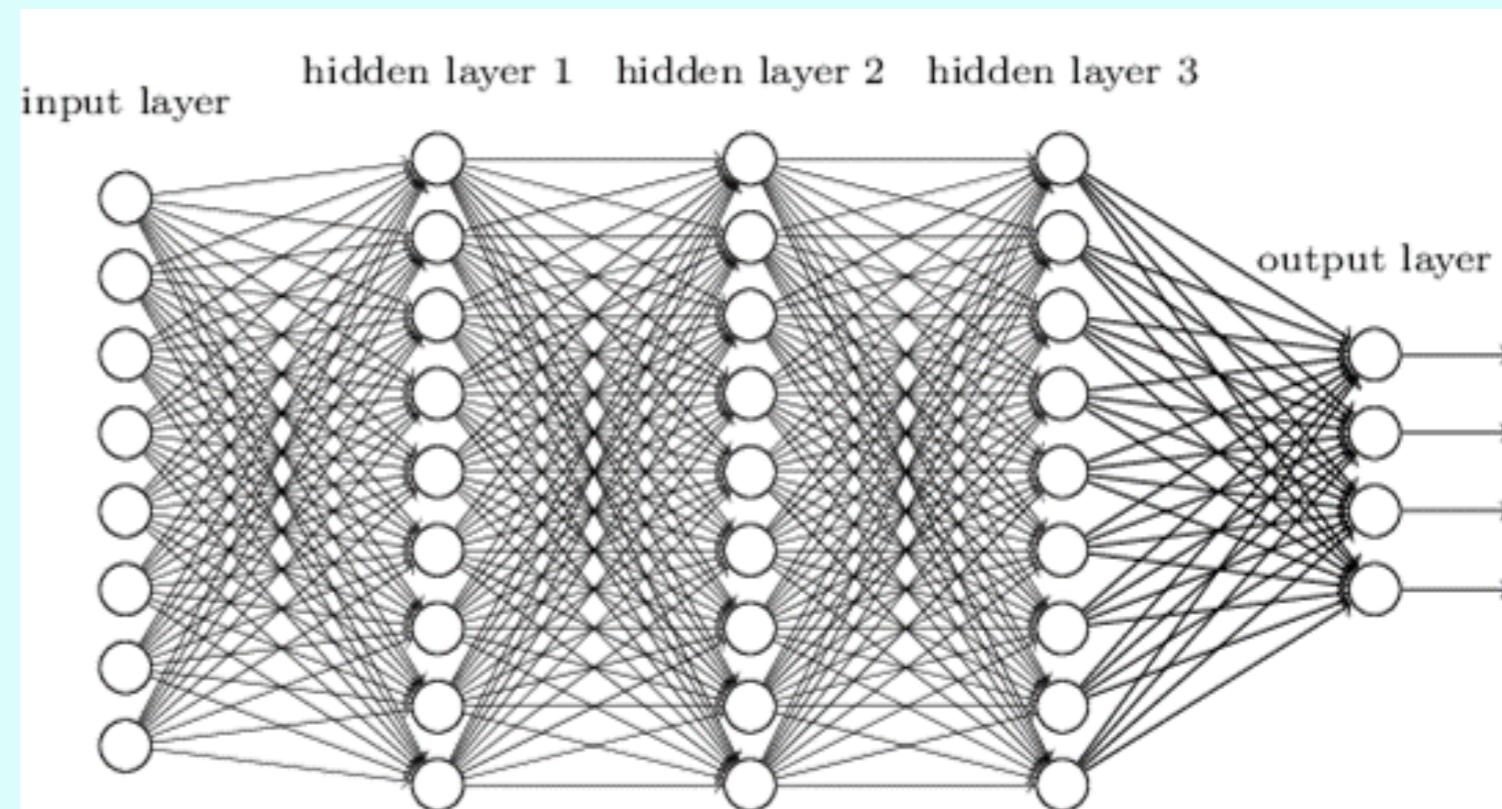
Basic unity **neuron**  
*inspired by biological neural systems.*



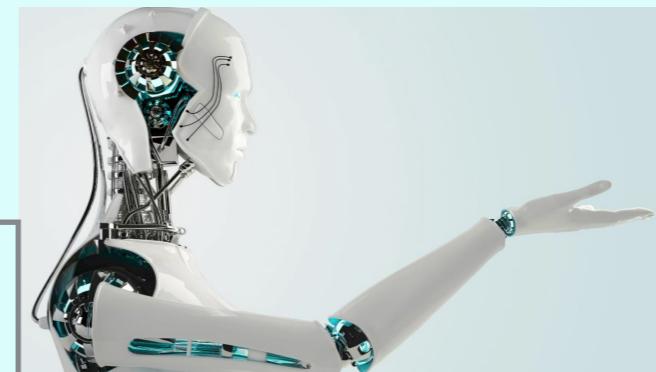
**Classical ANN**



**Deep ANN**



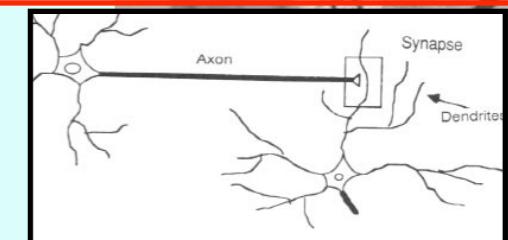
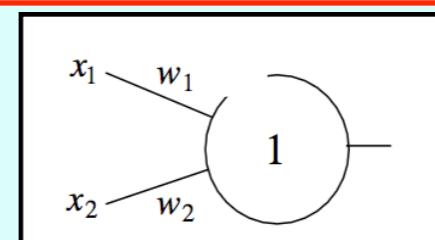
\*) Machine learning born from the ambitious goal of ***Artificial intelligence***



\*) Artificial Neural Network founding project:  
The **Perceptron** (Frank Rosenblatt **1957**)

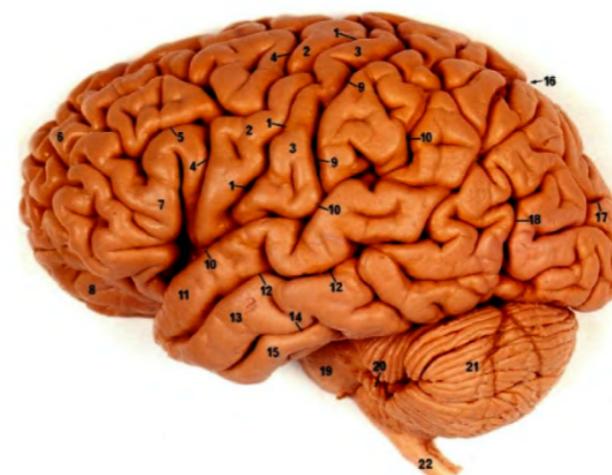
*inspired by the attempt of simulating biological neural systems.*

Basic unity **neuron**



#### An engineering perspective

- Compact
- Energy efficient (20 watts)
- $10^{12}$  Glial cells (power, cooling, support)
- $10^{11}$  Neurons (soma + wires)
- $10^{14}$  Connections (synapses)
- Volume = mostly wires.



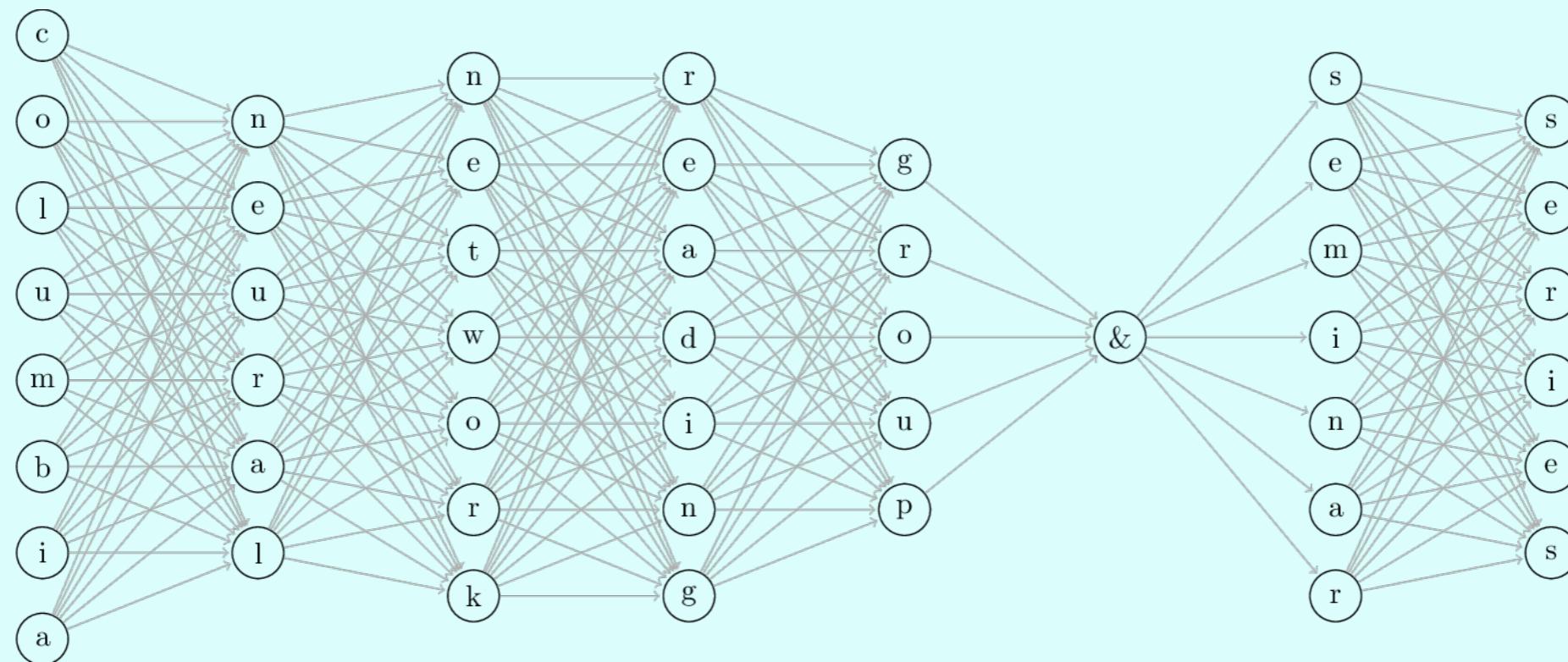
#### General computing machine?

- Slow for mathematical logic, arithmetic, etc.
- Very fast for vision, speech, language, social interactions, etc.
- Evolution: vision → language → logic.

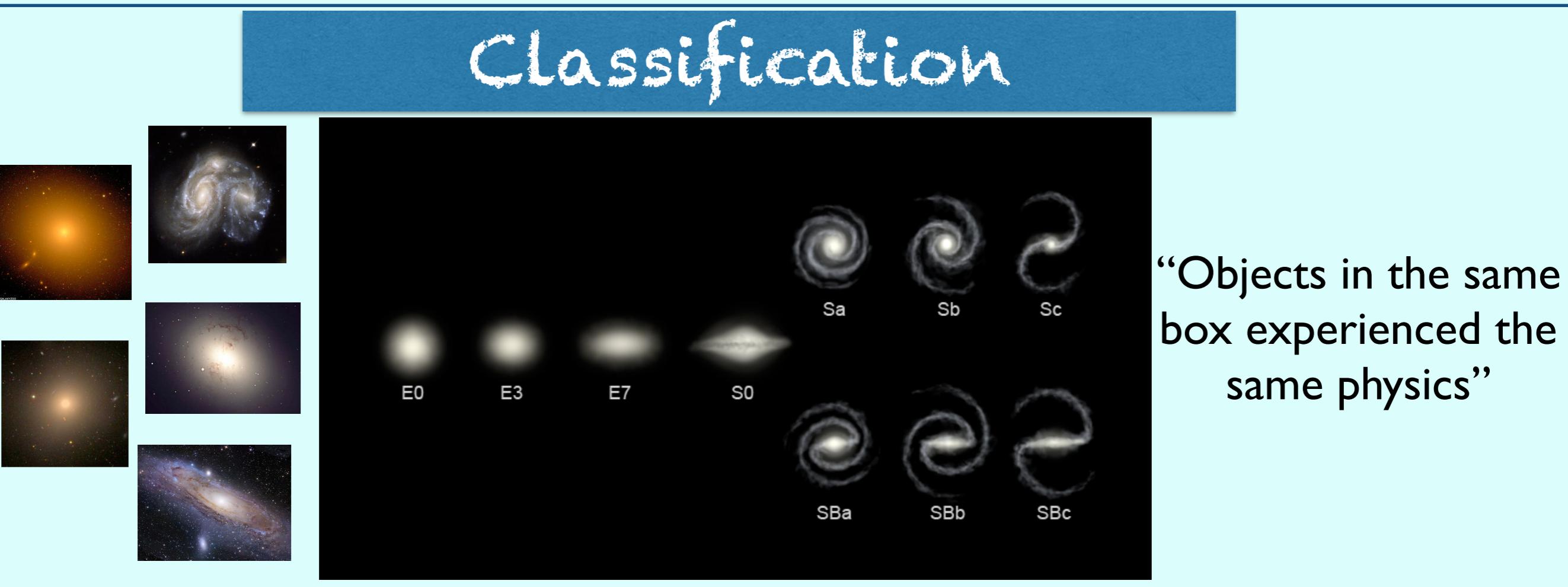
*Considering both the architecture and better tasks is good at...*

*...with DNN, we are getting closer to that original dream!*

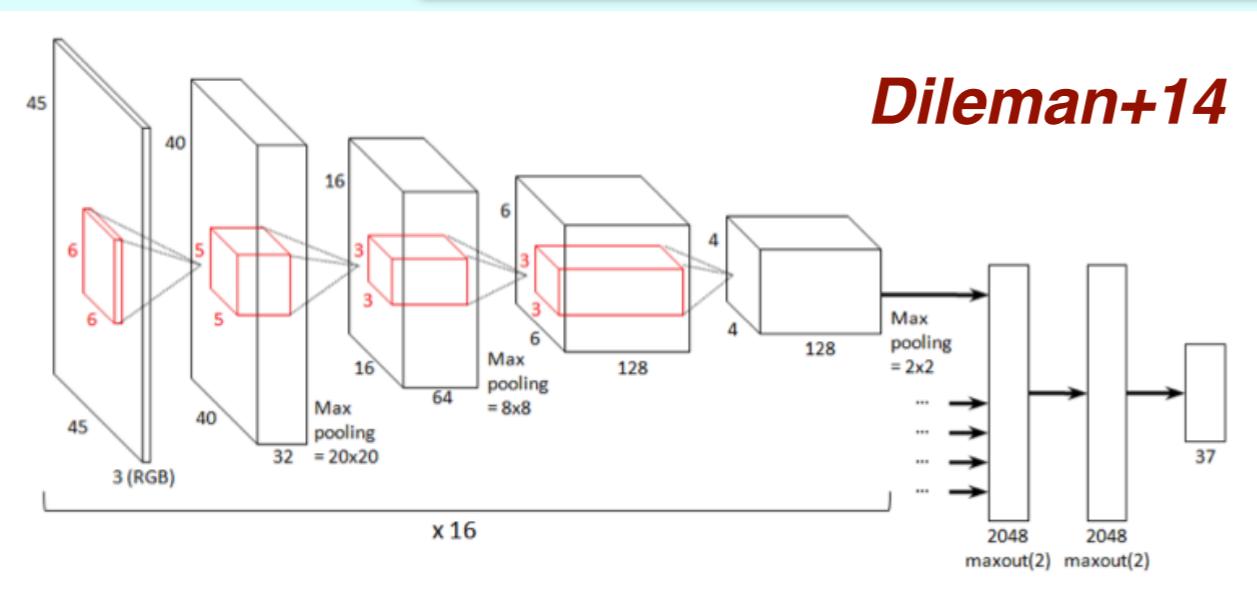
# DNN for Galaxy Morphology



# “Given a 2-D image of a galaxy, typical morphology studies:



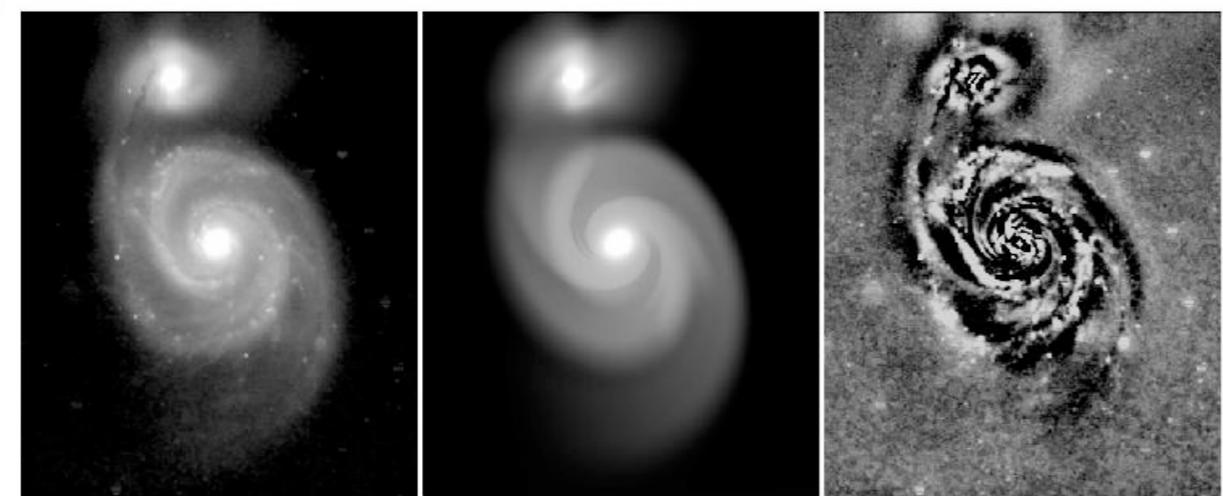
Deep Neural Network proved to be very effective



