Illuminating the Low Surface Brightness Galaxies in Dark Energy Survey with Transformers

Supervisor : Prof. dr hab. Marek Biesiada & dr Adam Zadrożny

Collaborators : dr. Junais, Prof. dr hab. Agnieszka Pollo, dr. Unnikrishnan Sureshkumar, Margherita Grespan, Prasad Sawant, Prof. dr hab. Katarzyna Małek

Outline

01

Introduction to galaxies. What are LSBG and the Importance of LSBGs

02

Current literature on searches for LSBGs and the role of ML.

03

Introduction to computer vision: CNNS and Transformers

04

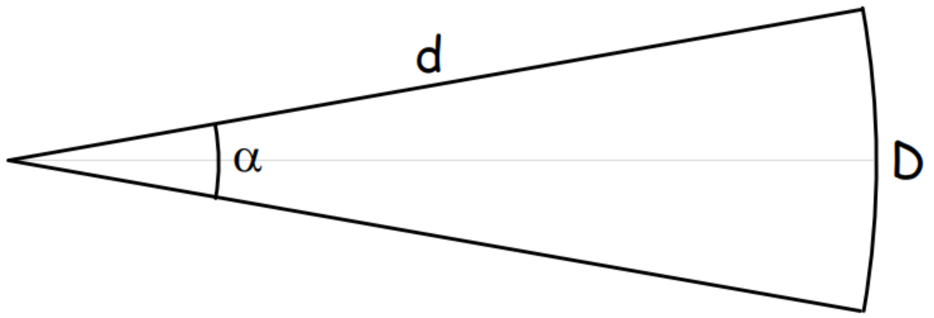
Search for LSBGs from DES and properties of LSBGs identified in DES.

Galaxies 101

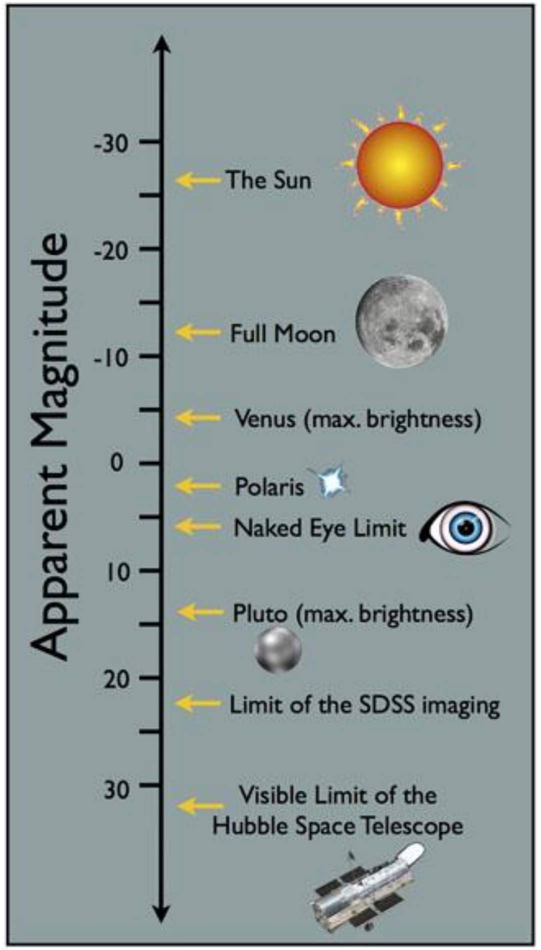
Surface Brightness and Magnitude

The surface brightness is the amount of light in that patch of sky divided by its area (in arsec2).

$$\alpha = \frac{D}{d}.$$



$$\mu(r) = \frac{\text{Flux}}{\alpha^2} = \frac{L}{4\pi d^2}\left(\frac{d}{D}\right)^2 = \frac{L}{4\pi D^2}$$



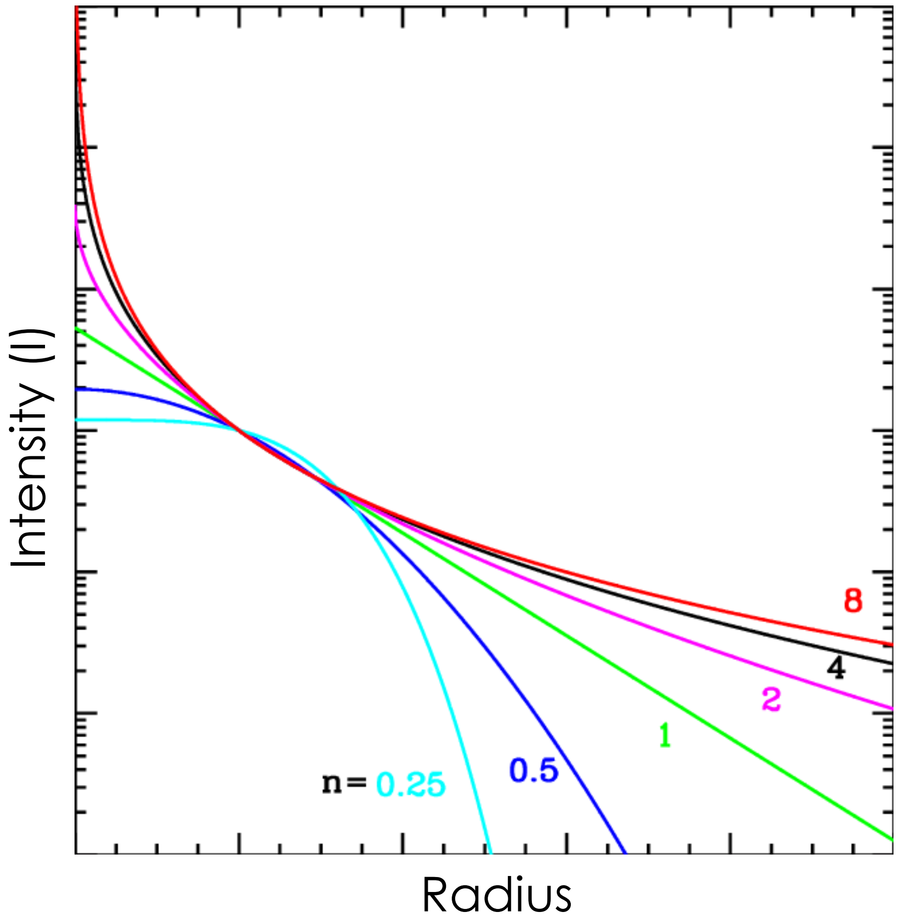
Sérsic Profile of Galaxies

The Sérsic profile is a mathematical function that describes how the surface brightness of a galaxy varies with distance r from its centre.

$$\mu(r) = \mu_e \exp\left[-b\left(\left(\frac{r}{r_e}\right)^{1/n} - 1\right)\right]$$

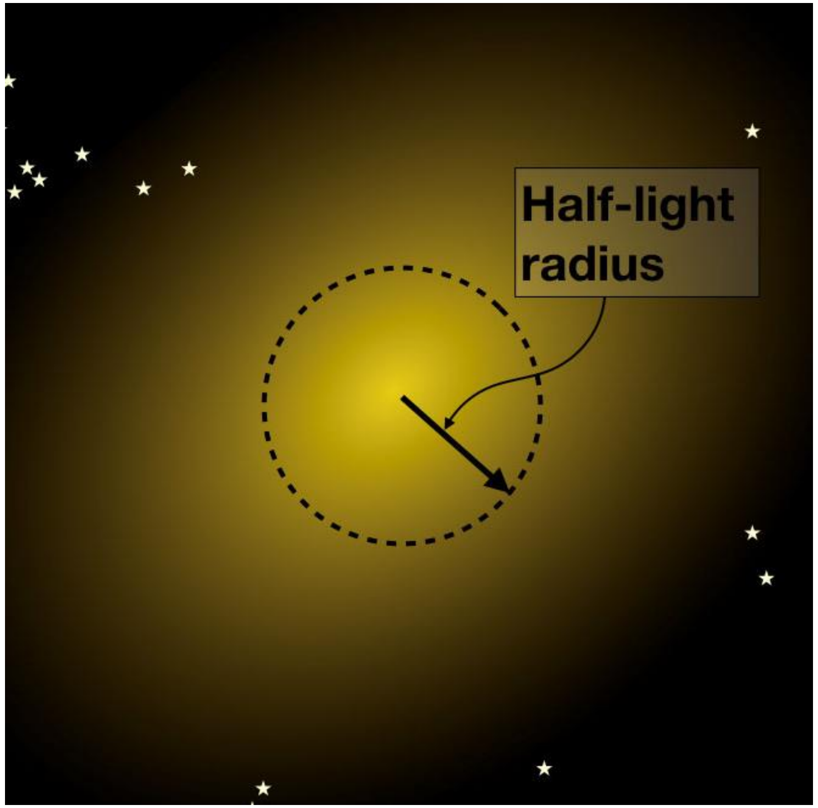
Sérsic index (n)

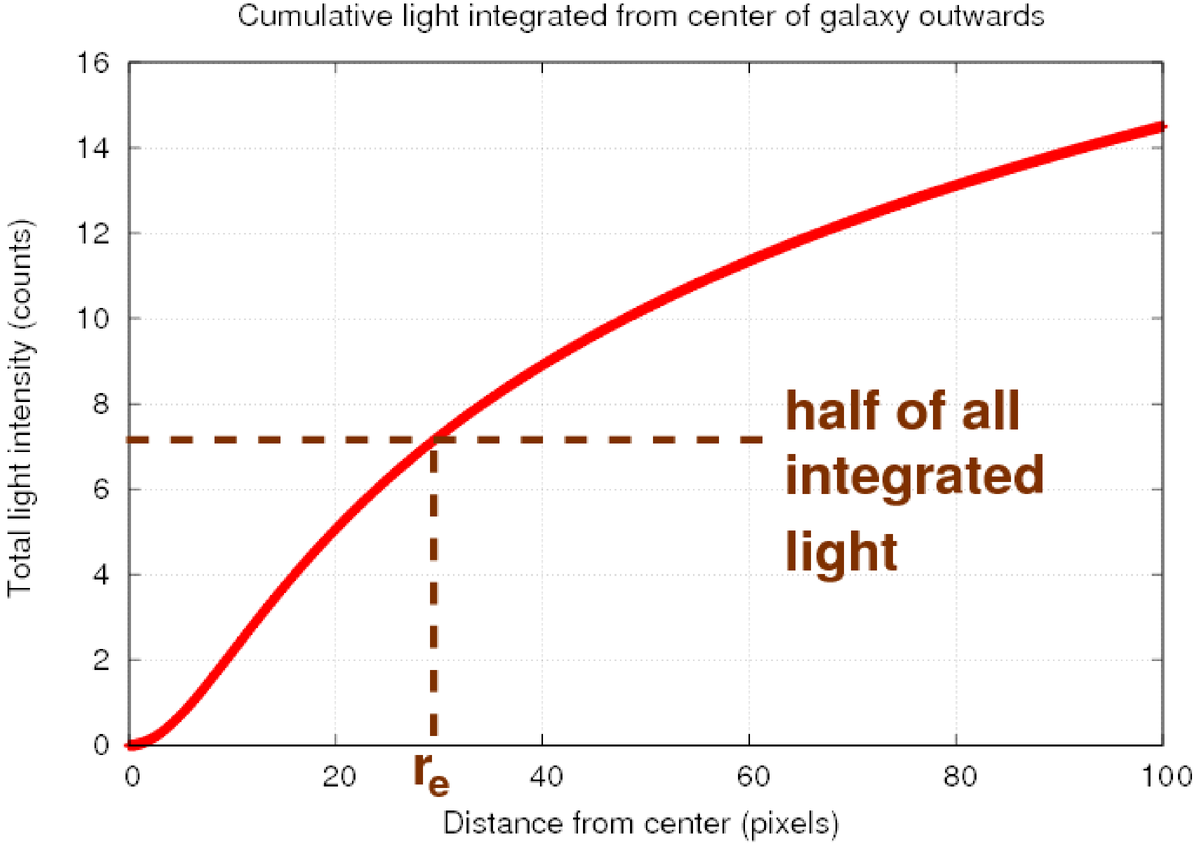
- n = 4 gives the de Vaucouleurs profile which is a rough approximation of ordinary elliptical galaxies.
- n = 1 gives the exponential profile which is a good approximation of spiral galaxy disks and a rough approximation of dwarf elliptical galaxies



Half-light Radius of Galaxies

The half-light (or 'effective') radius is the radius from within which half of the galaxy light is contained.