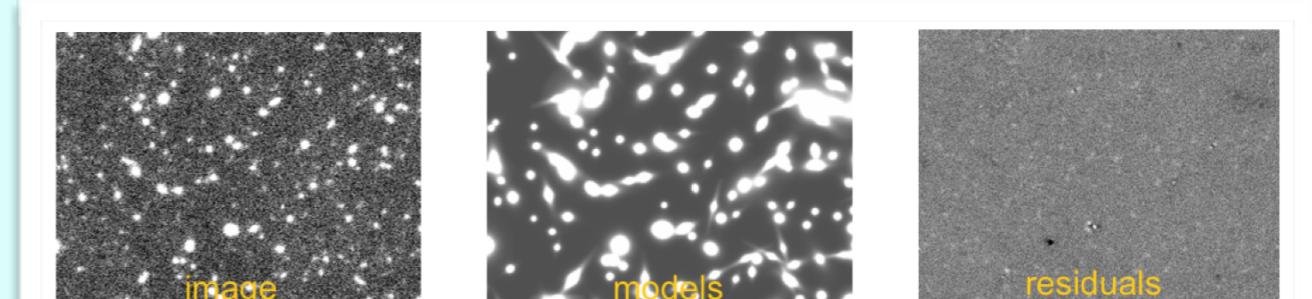
And at high-z with  
CANDELS FIELDS **Huertas-Company +15**

accuracy > 90%

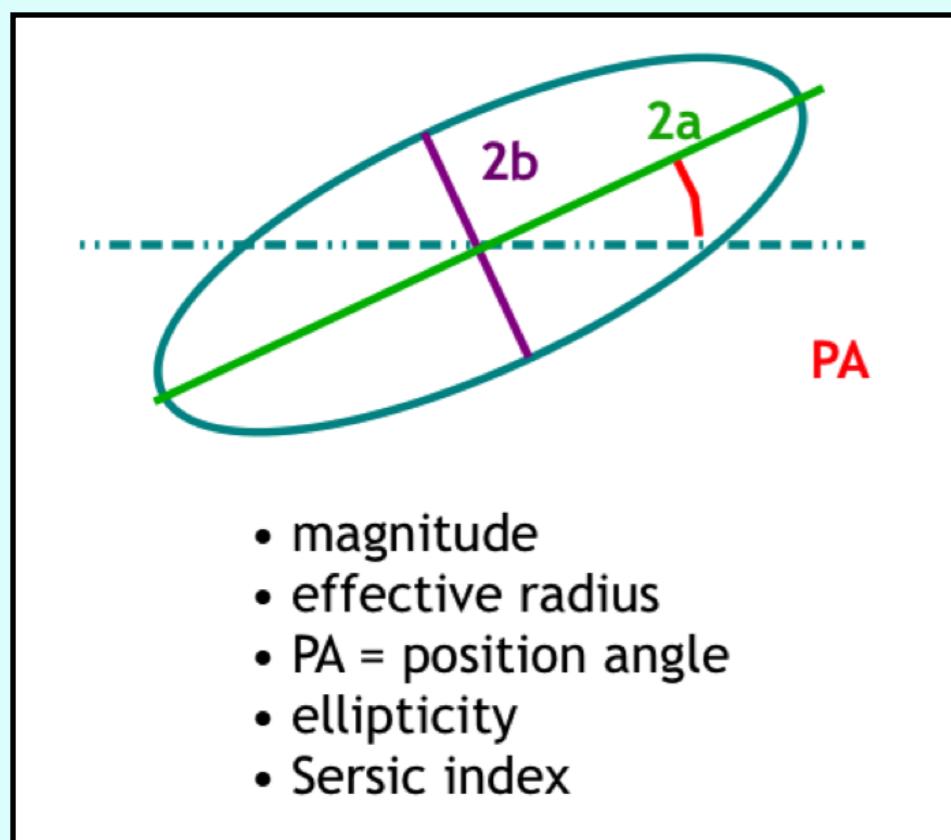
# Galaxy Fitting



model light profiles using parametric functions



the features of interest are summarized into a small set of numbers



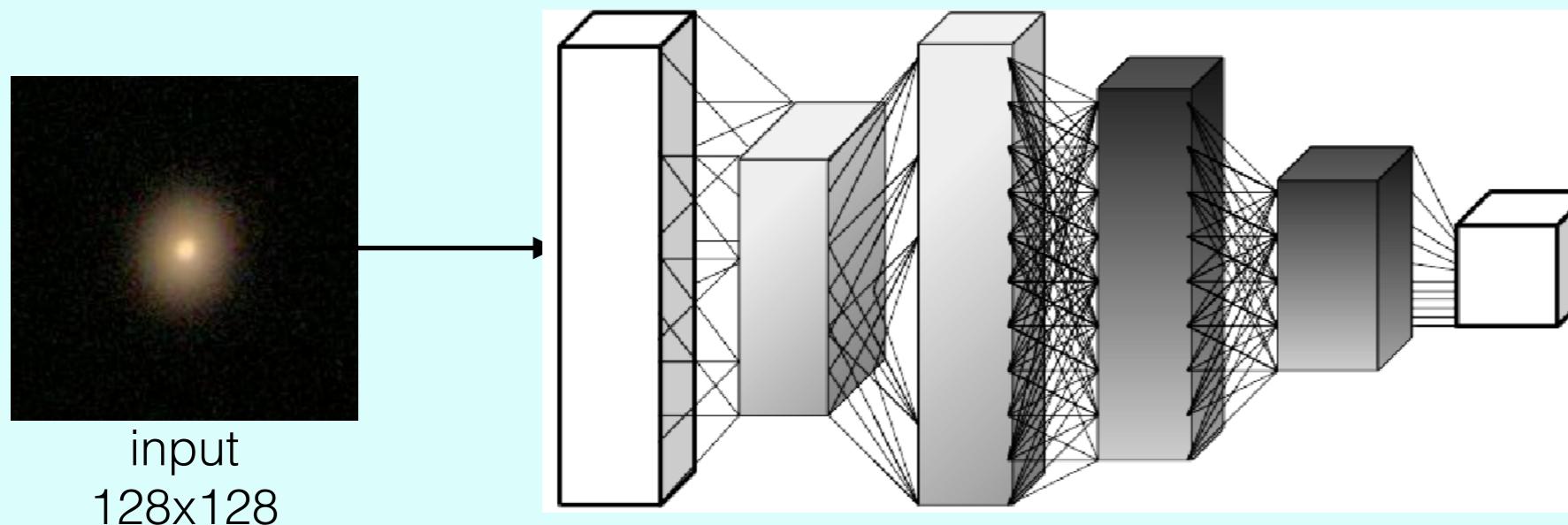
- magnitude
- effective radius
- PA = position angle
- ellipticity
- Sersic index

most popular codes:

- GALFIT (Peng et al., 2002, 2010)
- GIM2D (Simard et al, 2002)
- SExtractor (Bertin et al, TBD)

Our research: apply DNN for galaxy surface brightness profile fitting

# We developed a convolutional DNN algorithm to fit 1-component galaxies



Trained with 24,000

Validated with 6000

**Details on the true DNN  
architecture**



(to be submitted by November)

## Deep Neural Network for galaxy morphology

D. Tuccillo, M. Huertas, E. Decenciere, S.



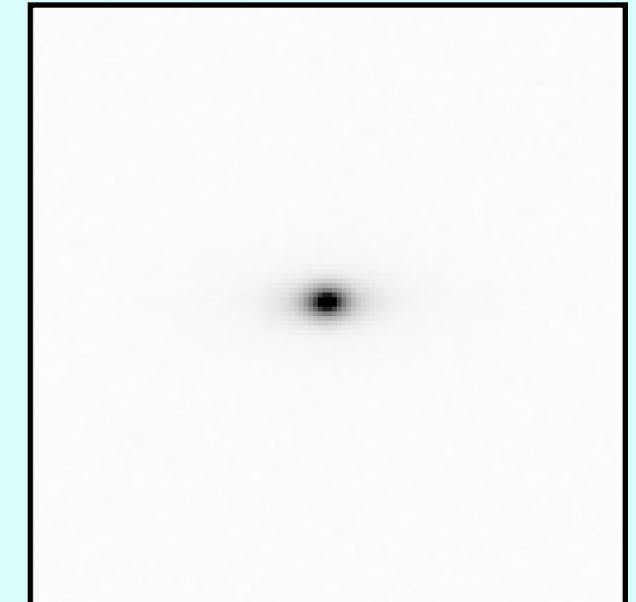
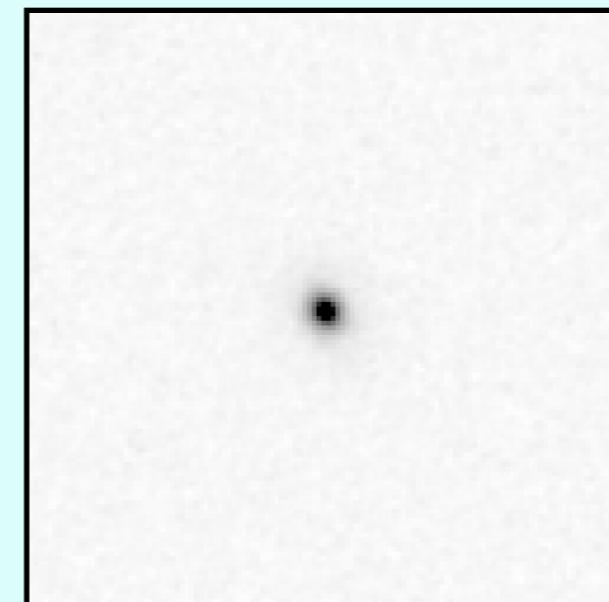
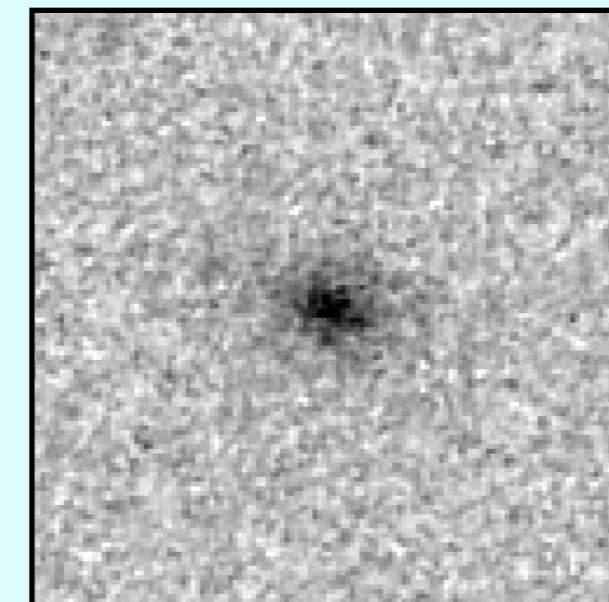
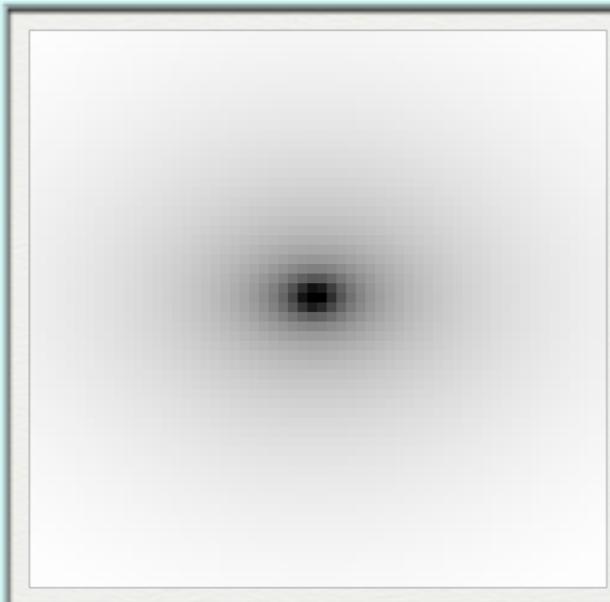
# We simulated 30,000 stamps of 1-component galaxies

Single Sersic HST/CANDELS

WITH REAL NOISE

PIXEL scale 0.06"

REAL PSF CANDELS



$0 < \text{RADIUS (arcsec)} < 1.9$

$18 < \text{MAG} < 23$

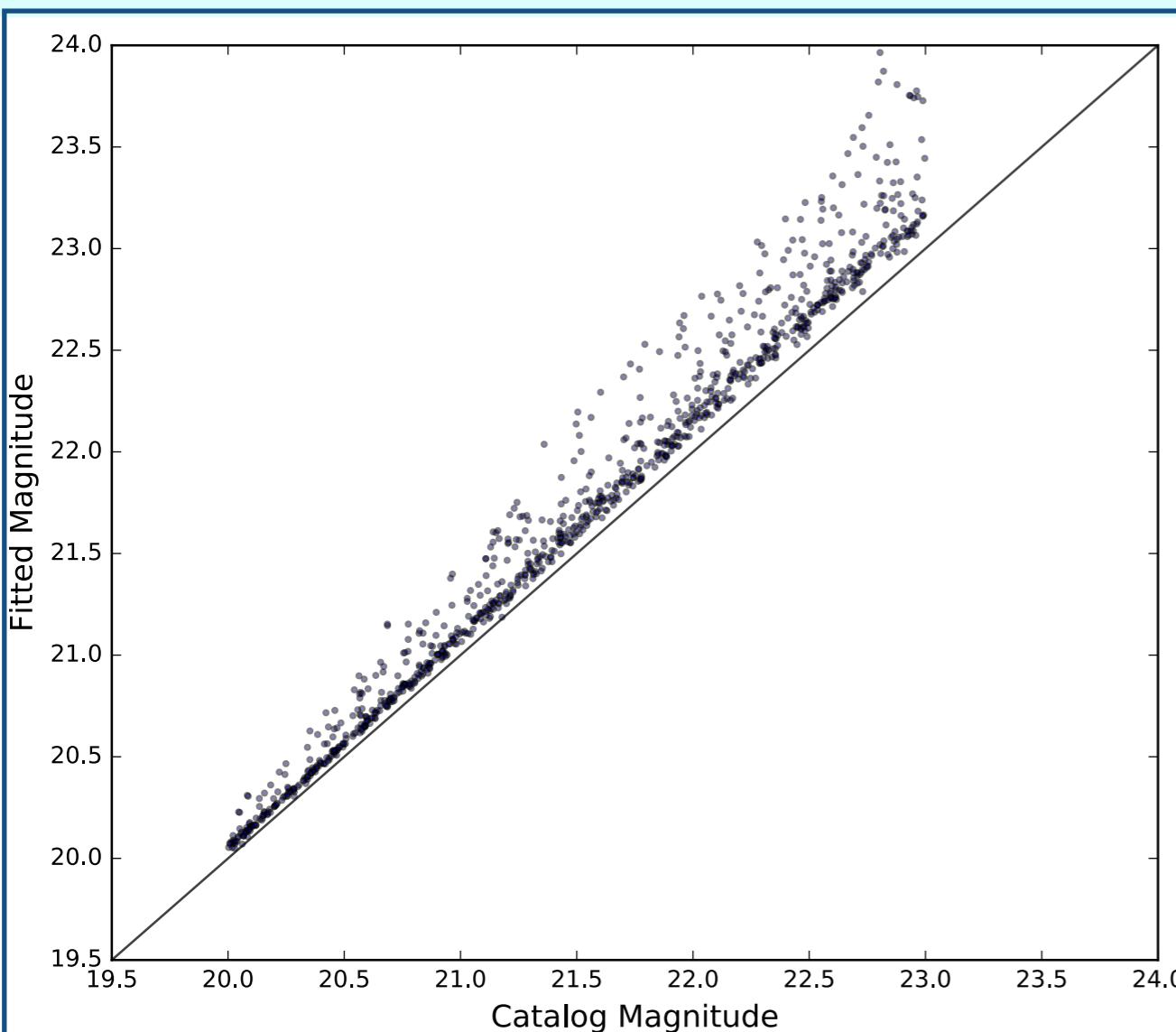
$0.2 < \text{ELLIPTICITY} < 0.8$

$0.3 < \text{SERSIC INDEX} < 6.3$

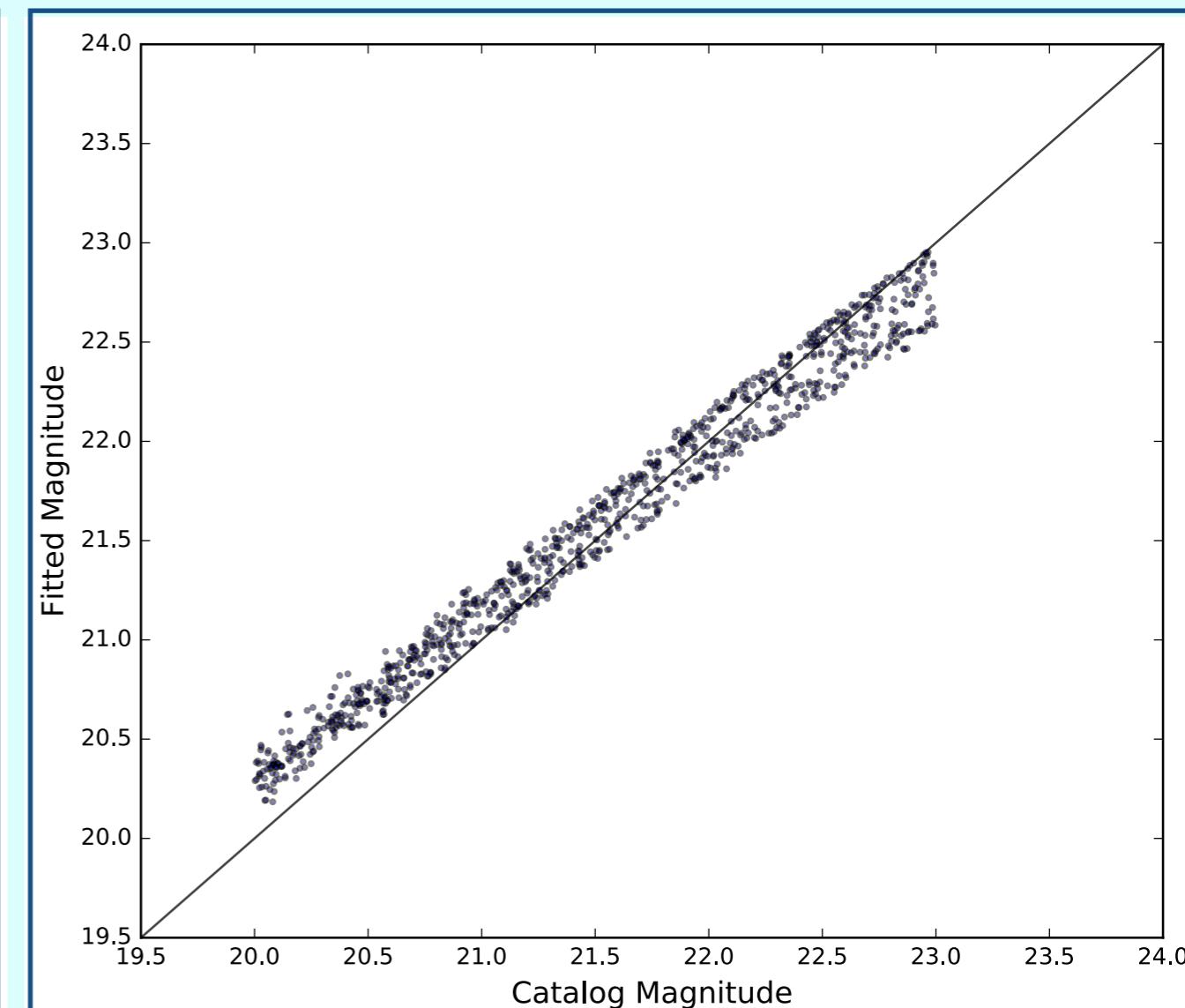
$0 < \text{Position Angle (degree)} < 180$