LOW SURFACE BRIGHTNESS GALAXIES

Image of UGC 477 taken by NASA/ESA Hubble Space Telescope. Image taken from: http://www.spacetelescope.org/images/potw1614a/

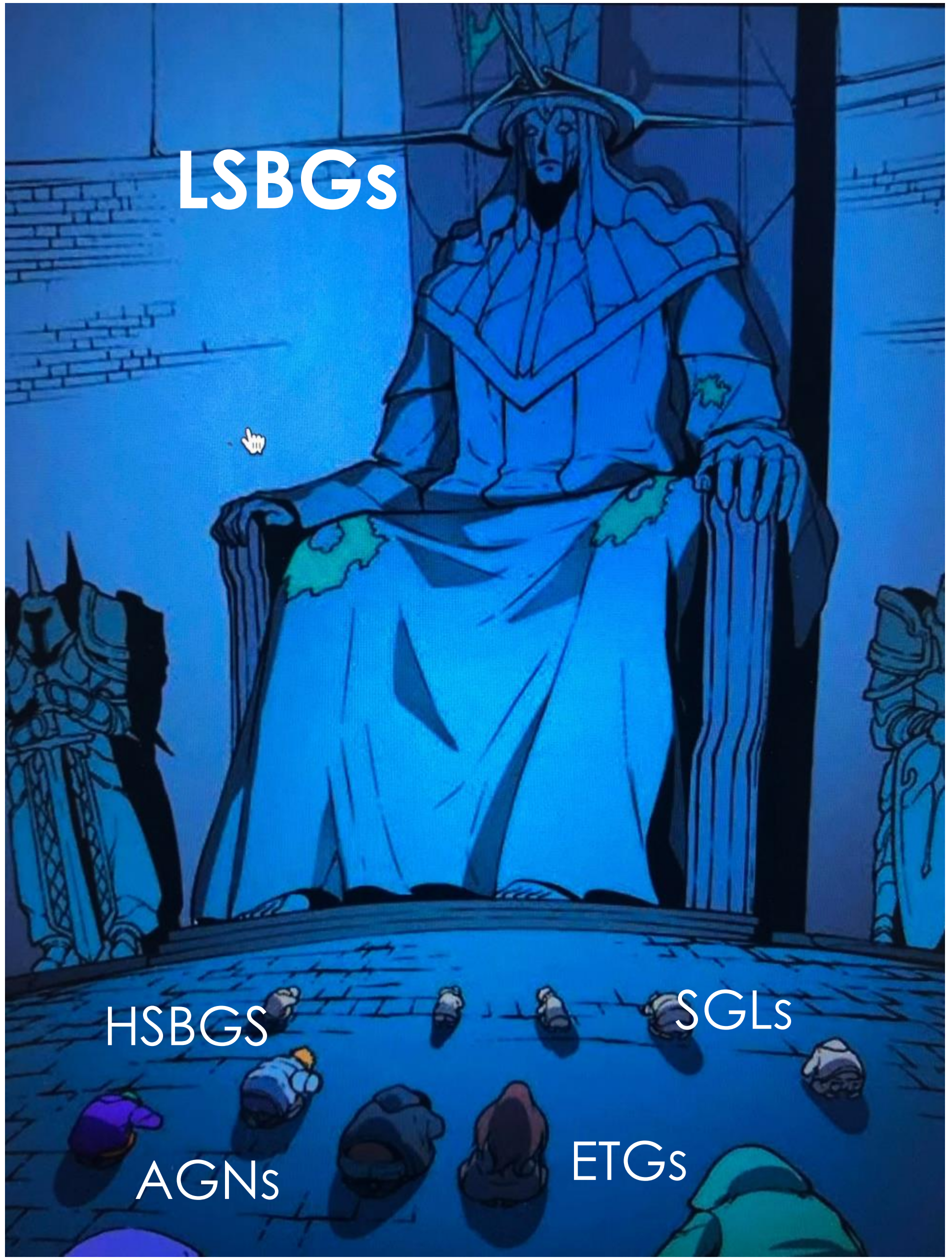
What is an LSBG ?

Low-surface brightness galaxies (LSBGs) are conventionally defined as galaxies with a central surface brightness fainter than the night sky ($\mu(g) > 22$ mag/arcsec^2).

Examples of LSBGs from Dark Energy Survey (DES)

Low surface brightness galaxies may account for up to 50% of the total population of galaxies.

LSBGs can significantly contribute to our understanding of galaxy evolution.