# Applied the result of learning on 1000 simulated galaxies

← Magnitude →



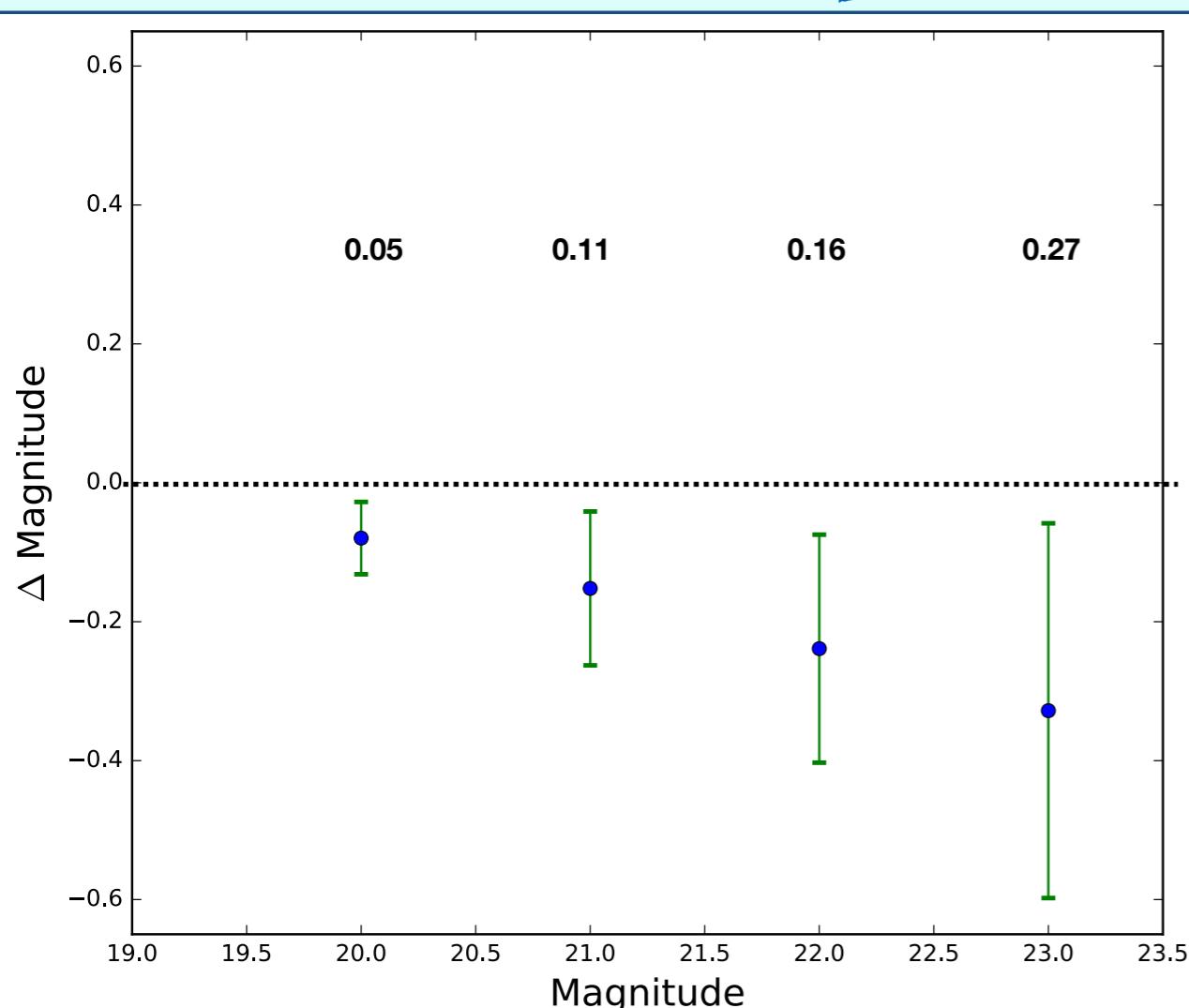
GALFIT-SExtractor



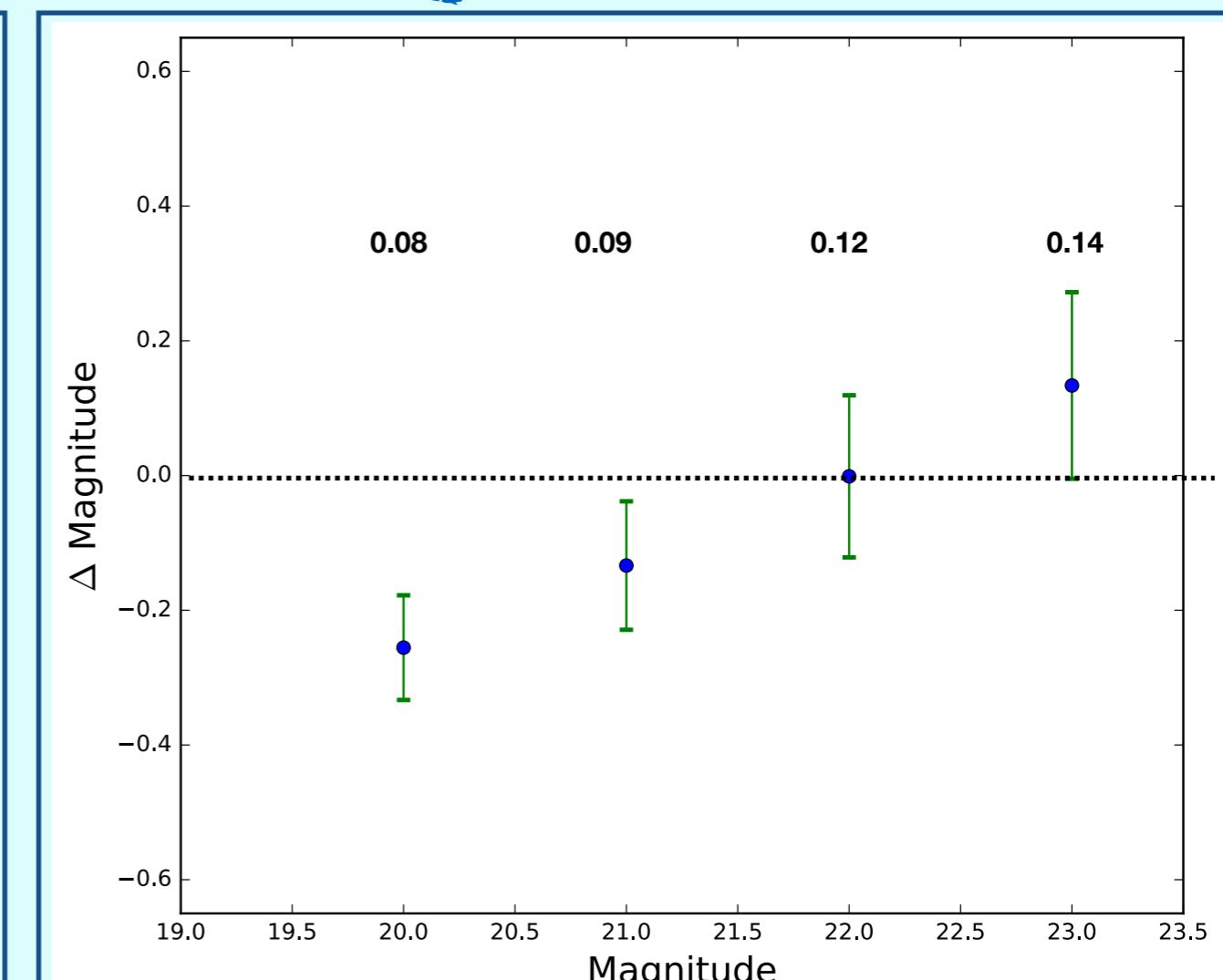
DNN

# Applied the result of learning on 1000 simulated galaxies

Magnitude



GALFIT-SExtractor

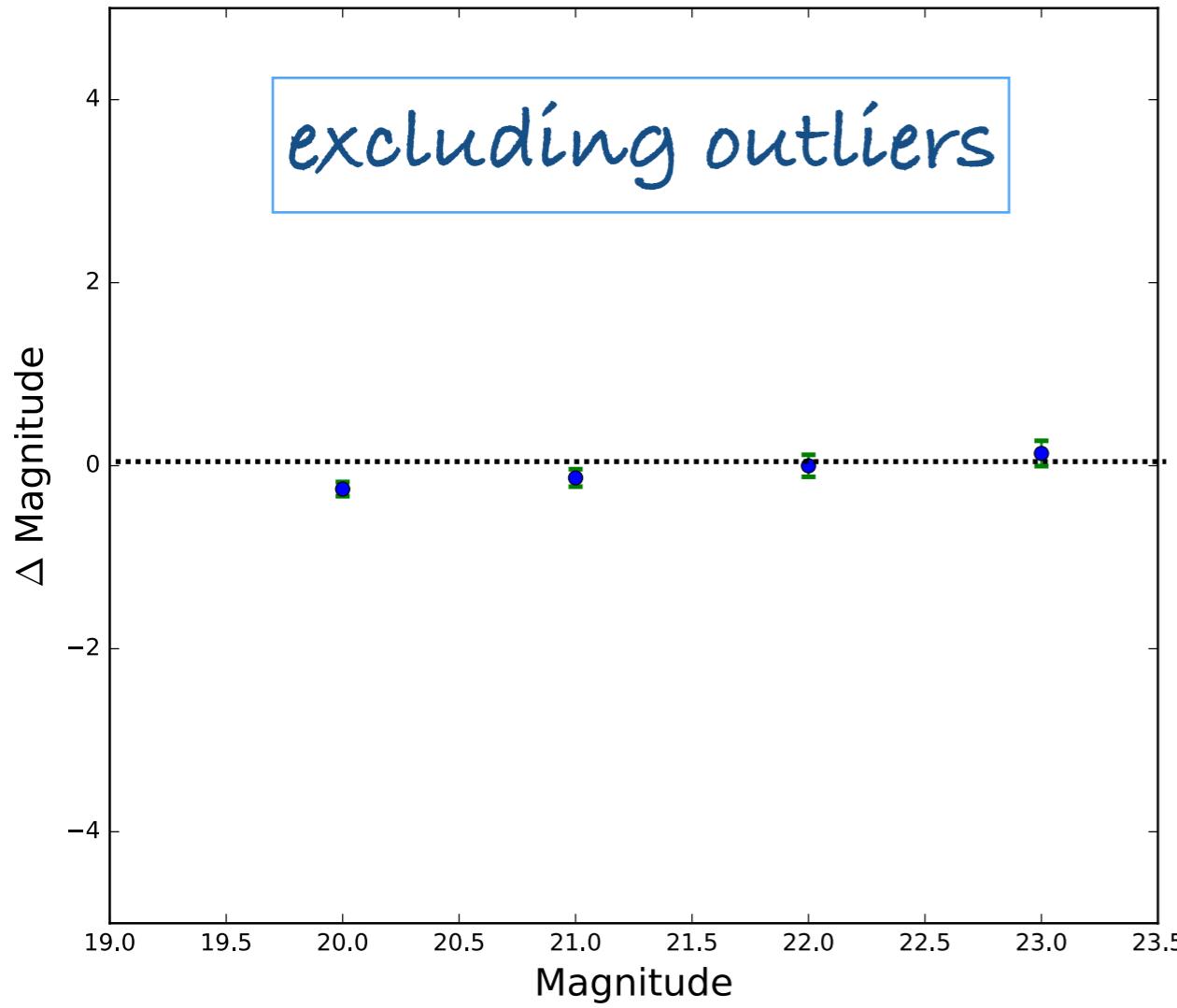


DNN

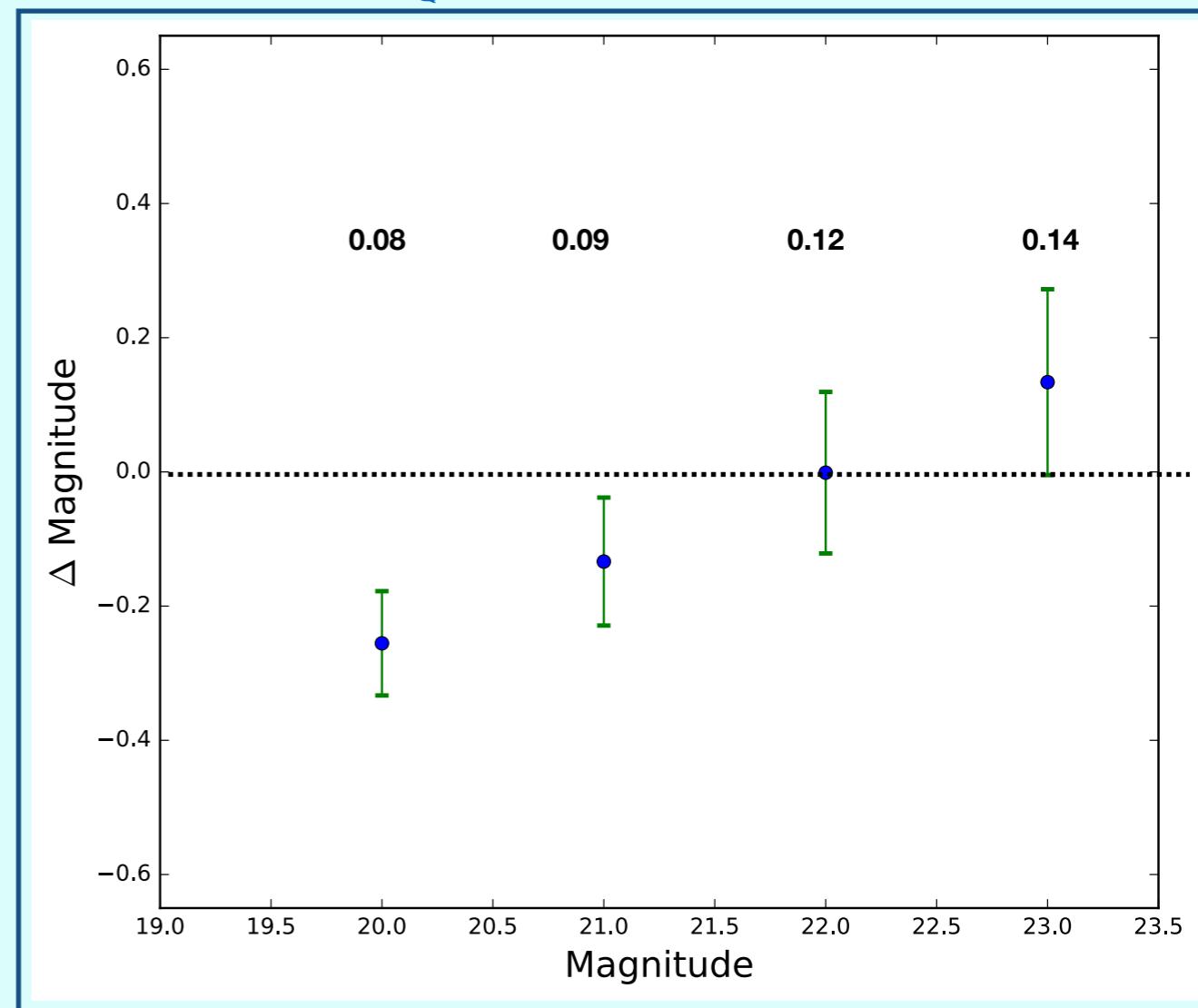
# Applied the result of learning on 1000 simulated galaxies

Magnitude

excluding outliers



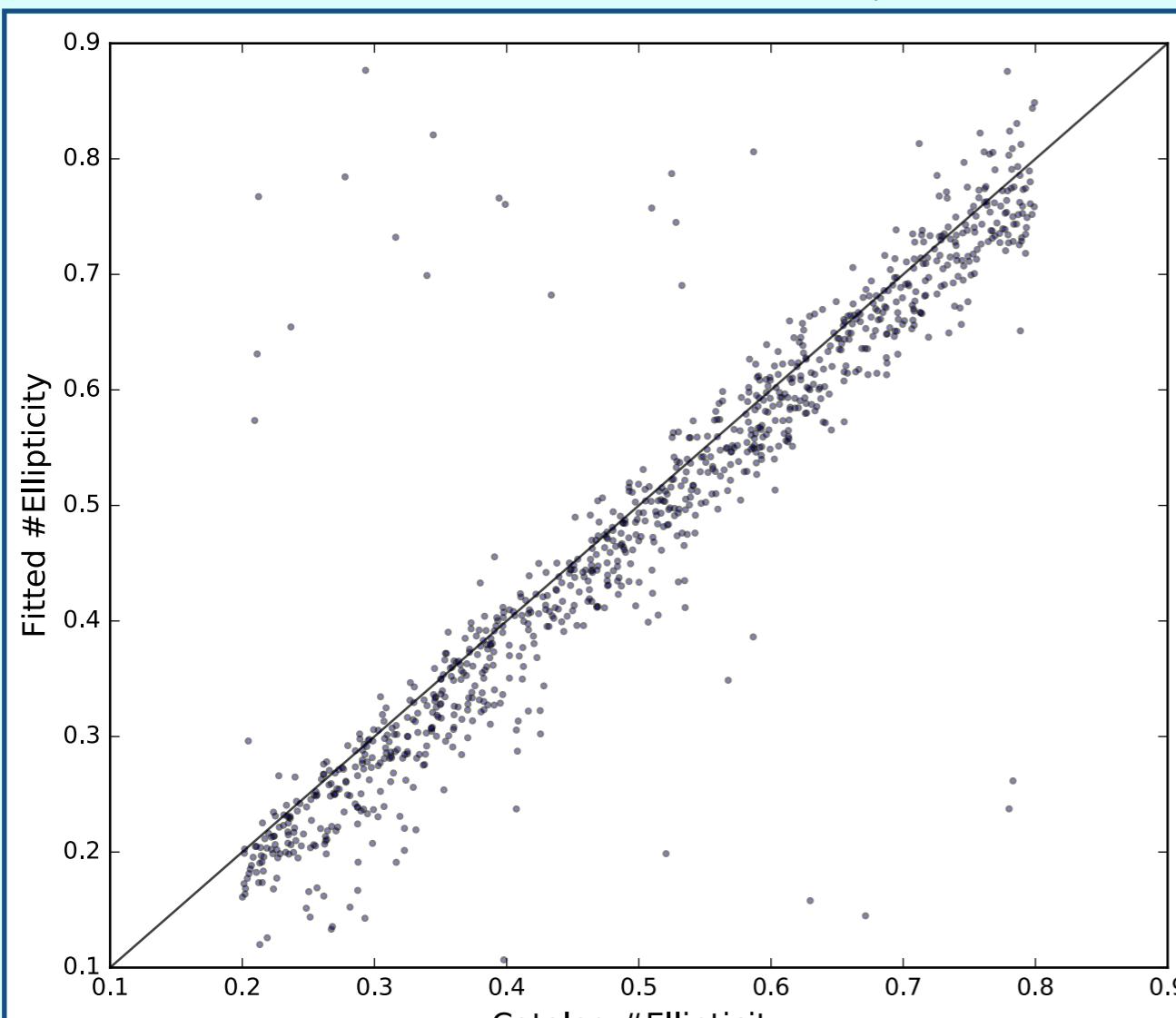
GALFIT-SExtractor



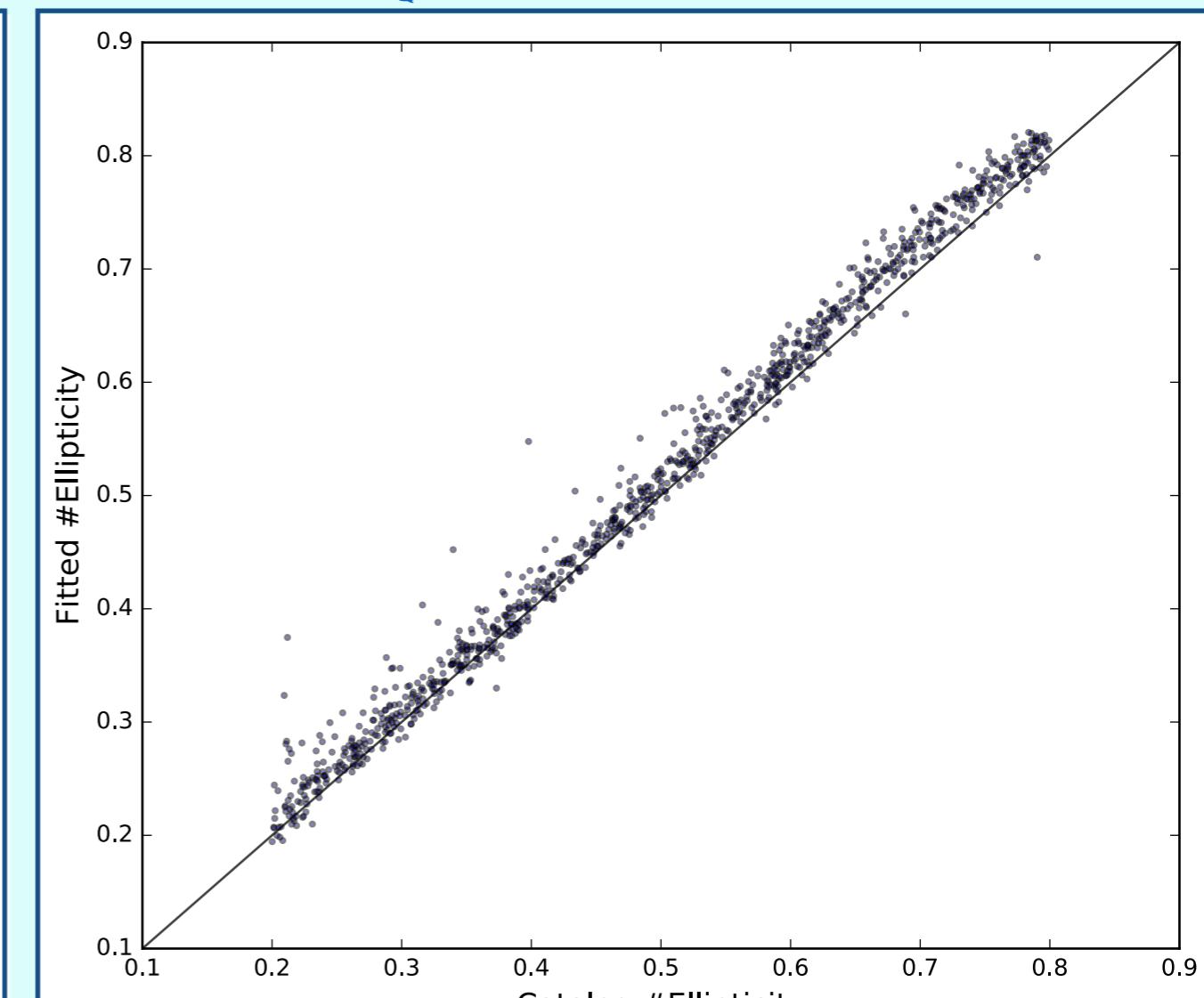
DNN

# Applied the result of learning on 1000 simulated galaxies

Ellipticity



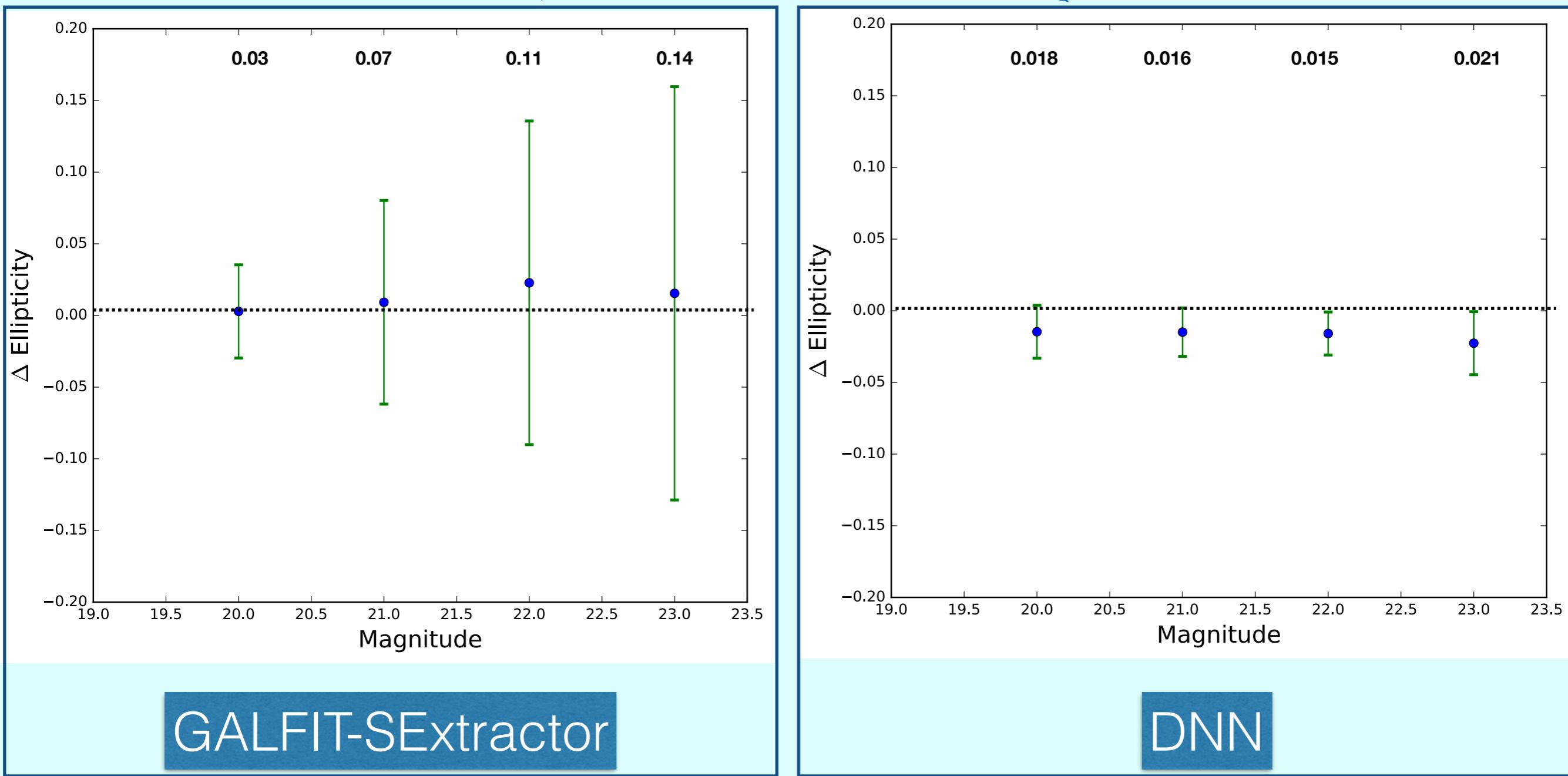
GALFIT-SExtractor



DNN

# Applied the result of learning on 1000 simulated galaxies

Ellipticity

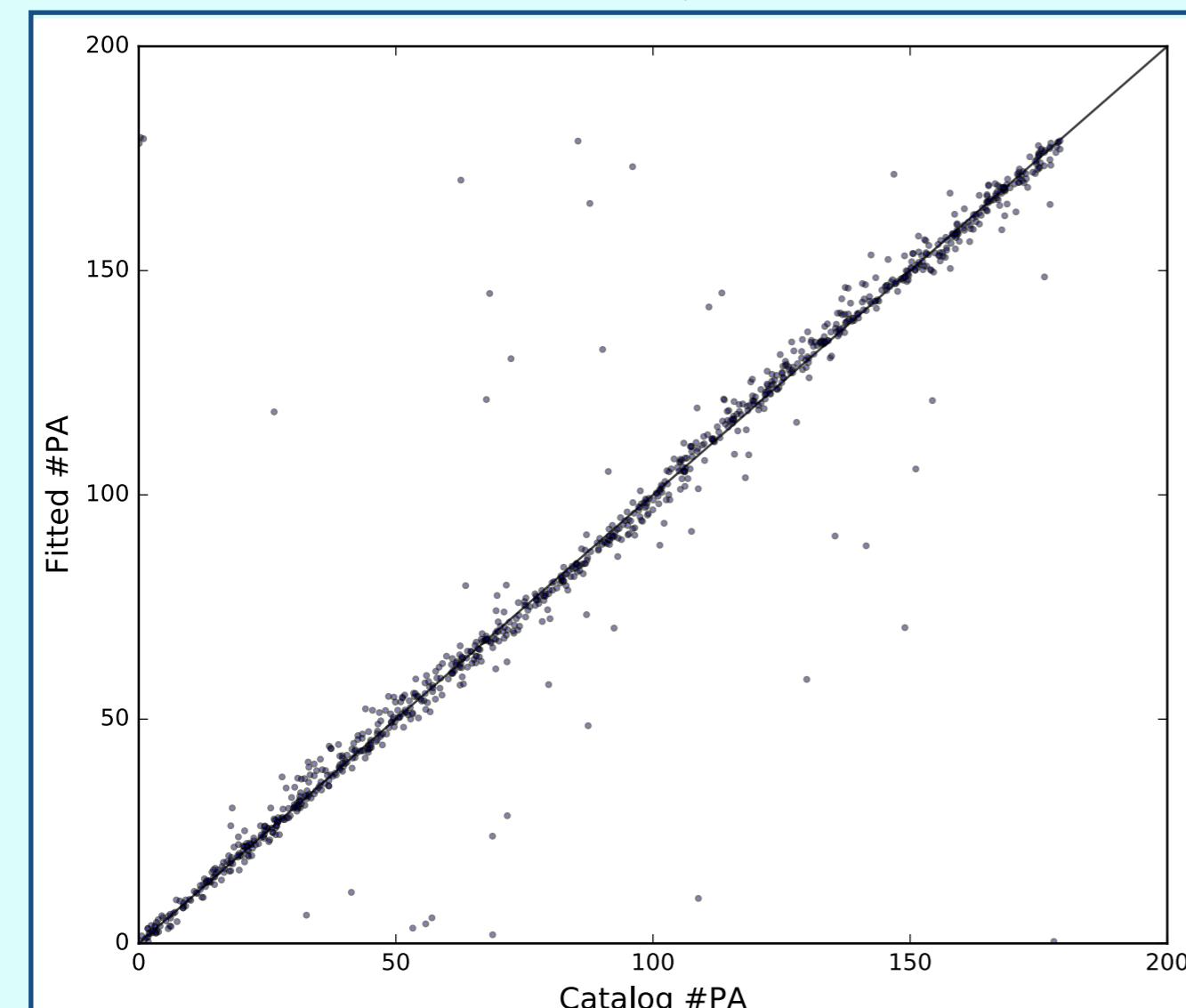


GALFIT-SExtractor

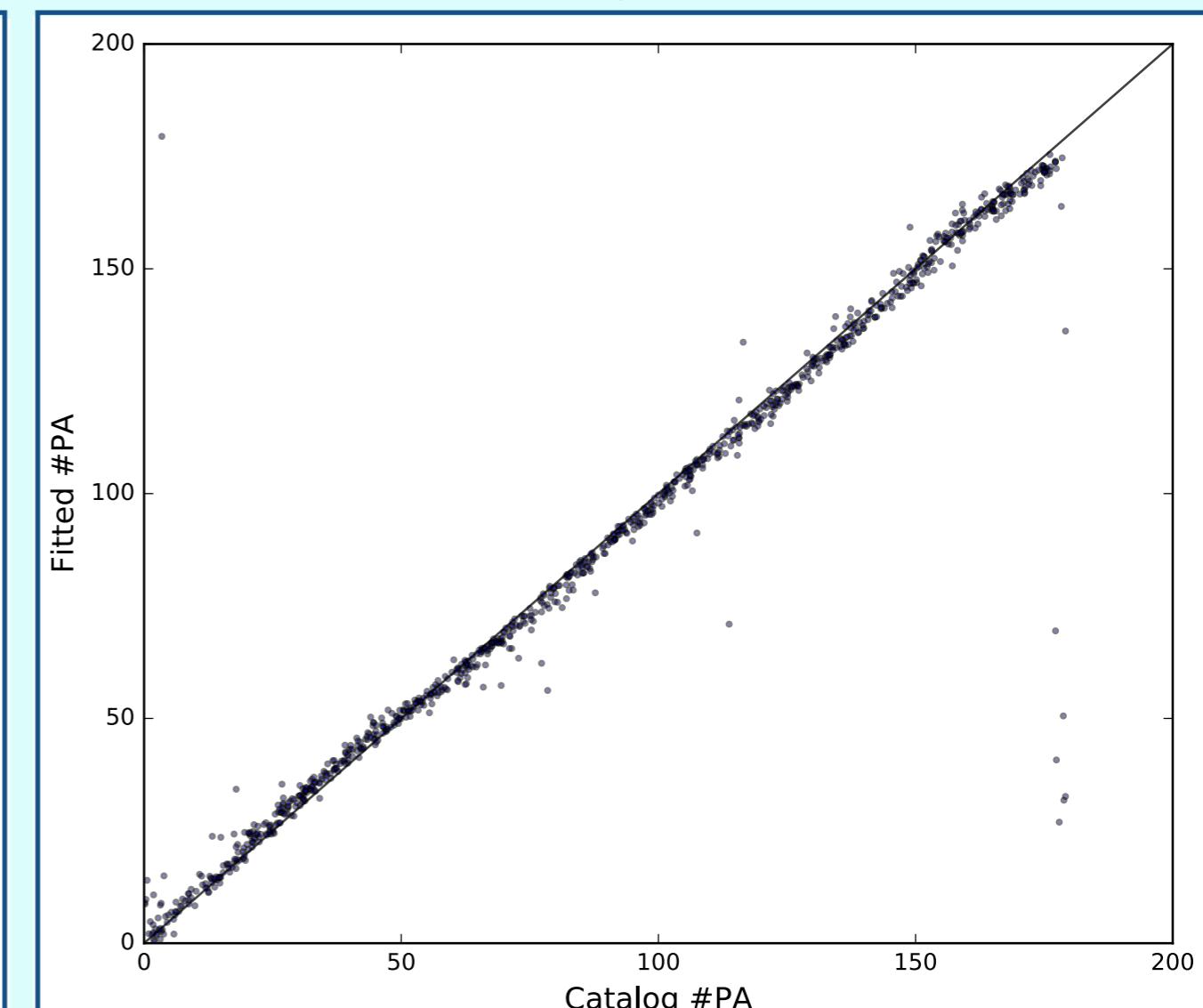
DNN