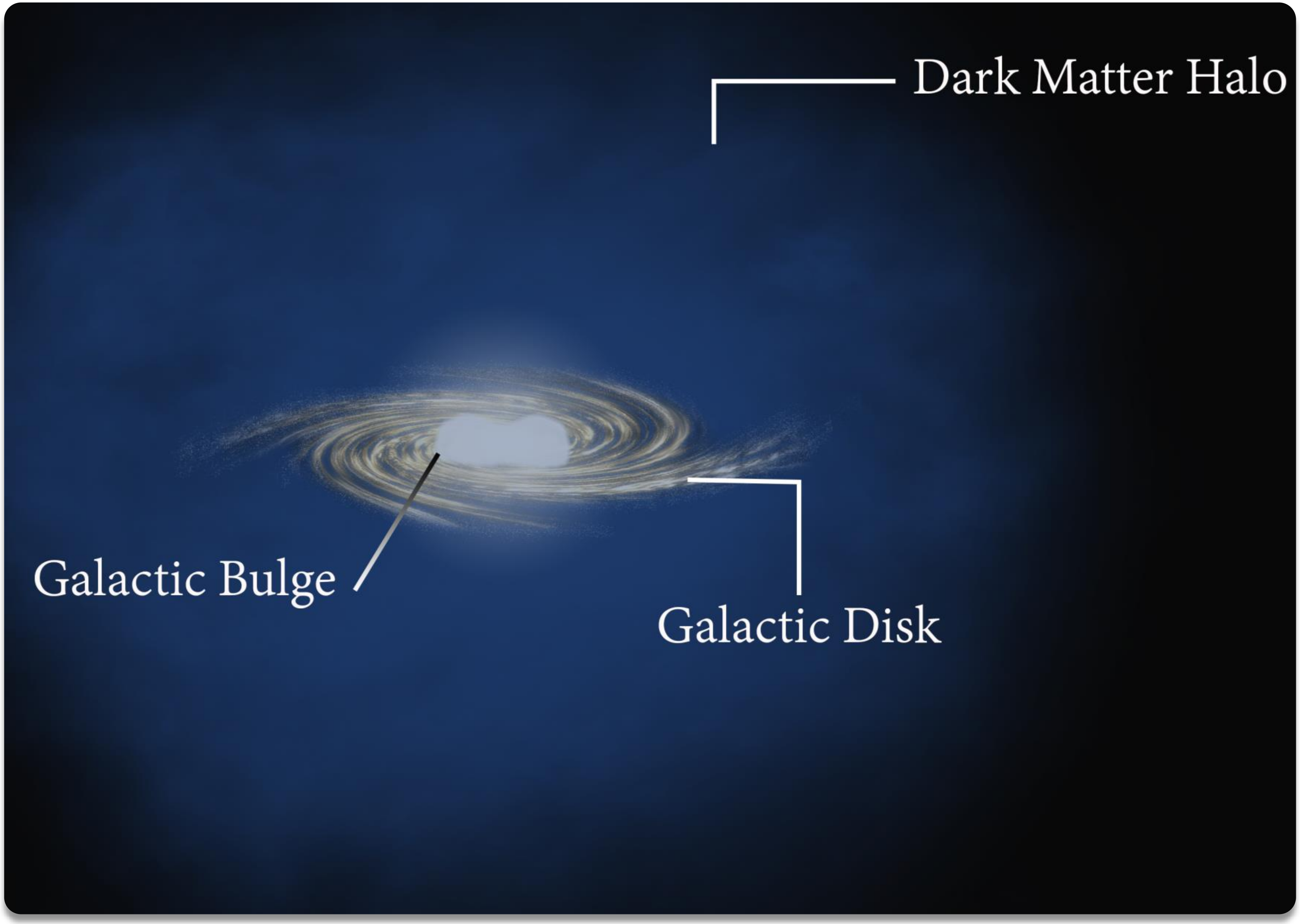
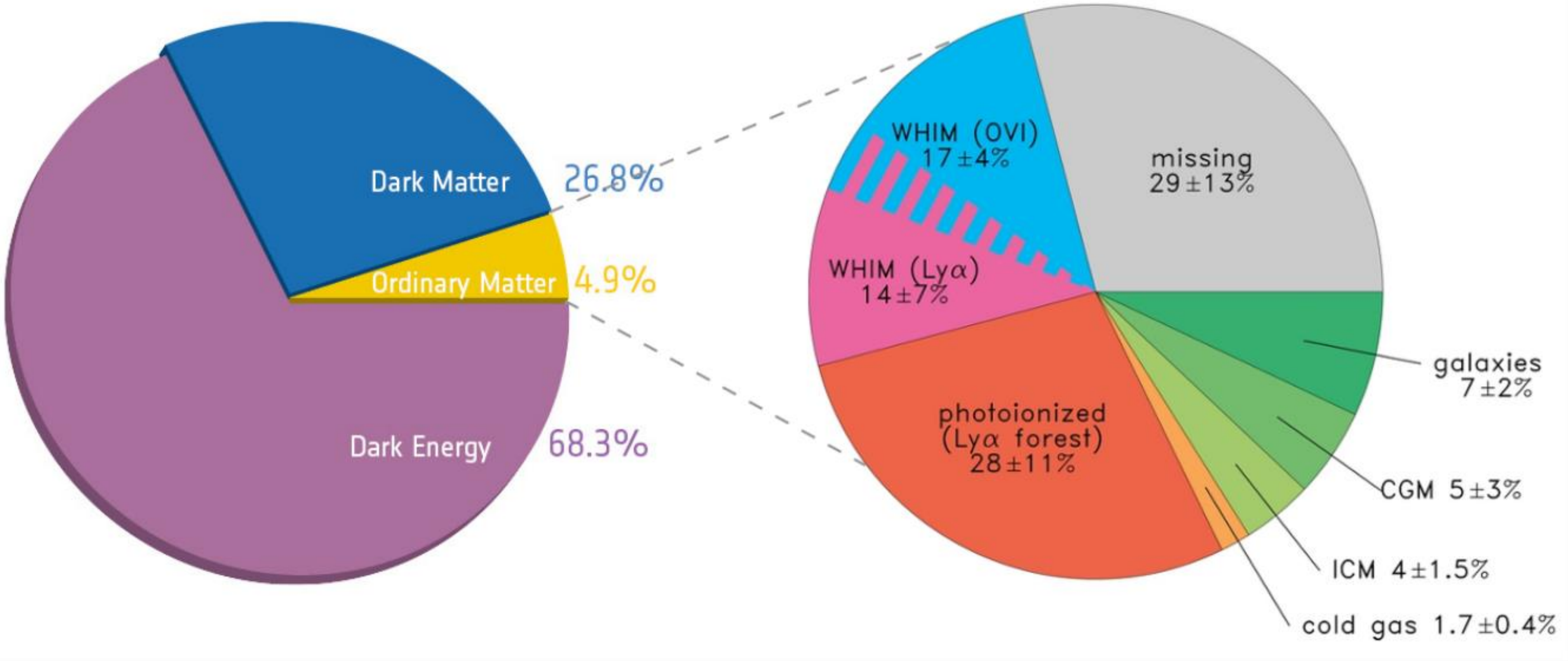


Image Credit: L Jaramillo and O Macias, Virginia Tech

‘Extremely dominated by dark matter, they may also be the location for at least some fraction of the missing matter in the Universe.

Missing Baryon Problem

The missing baryon problem is an observed discrepancy between the amount of baryonic matter detected from shortly after the Big Bang and from more recent epochs.