# Applied the result of learning on 1000 simulated galaxies

Position Angle



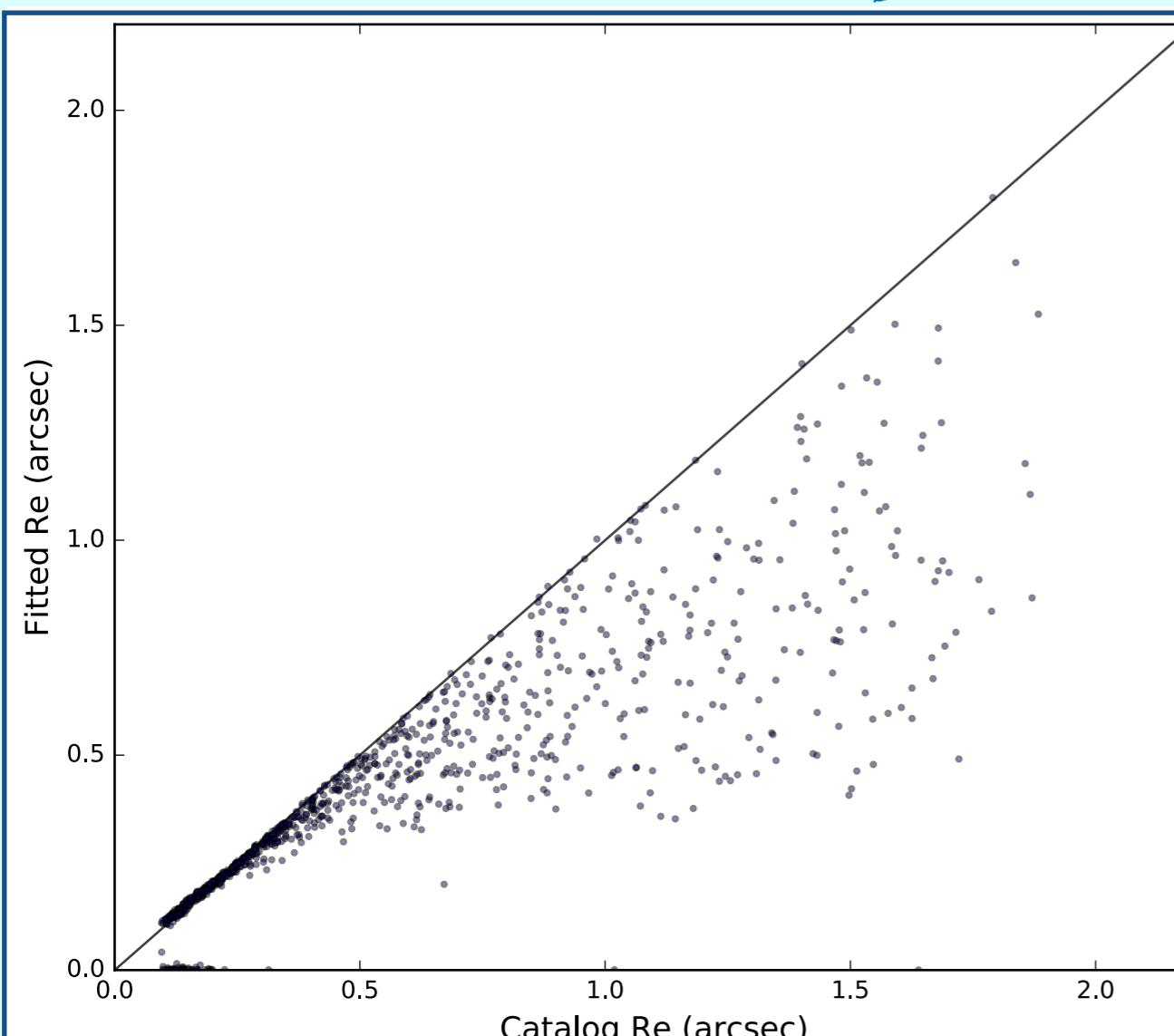
GALFIT-SExtractor



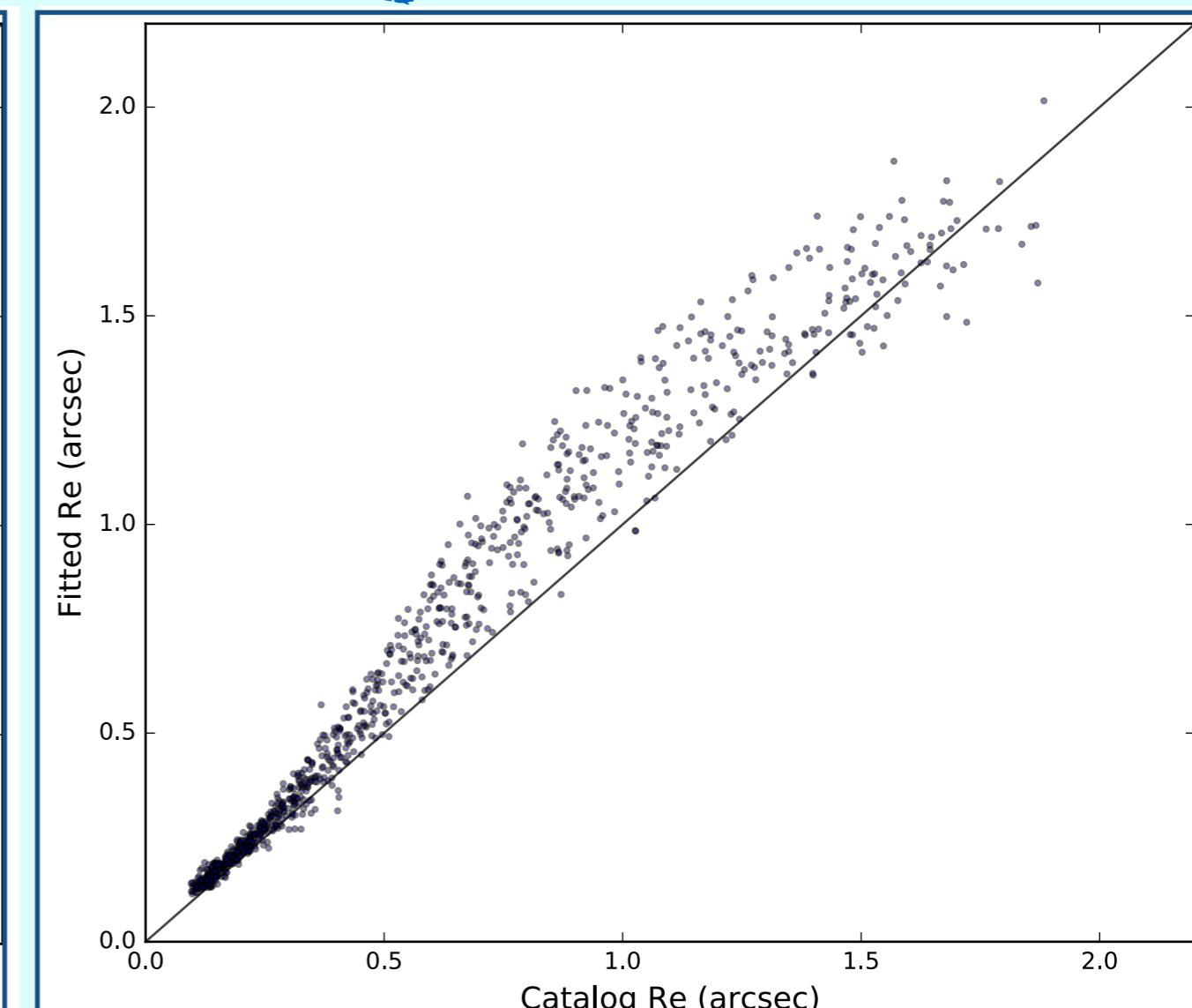
DNN

# Applied the result of learning on 1000 simulated galaxies

Radius

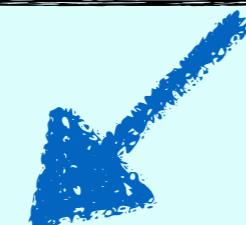


GALFIT-SExtractor

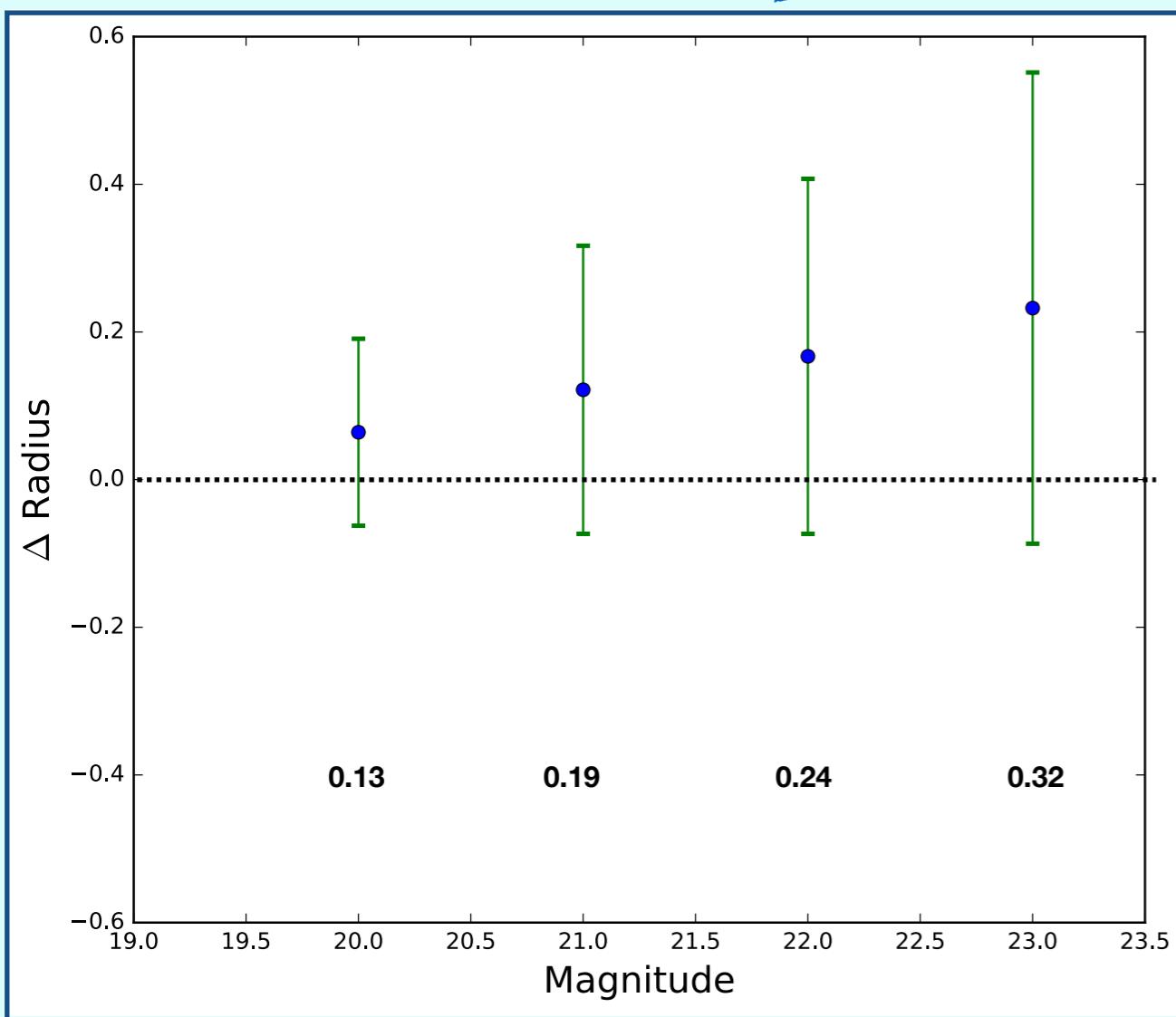
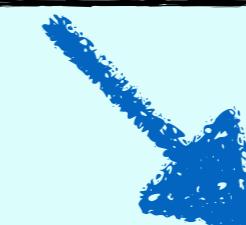


DNN

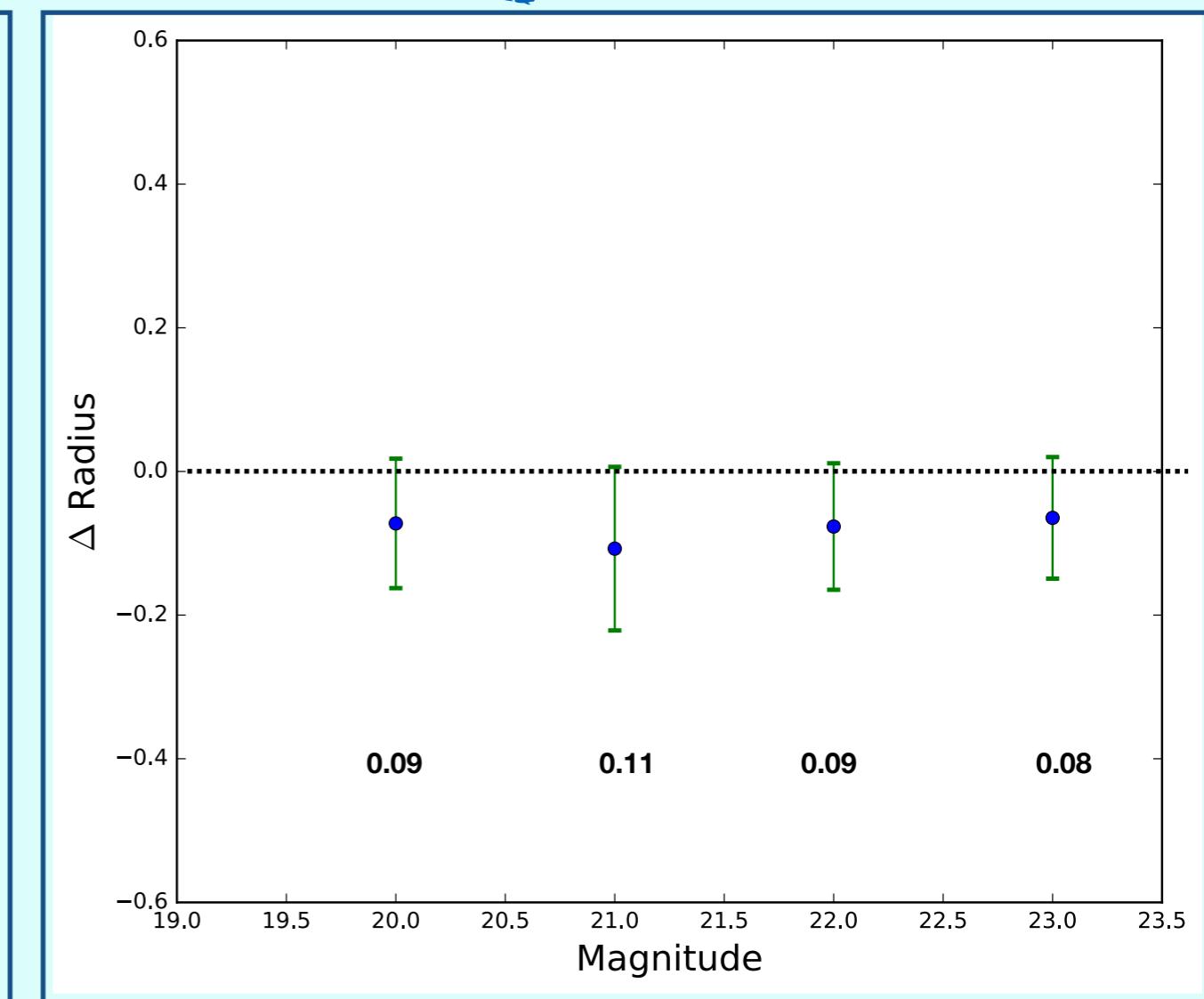
# Applied the result of learning on 1000 simulated galaxies