ESA/Planck; Shull et al. 2012

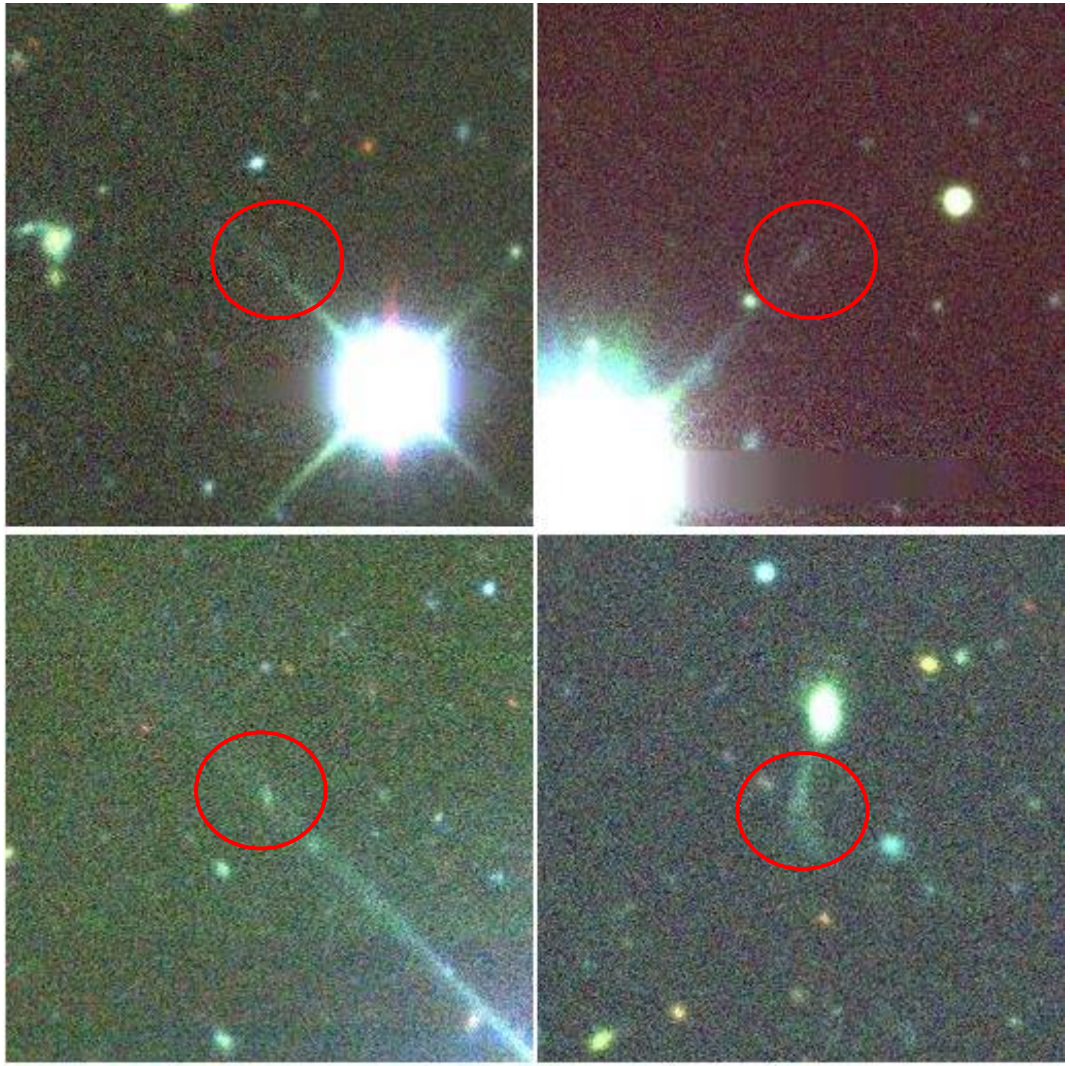
Finding LSBGs

Why it is hard to detect LSBGs : Artefacts

Faint, compact objects blended in the diffuse light from nearby bright stars or giant elliptical galaxies;

Tidal ejecta connected to high-surface brightness host galaxies.

Eliminating the sky background to detect the LSBGs



Searches for LSBGs in Large Scale Surveys

Greco et al. (2018) identified 781 LSBGs (from ~ **200** deg^2) from 1521 candidates (**50**% success rate) in HSC SSP with a galaxy modelling pipeline.

Tanoglidis et al. (2021) identified 23,790 LSBGs (from ~ **5000** deg^2) from to 44,979 candidates (**53**% success rate) in DES.

Visual inspection is the currently reliable way to confirm if it is an LSBG or not.

LSST and EUCLID

The upcoming large-scale surveys, such as LSST and Euclid are expected to observe 10^5 **LSBGs**.

With the current techniques it means ~ **10^5 artefacts.**

NCBJ is also an active member of the LSST collaboration.

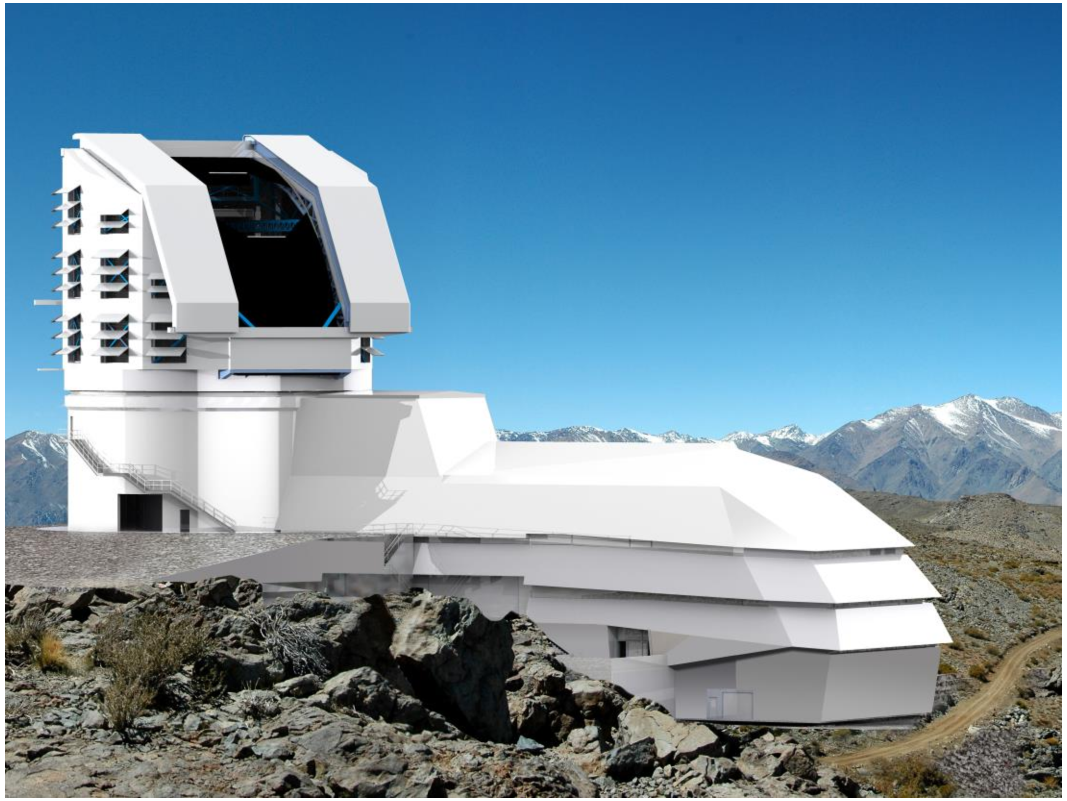


Image taken from https://astronomy.com/news/2017/12/the-lsst-and-big-data-science

Deep Learning to the Rescue

CLASSIFICATION OF QUASARS, GALAXIES, AND STARS USING MULTI-MODAL DEEP LEARNING

Astronomy & Astrophysics manuscript no. Revised
December 27, 2022

Finding strong gravitational lenses through self-attention

Study based on the Bologna Lens Challenge

Hareesh Thuruthipilly[1], Adam Zadrozny[1], Agnieszka Pollo[1,2], and Marek Biesiada[1,3]

MNRAS 000, 1–17 (2015) Preprint 28 April 2023 Compiled using MNRAS LaTeX

Distinguishing a planetary transit from false positives: a Transformer-based classification for planetary transit signals

Helem Salinas,[1★] Karim Pichara,[1†] Rafael Brahm,[2,3‡] Francisco Pérez-Galarce,[1§] and Doming
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The Astrophysical Journal, 909:27 (17pp), 2021 March 1 https://doi.org/10.3847/1538-4357/abd62b

Discovering New Strong Gravitational Lenses in the DESI Legacy Imaging Surveys

X. Huang[1], C. Storfer[1], A. Gu[2,3], V. Ravi[4], A. Pilon[1], W. Sheu[2,3], R. Venguswamy[5], S. Banka[3], A. Dey[6], M. Landriau[7], D. Lang[8,9,10], A. Meisner[6], J. Moustakas[11], A. D. Myers[12], R. Sajith[2,3], E. F. Schlafly[13], and D. J. Schlegel[7]
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Abstract