Radius



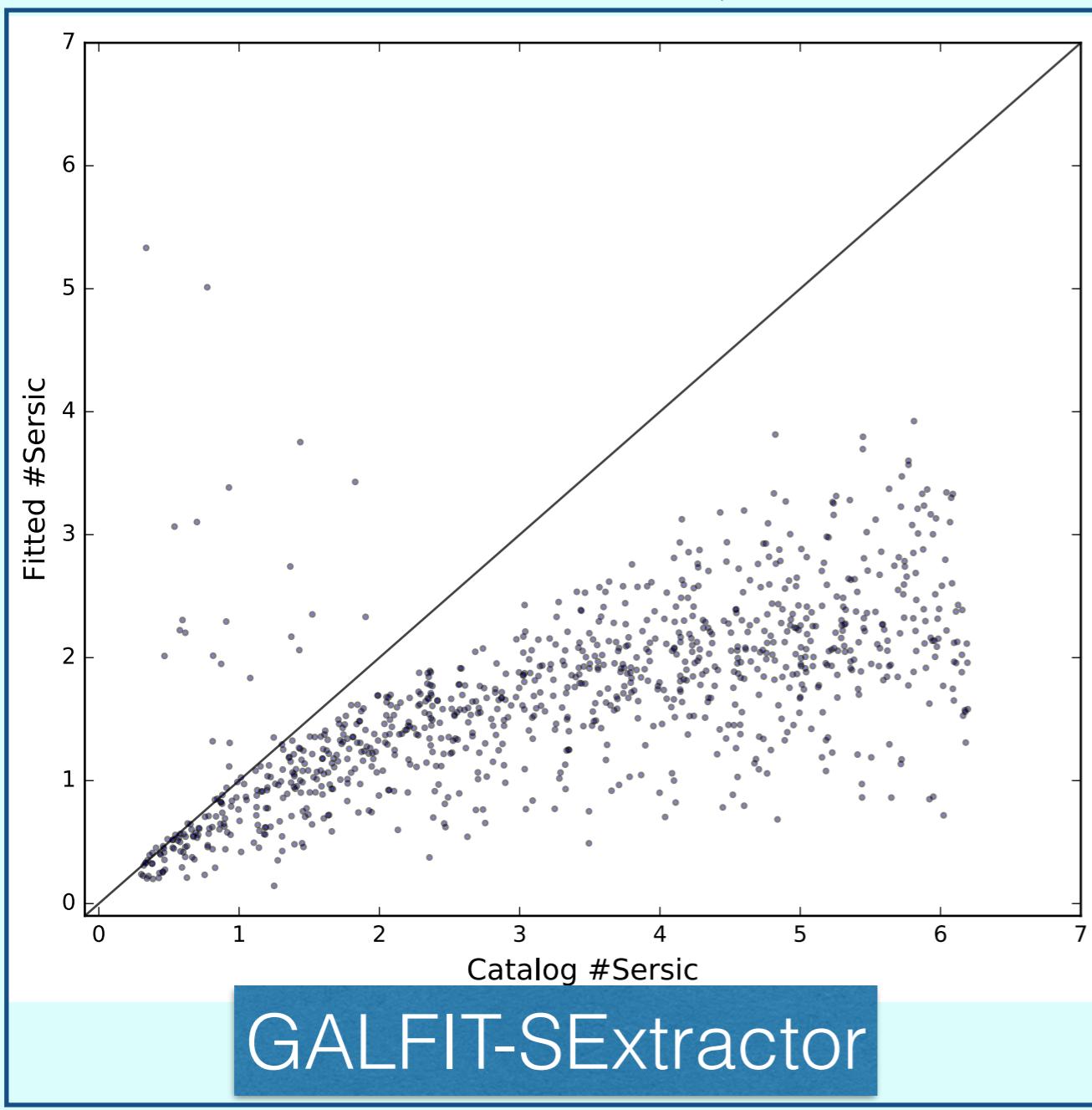
GALFIT-SExtractor



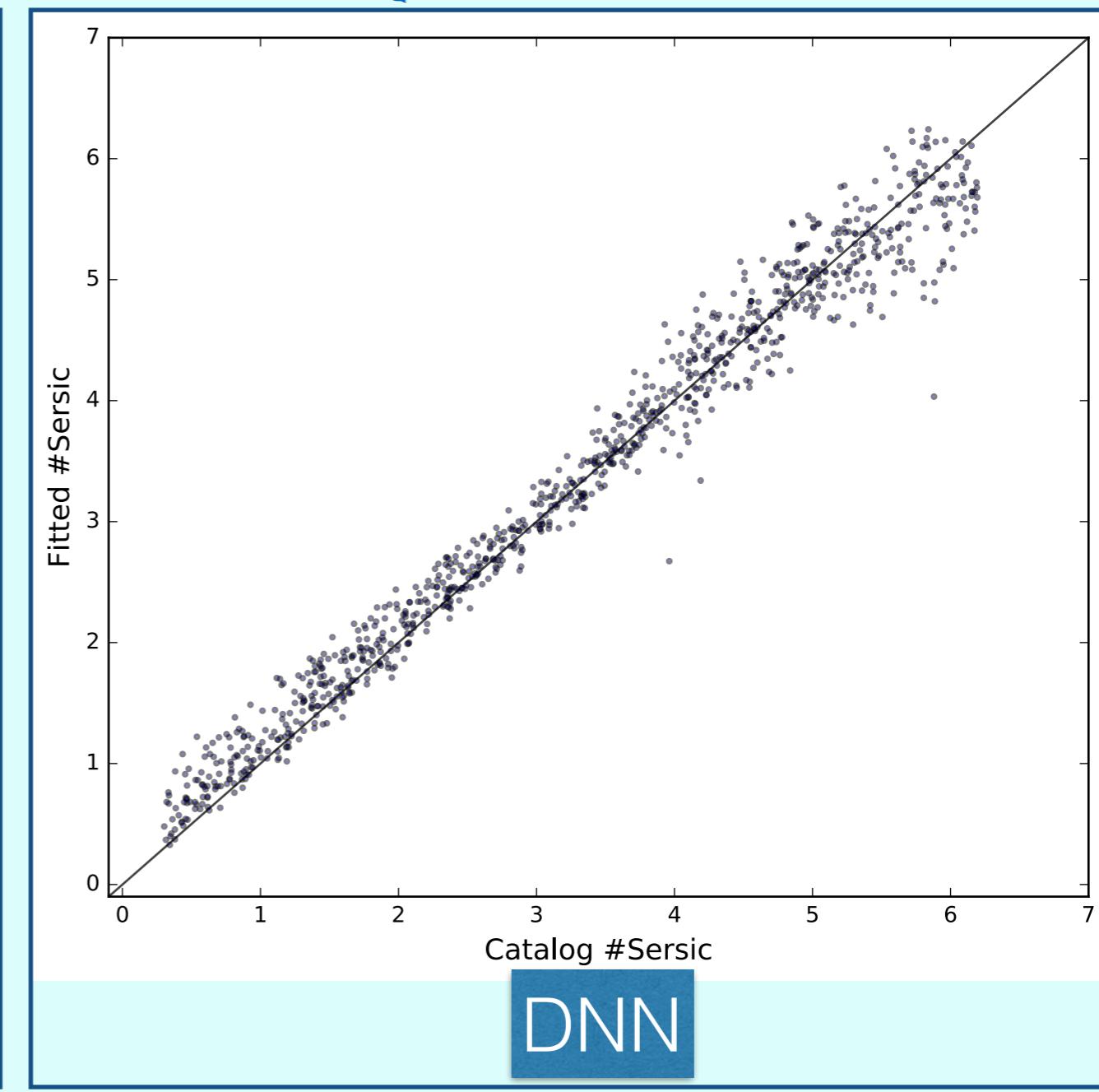
DNN

# Applied the result of learning on 1000 simulated galaxies

Sersic index



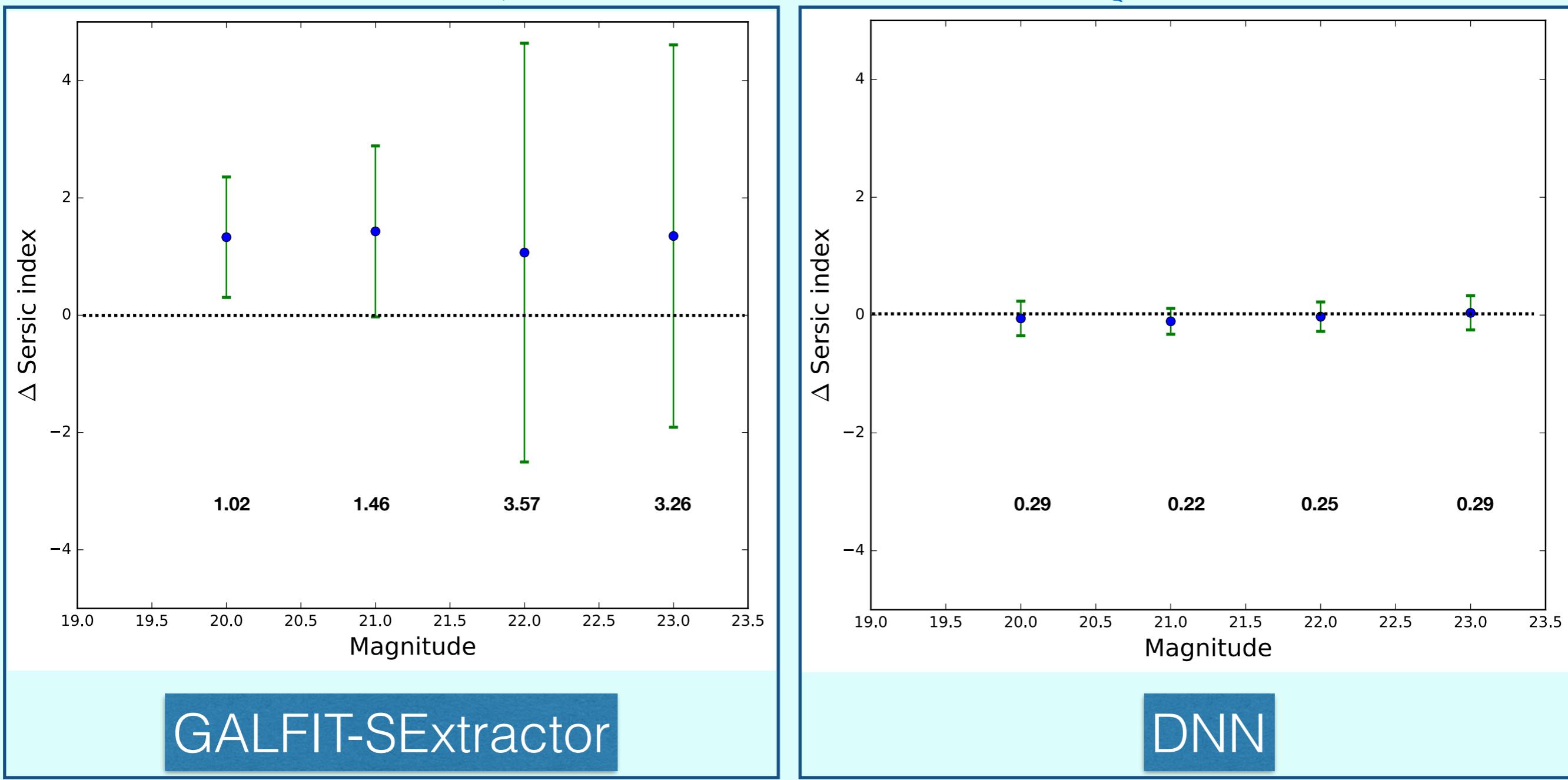
GALFIT-SExtractor



DNN

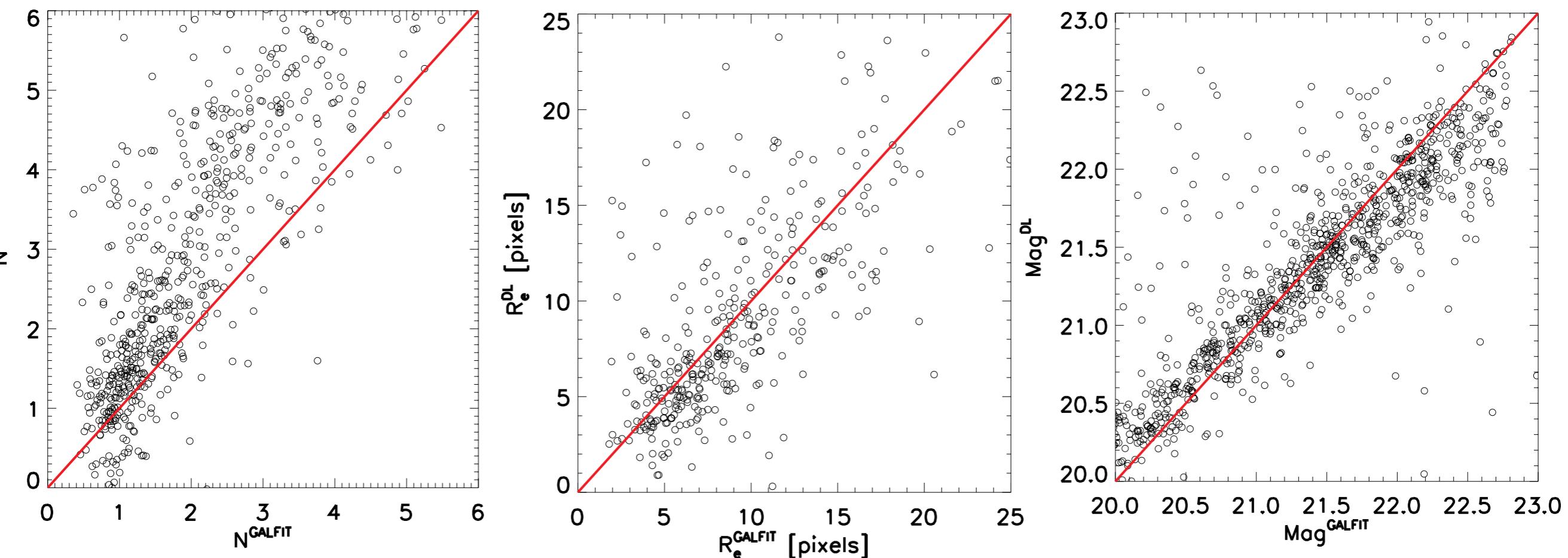
# Applied the result of learning on 1000 simulated galaxies

↙ Sersic index ↘



# Transfer learning

Applied what the DNN learned from simulation to 1000  
**real HST galaxies z~1**



Sersic index

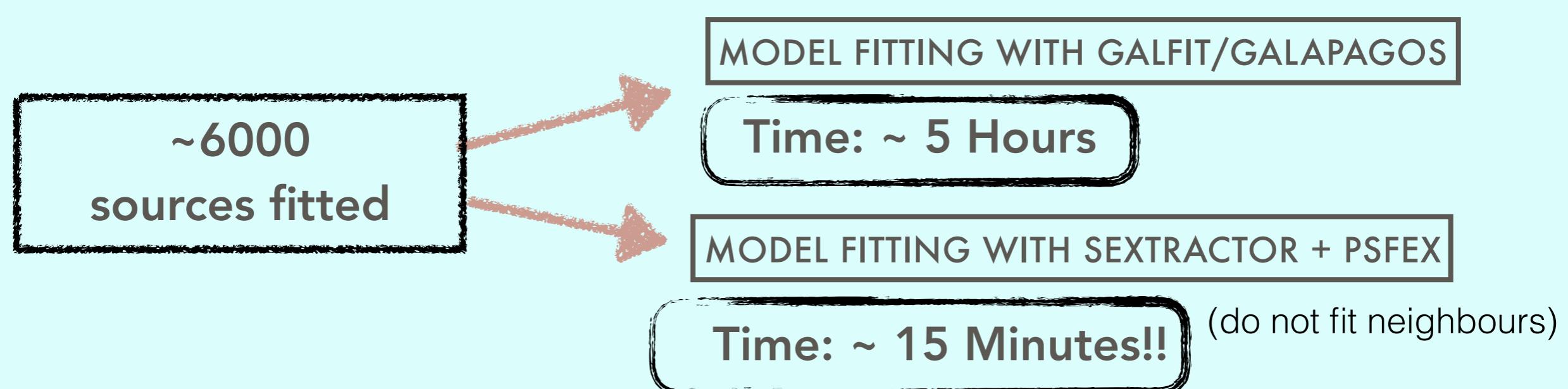
Radius

Mag

Parameters from “careful” GALFIT fitting

# But, is it our motivation to improve results of old softwares?

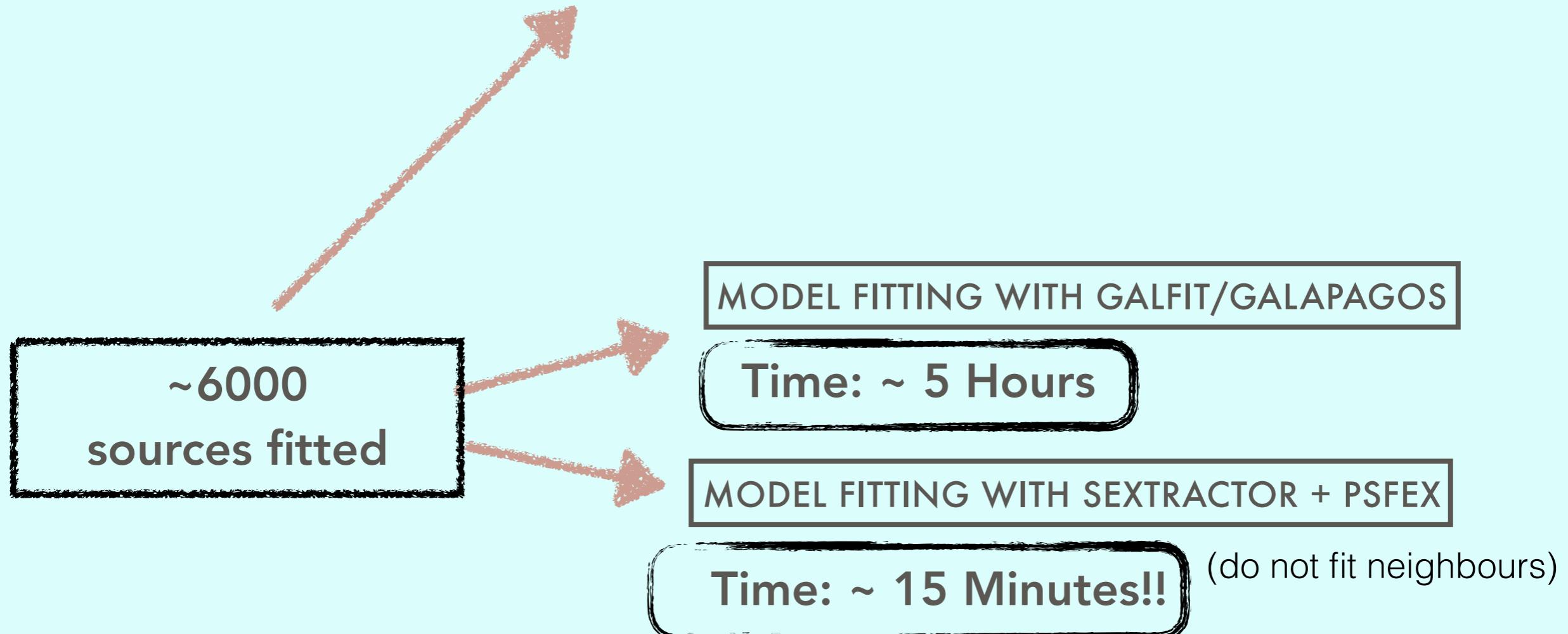
....not really



# But, is it our motivation to improve results of old softwares?

OUR DNN

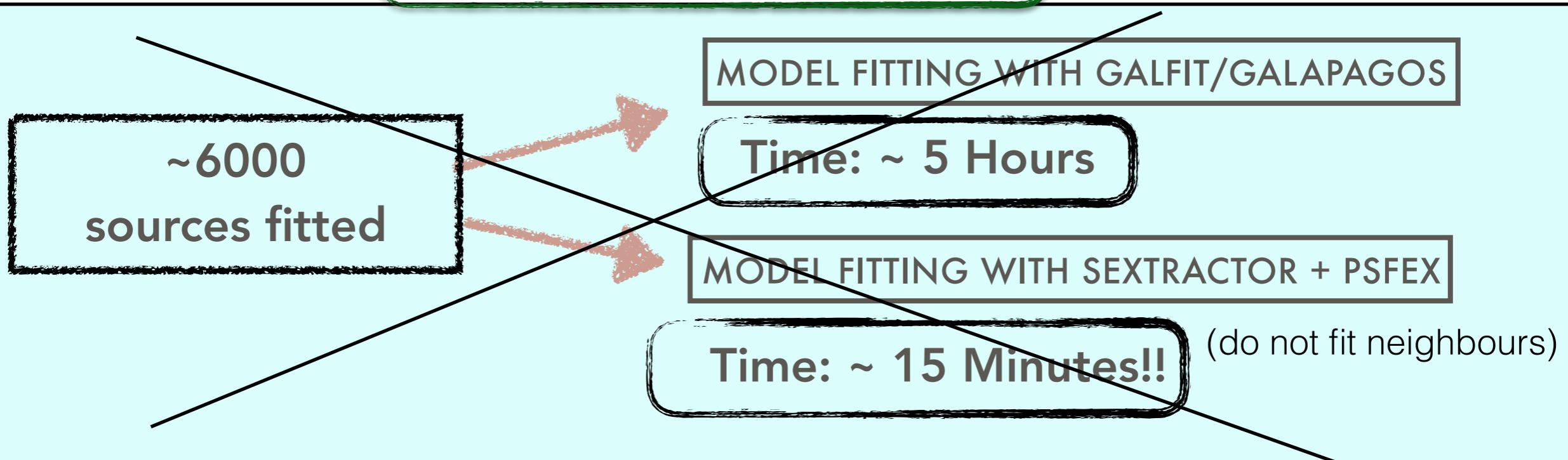
Takes ~2 minutes to train/validate 6000 sources  
and, more important, once trained takes <5 seconds to fit 6000 sources



# But, is it our motivation to improve results of old softwares?

[http://www.euclid-ec.org/?page\\_id=2581](http://www.euclid-ec.org/?page_id=2581)