We have conducted a search for new strong gravitational lensing systems in the Dark Energy Spectroscopic Instrument Legacy Imaging Surveys' Data Release 8. We use deep residual neural networks, building on previous work presented by Huang et al. These surveys together cover approximately one-third of the sky visible from the

A&A 657, A90 (2022)
https://doi.org/10.1051/0004-6361/202141393

Astronomy & Astrophysics

Euclid preparation

XIII. Forecasts for galaxy morphology with the *Euclid* Survey using deep generative models

Euclid Collaboration: H. Bretonnière[1,2], M. Huertas-Company[2,3,4,5], A. Boucaud[2], F. Lanusse[6], E. Jullo[7], E. Merlin[8], D. Tuccillo[9], M. Castellano[8], J. Brinchmann[10,11], C. J. Conselice[12], H. Dole[1], R. Cabanac[13], H. M. Courtois[14], F. J. Castander[15,16], P. A. Duc[17], P. Fosalba[15,16], D. Guinet[14], S. Kruk[18], U. Kuchner[19], S. Serrano[15,16], E. Soubrie[1], A. Tramacere[20], L. Wang[21,22], A. Amara[23], N. Auricchio[24], R. Bender[25,26], C. Bodendorf[26], D. Bonino[27], E. Branchini[28,29], S. Brau-Nogue[13], M. Brescia[30], V. Capobianco[27], C. Carbone[31], J. Carretero[32], S. Cavuoti[30,33,34], A. Cimatti[35,36], R. Cledassou[37,38], G. Congedo[39], L. Conversi[40,41], Y. Copin[42], L. Corcione[27], A. Costille[7], M. Cropper[43], A. Da Silva[44,45], H. Degaudenzi[20], M. Douspis[1], F. Dubath[20], C. A. J. Duncan[46], X. Dupac[41], S. Dusini[47], S. Farrens[6], S. Ferriol[42], M. Frailis[48], E. Franceschi[24], M. Fumana[31],

The Astrophysical Journal, 921:177 (14pp), 2021 November 10 https://doi.org/10.3847/1538-4357/ac1da

Capturing the Physics of MaNGA Galaxies with Self-supervised Machine Learning

Regina Sarmiento[1,2], Marc Huertas-Company[1,2,3], Johan H. Knapen[1,2], Sebastián F. Sánchez[4], Helena Domínguez Sánchez[5,6], Niv Drory[7], and Jesus Falcón-Barroso[1,2]
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[5] Department of Physics and Astronomy, University of Pennsylvania, Philadelphia, PA 19104, USA
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Abstract

As available data sets grow in size and complexity, advanced visualization tools enabling their exploration and analysis become more important. In modern astronomy, integral field spectroscopic galaxy surveys are a clear

MNRAS 000, 1–15 (2021) Preprint 13 May 2021 Compiled using MNRAS LaTeX style file v3.0

Lenses In VoicE (LIVE): Searching for strong gravitational lenses in the VOICE@VST survey using Convolutional Neural Networks

Fabrizio Gentile,[1] Crescenzo Tortora,[2] Giovanni Covone,[1,2,3★] Léon V. E. Koopmans,[4] Chiara Spiniello,[2,5] Zuhui Fan,[6] Rui Li,[7] Dezi Liu,[6] Nicola R. Napolitano,[2,7] Mattia Vaccari[8,9] and Liping Fu[10]
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A&A 644, A163 (2020)
https://doi.org/10.1051/0004-6361/202038219

Astronomy & Astrophysics

HOLISMOKES

II. Identifying galaxy-scale strong gravitational lenses in Pan-STARRS using convolutional neural networks★

R. Cañameras[1], S. Schuldt[1,2], S. H. Suyu[1,2,3], S. Taubenberger[1], T. Meinhardt[4], L. Leal-Taixé[4], C. Lemon[5], K. Rojas[5], and E. Savary[5]

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The Astrophysical Journal, 899:30 (14pp), 2020 August 10 https://doi.org/10.3847/1538-4357/ab9dfa

New High-quality Strong Lens Candidates with Deep Learning in the Kilo-Degree Survey

R. Li[1], N. R. Napolitano[1], C. Tortora[2], C. Spiniello[3], L. V. E. Koopmans[4], Z. Huang[1], N. Roy[1], G. Vernardos[4,5], S. Chatterjee[4], B. Giblin[6], F. Getman[3], M. Radovich[7], G. Covone[3,8,9], and K. Kuijken[10]
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[6] Institute for Astronomy, University of Edinburgh, Blackford Hill, Edinburgh, EH9 3HJ, UK
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Received 2020 April 3; revised 2020 June 2; accepted 2020 June 16; published 2020 August 10

Computer Vision

Convolutional Neural Networks

Convolutional Neural Networks (CNNs) use convolution operations to extract meaningful features from images or other structured data.

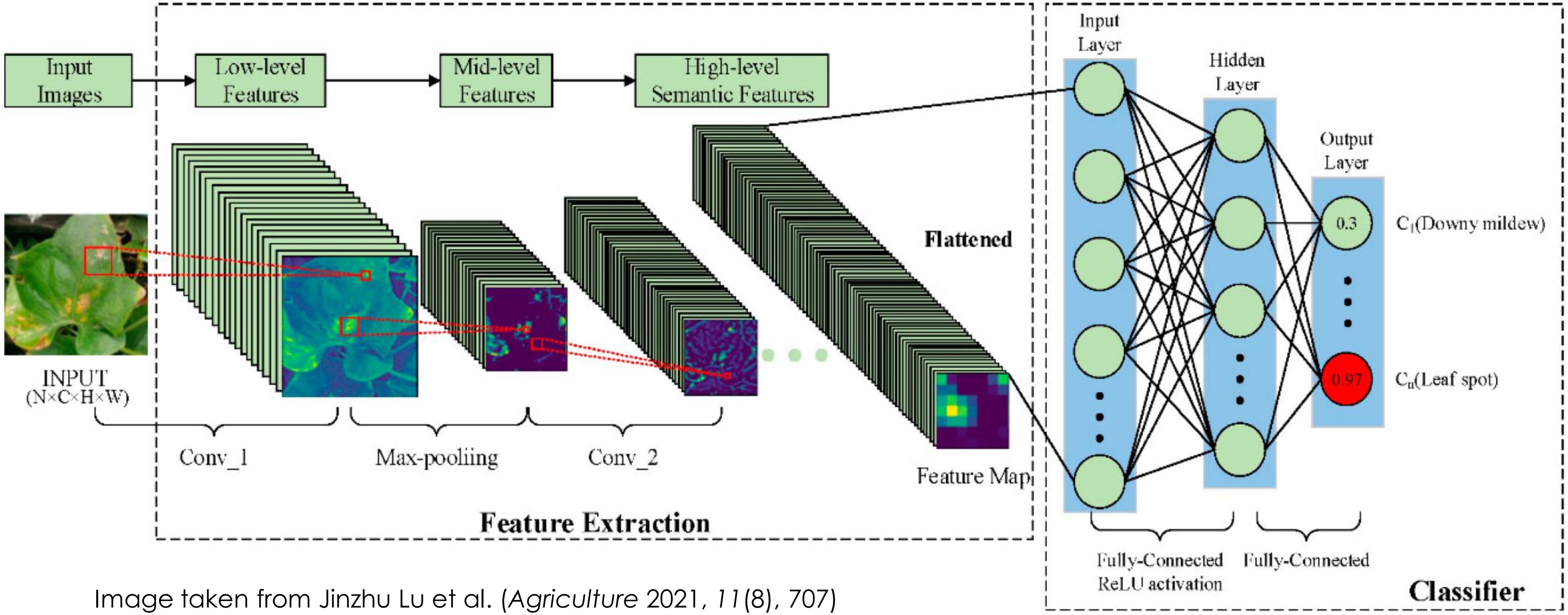
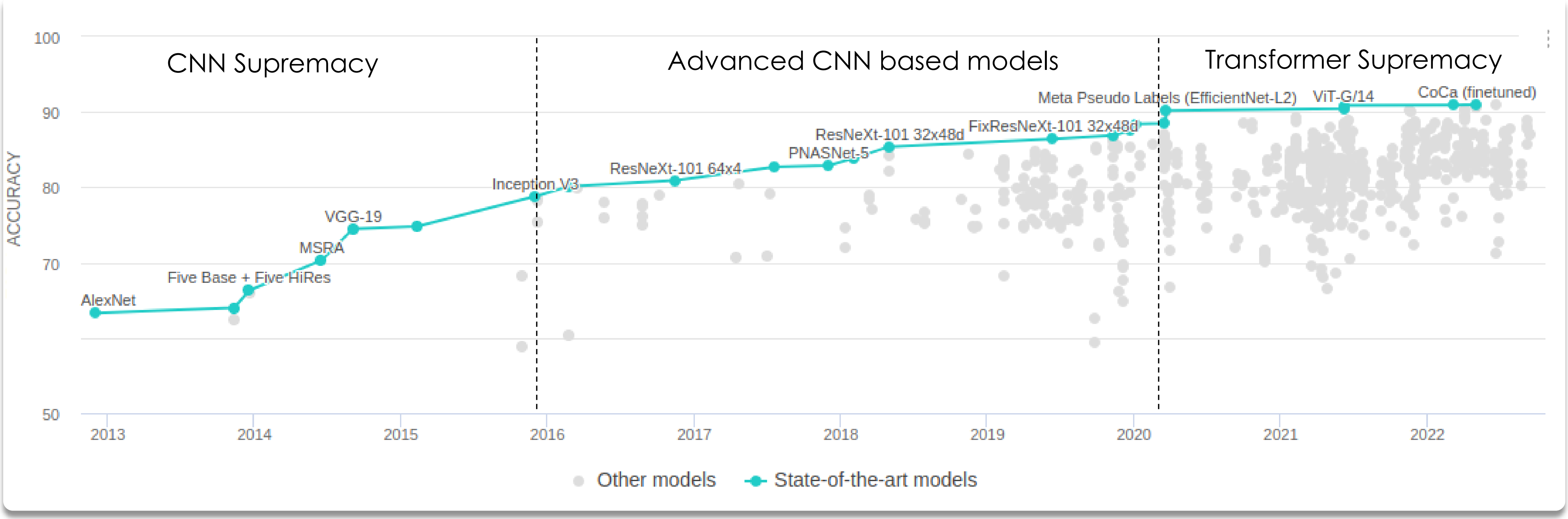


Image taken from Jinzhu Lu et al. (*Agriculture* 2021, *11*(8), 707)