SURVEYS					
	Area (deg <sup>2</sup> )	Description			
Wide Survey	<b>15,000 deg<sup>2</sup></b>	Step and stare with 4 dither pointings per step.			
Deep Survey	<b>40 deg<sup>2</sup></b>	In at least 2 patches of > 10 deg <sup>2</sup> 2 magnitudes deeper than wide survey			
Wavelength range	550– 900 nm	Y (920-1146nm),	J (1146-1372 nm)	H (1372-2000nm)	1100-2000 nm
Sensitivity	24.5 mag 10 $\sigma$ extended source	24 mag 5 $\sigma$ point source	24 mag 5 $\sigma$ point source	24 mag 5 $\sigma$ point source	$3 \cdot 10^{-16}$ erg cm-2 s-1 3.5 $\sigma$ unresolved line flux $z$ of $n=5 \times 10^7$ galaxies
Shapes + Photo-z of $n = 1.5 \times 10^9$ galaxies					



# List of Tasks

**1) Morphological classification**

Dileman+14 Huertas-Company +15



DONE

**2) DNN for 1 component Galaxies**



DONE

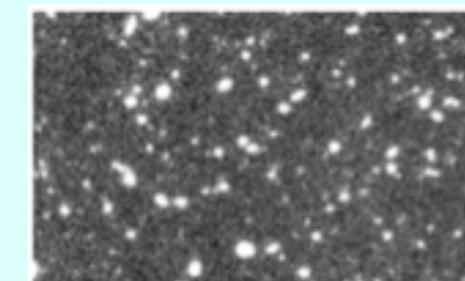
**3) DNN for 2 component Galaxies**



**4) Improve transfer learning**

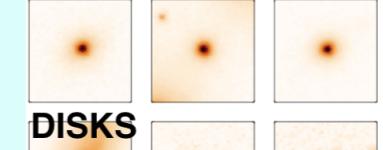
**5) Segmentation**

**6) A whole DNN machine:**



Classification

SPHEROIDS



DISKS



IRR



morphological parameters

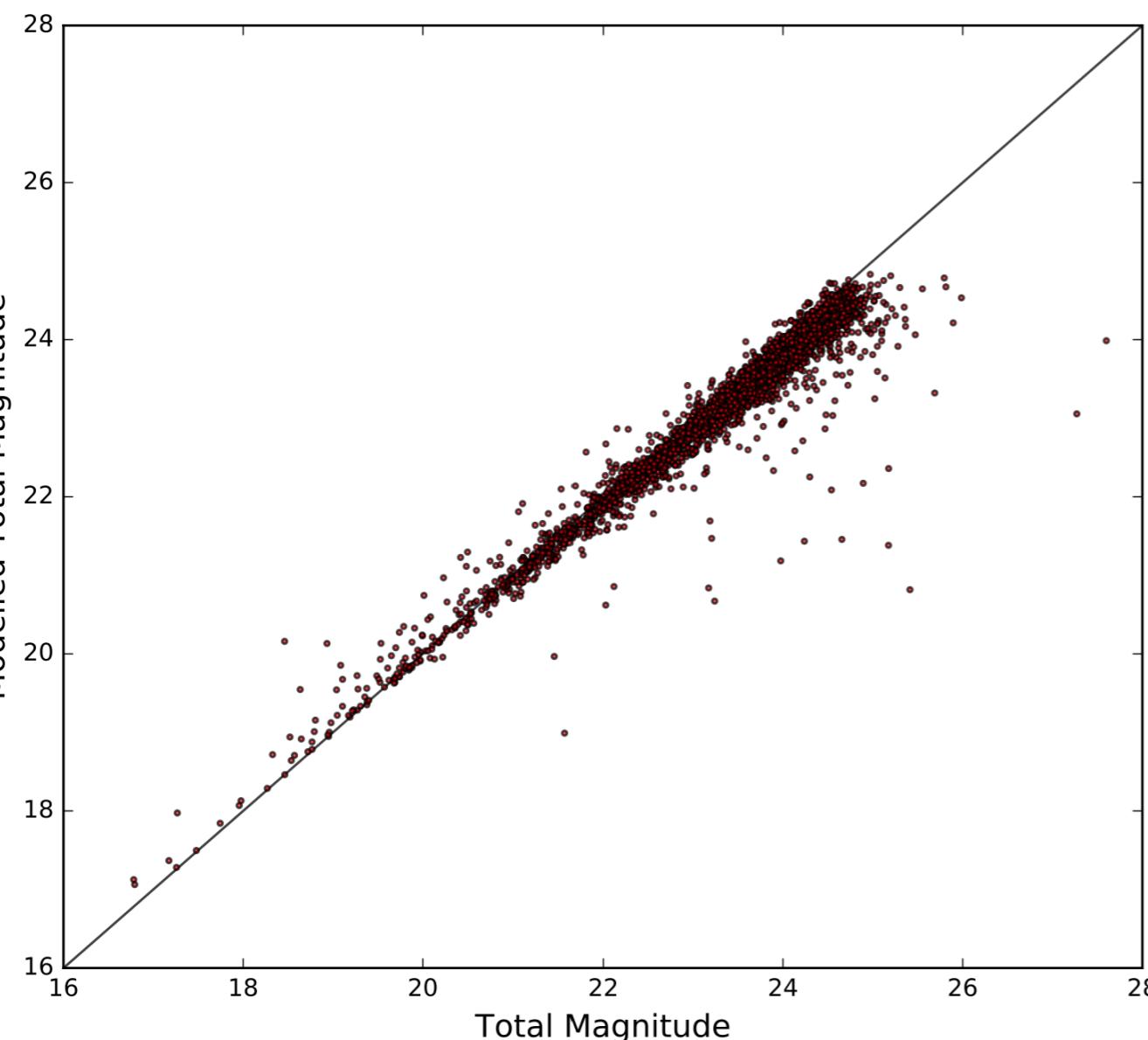
# First results 2 components galaxies

WITH REAL NOISE  
REAL PSF CANDELS  
PIXEL SCALE 0.06''

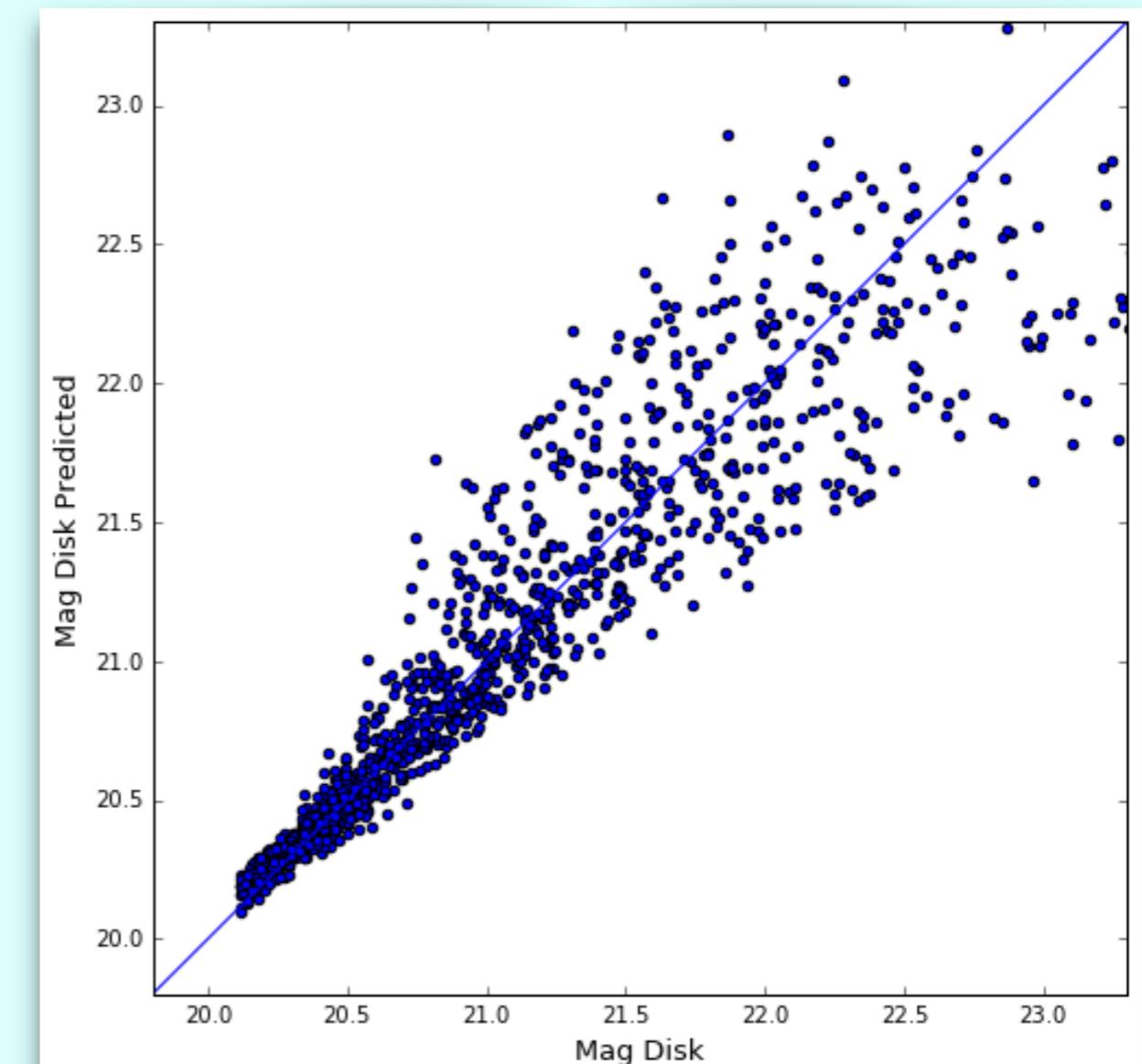
Double Sersic HST galaxies

VARIABLE BULGE/DISK RADIUS  
VARIABLE B/T

18 < MAG < 24  
VARIABLE SERCICS

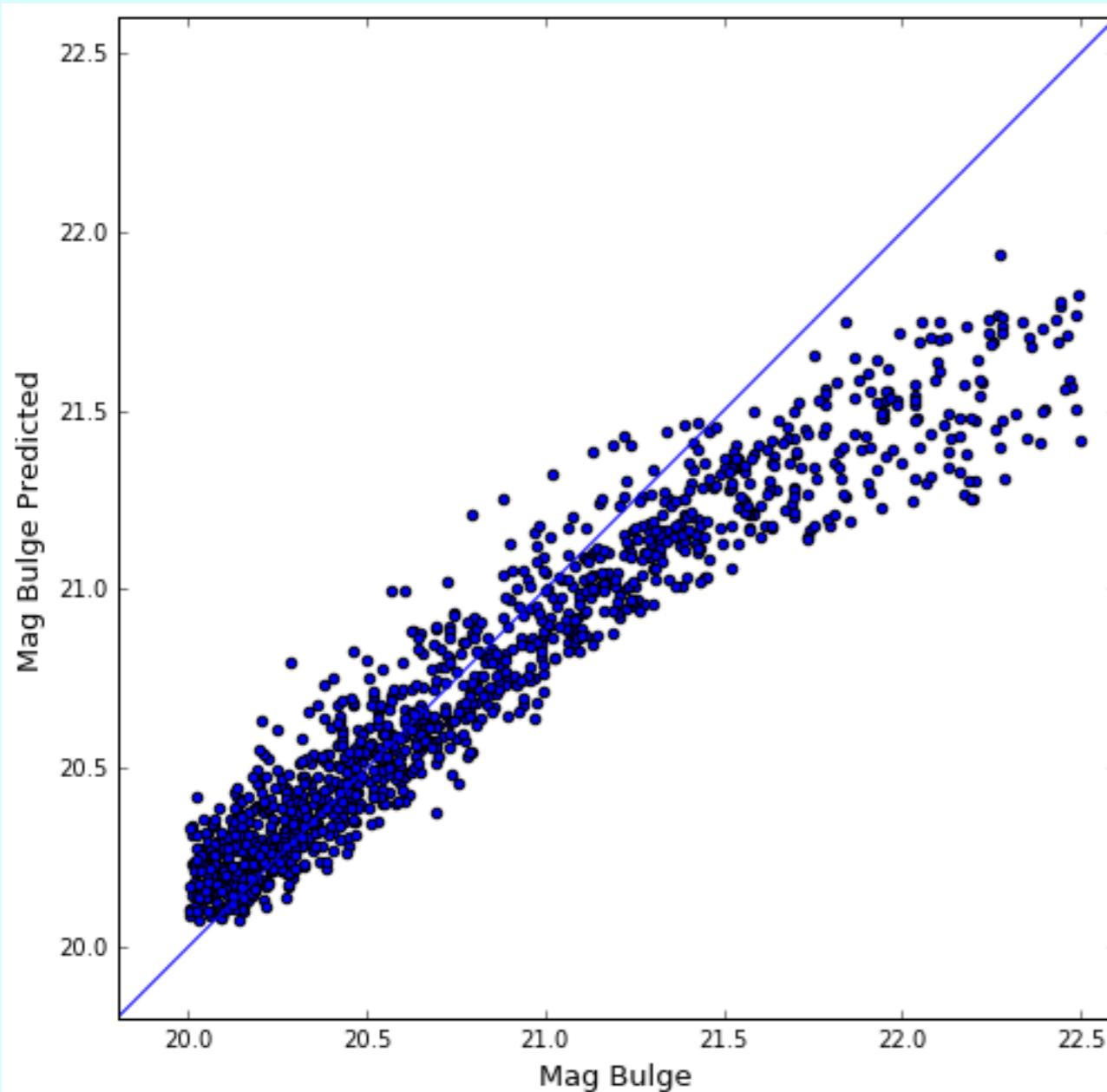


Total Magnitude

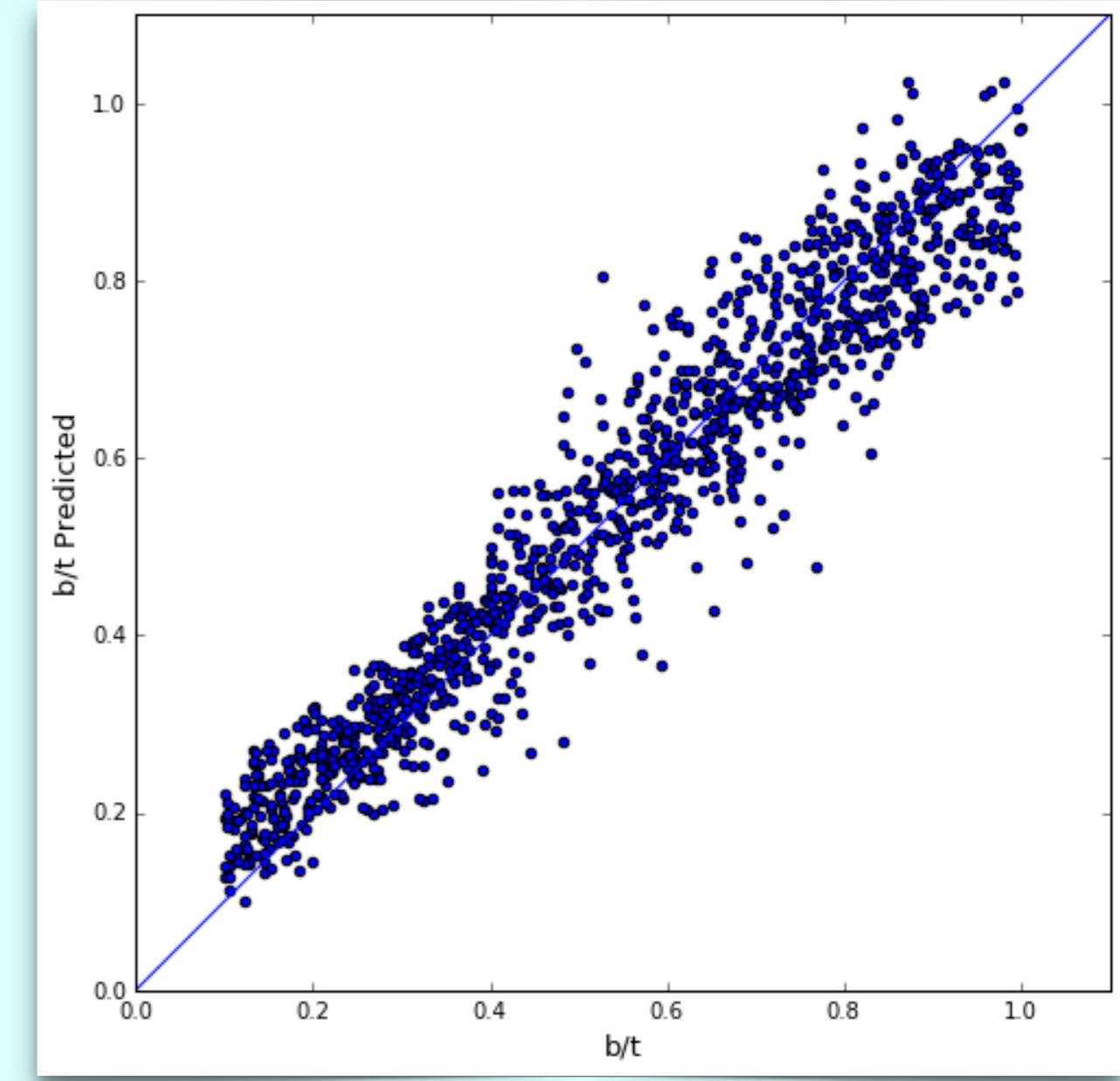


Disk Magnitude

# First results 2 components galaxies

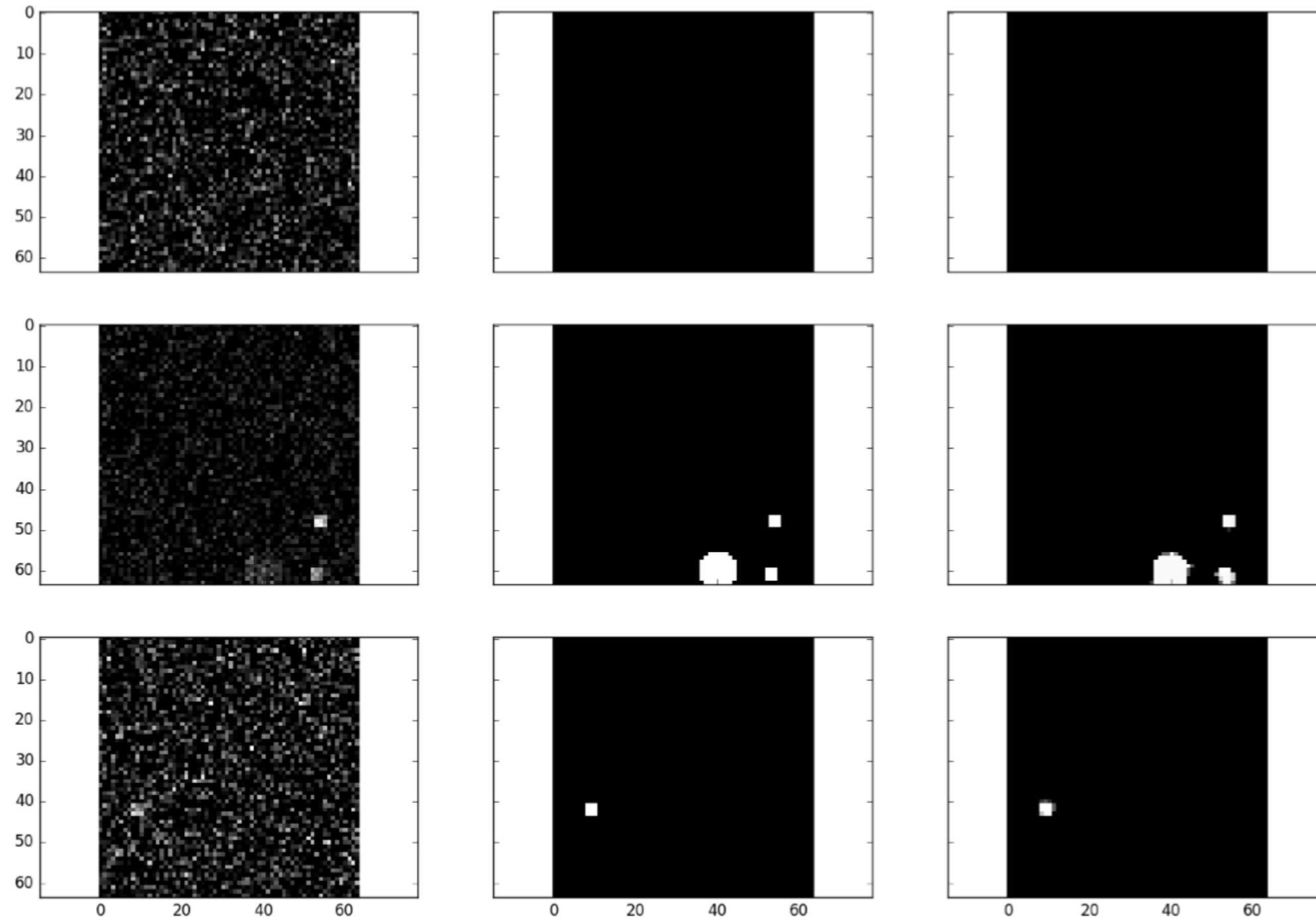


Bulge magnitude



B/T

# First results on segmentation



variable size

variable noise

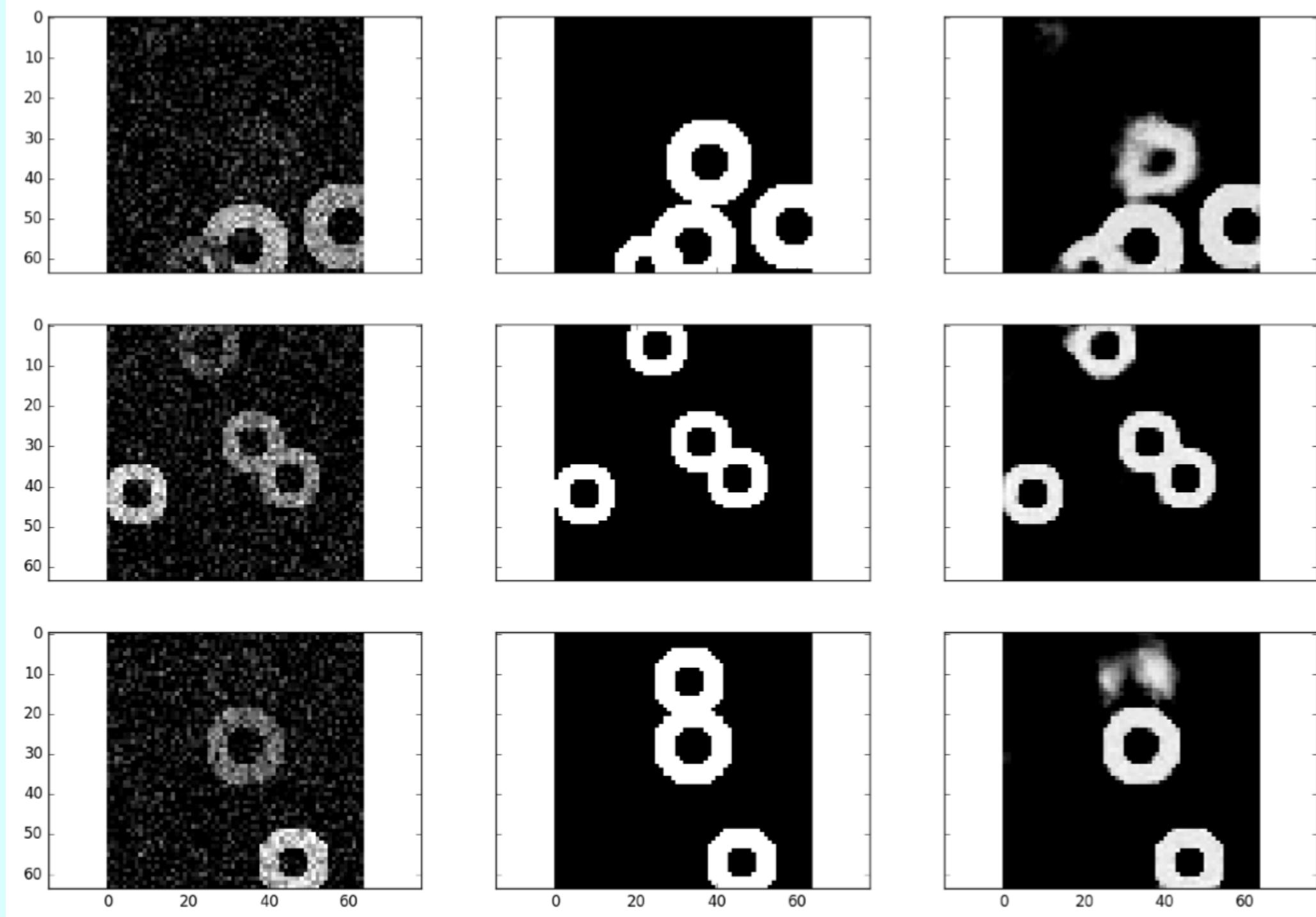
Results: disks

Fully convolutional networks for semantic segmentation [Long et al., 2015]

U-Net: convolutional networks for biomedical image segmentation (Ronneberger [Ronneberger et al., 2015])

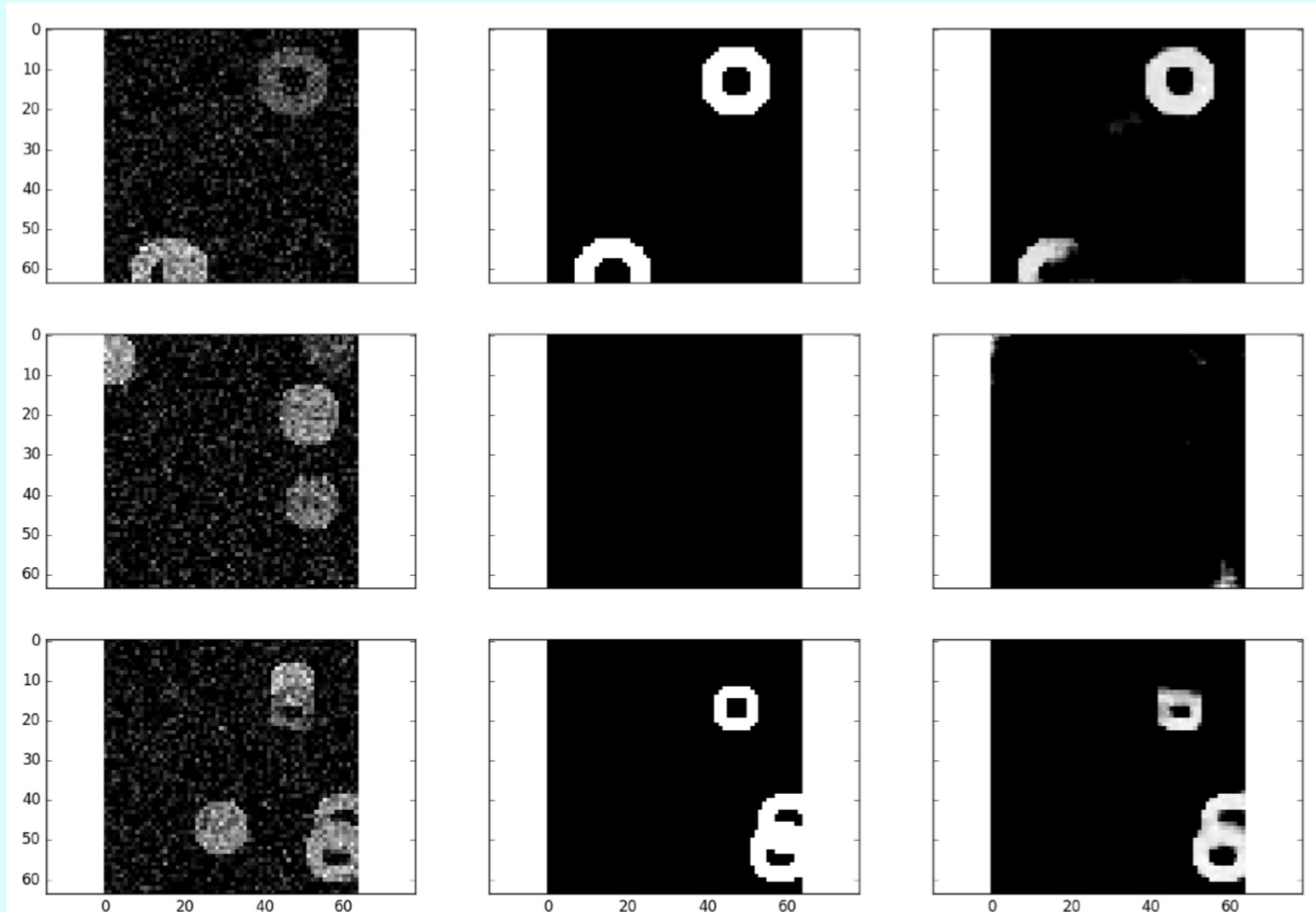
SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation [Badrinarayanan et al., 2015]

## First results on segmentation



Results: rings

# First results on segmentation



Results: rings and disks



task: find rings

# List of Tasks

## 1) Morphological classification

Dileman+14 Huertas-Company +15



DONE

## 2) DNN for 1 component Galaxies



DONE

## 3) DNN for 2 component Galaxies



Going deeper



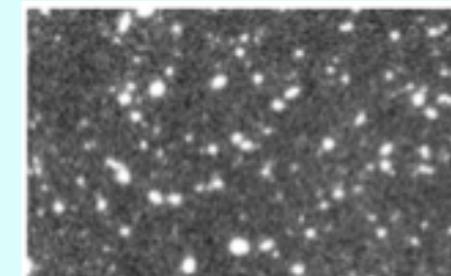
## 4) Improve transfer learning



## 5) Segmentation



## 6) A whole DNN machine:



Classification

SPHEROIDS



DISKS



IRR



morphological parameters

# List of Tasks

## 1) Morphological classification

Dileman+14 Huertas-Company +15



DONE

## 2) DNN for 1 component Galaxies

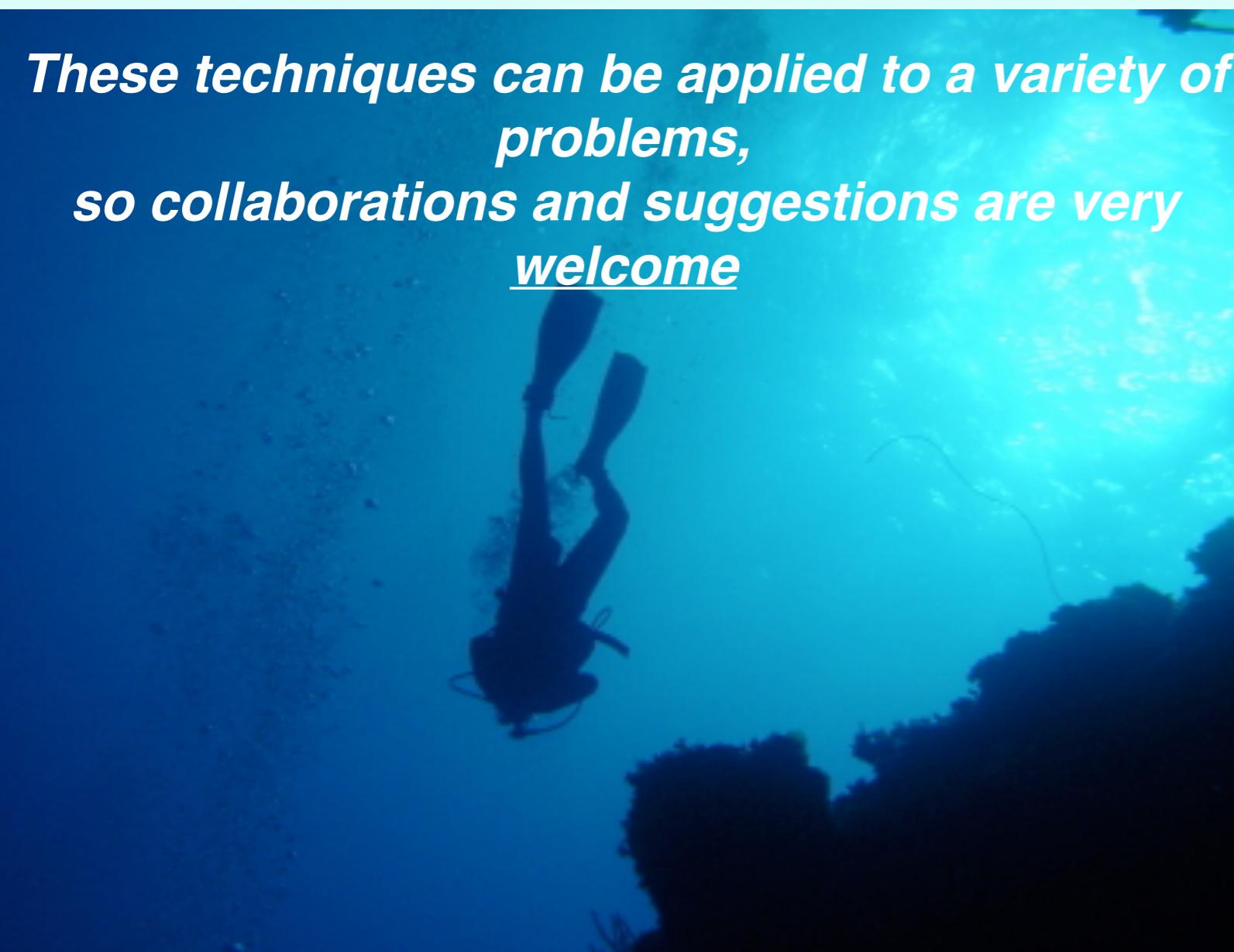


DONE

## 3) DNN for 2 component Galaxies



*These techniques can be applied to a variety of problems,  
so collaborations and suggestions are very welcome*



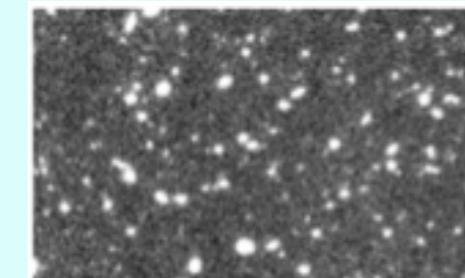
## 4) Improve transfer learning



## 5) Segmentation

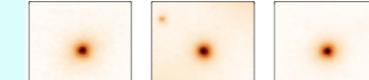


## 6) A whole DNN machine:



↓  
Classification

SPHEROIDS



DISKS



IRR



↓  
↓  
↓  
morphological parameters

Thanks for listening!



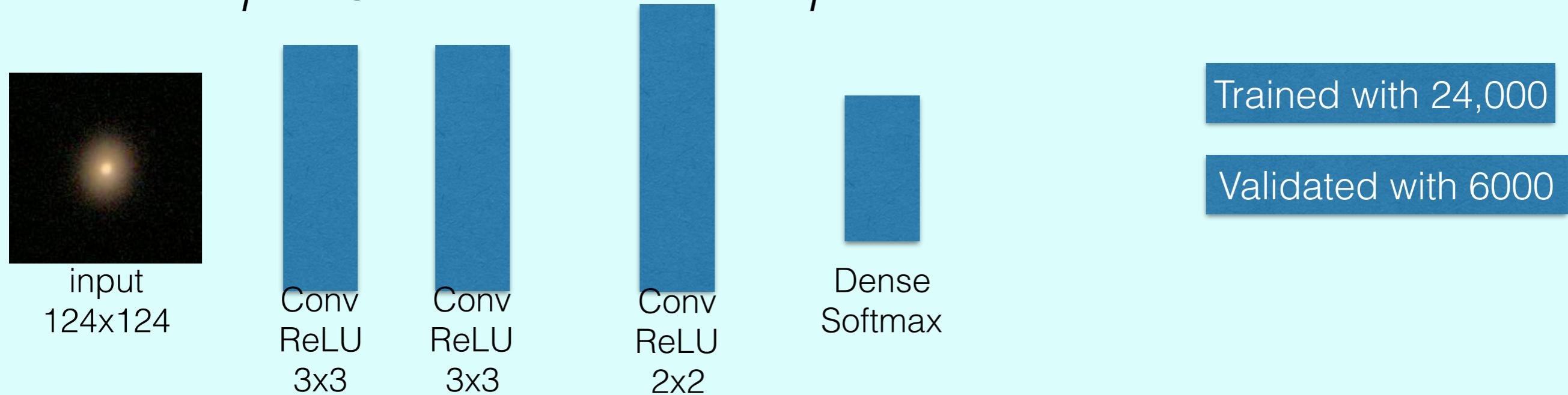
# Thanks for listening!





We developed a DNN algorithm.  
Used 30,000 stamps of 1-component galaxies

*Example Convolutional Deep Neural Network*



**Details on the true DNN  
architecture**



(to be submitted by November)

**Deep Neural Network for galaxy morphology**

D. Tuccillo, M. Huertas, E. Decenciere, S.