Current Trend in Computer Vision



Each attention head can be implemented in parallel

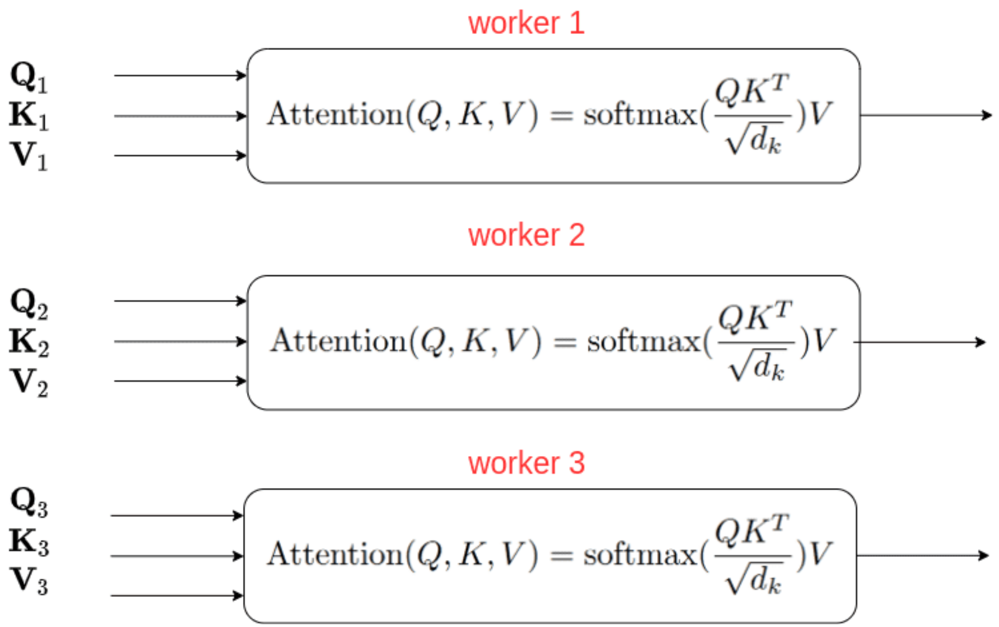


Image credits :https://theaisummer.com/self-attention/

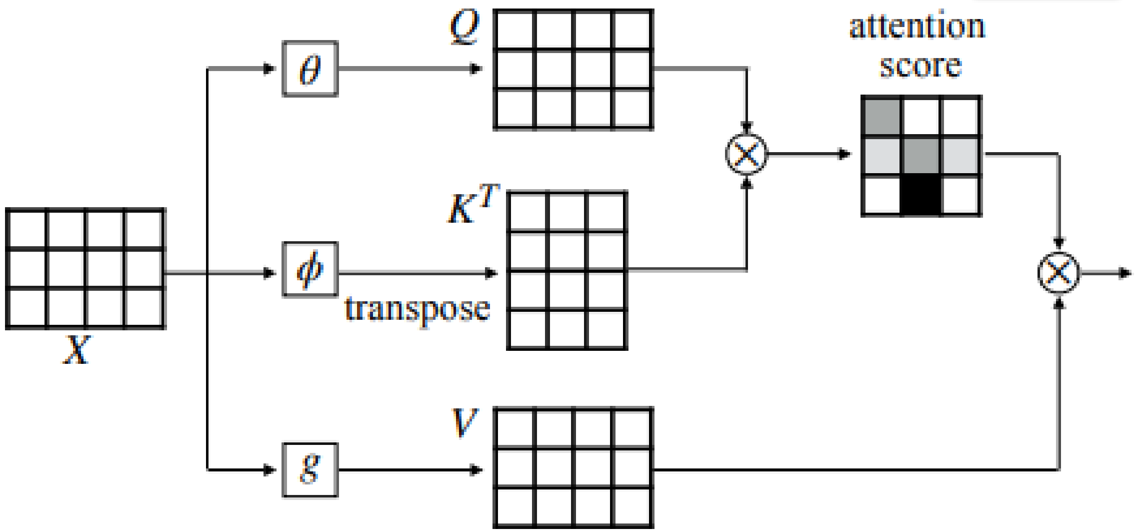
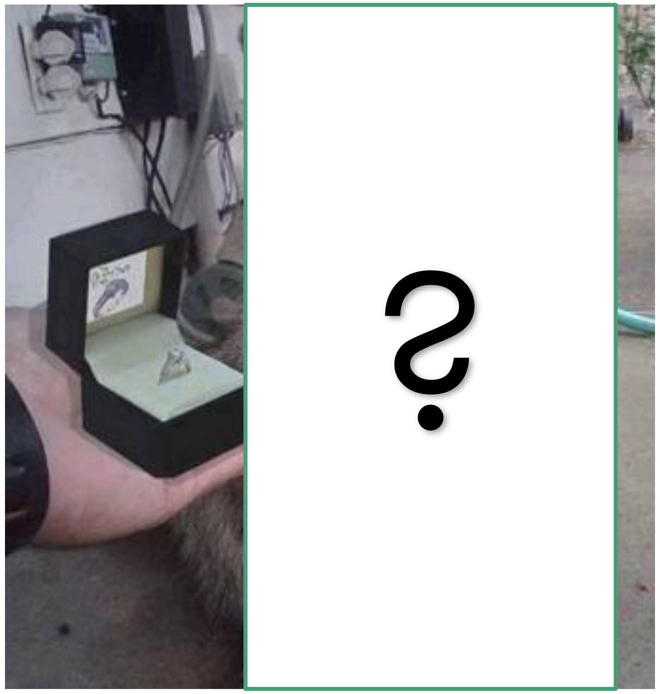
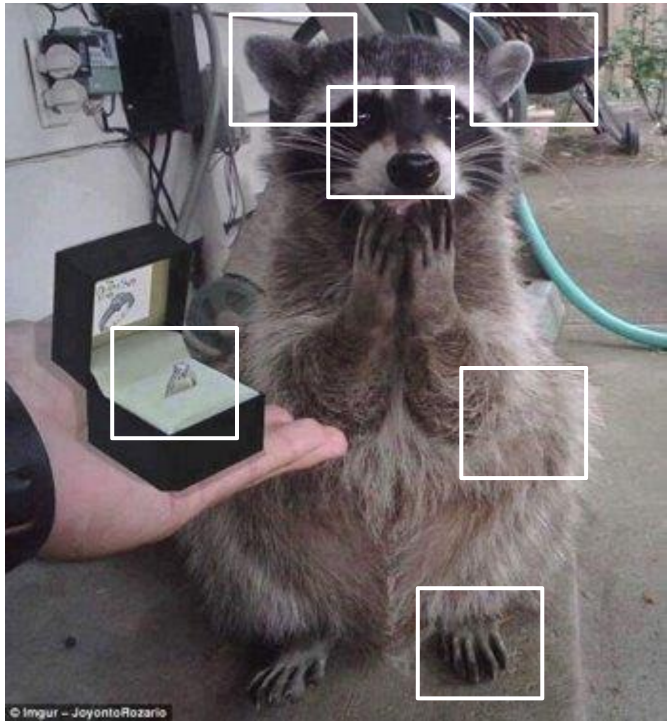


Image credits : https:// blogs.oracle.com/datascience/multi-head-self-attention-in-nlp

Transformers and Self-Attention

Attention in Action





LSBG Detection Transformer (LSBG DETR)

We can assume that the Encoder model works in 3 phases.

•**CNN** – To extract the Features

•**Encoder** – To filter the relevant Features of the image

•**FFN** – To learn the relevant Features

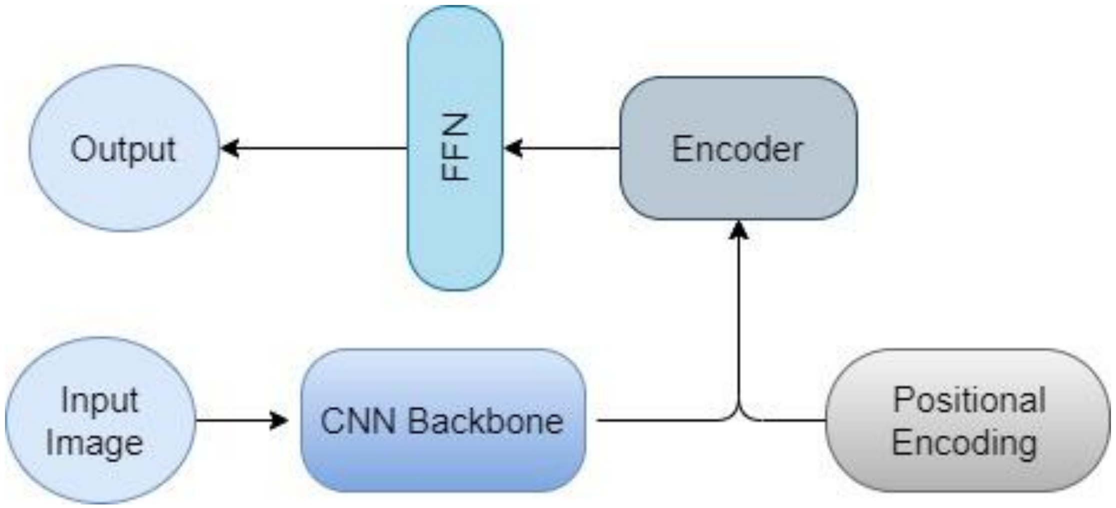


Image taken from Thuruthipilly et al. (2022)

LSBG Vision Transformer

- The Vision Transformer (ViT) divides an image into a grid of patches and feed it to a transformer encoder layer.

- Flattened patches are processed through multiple transformer layers, and make predictions.

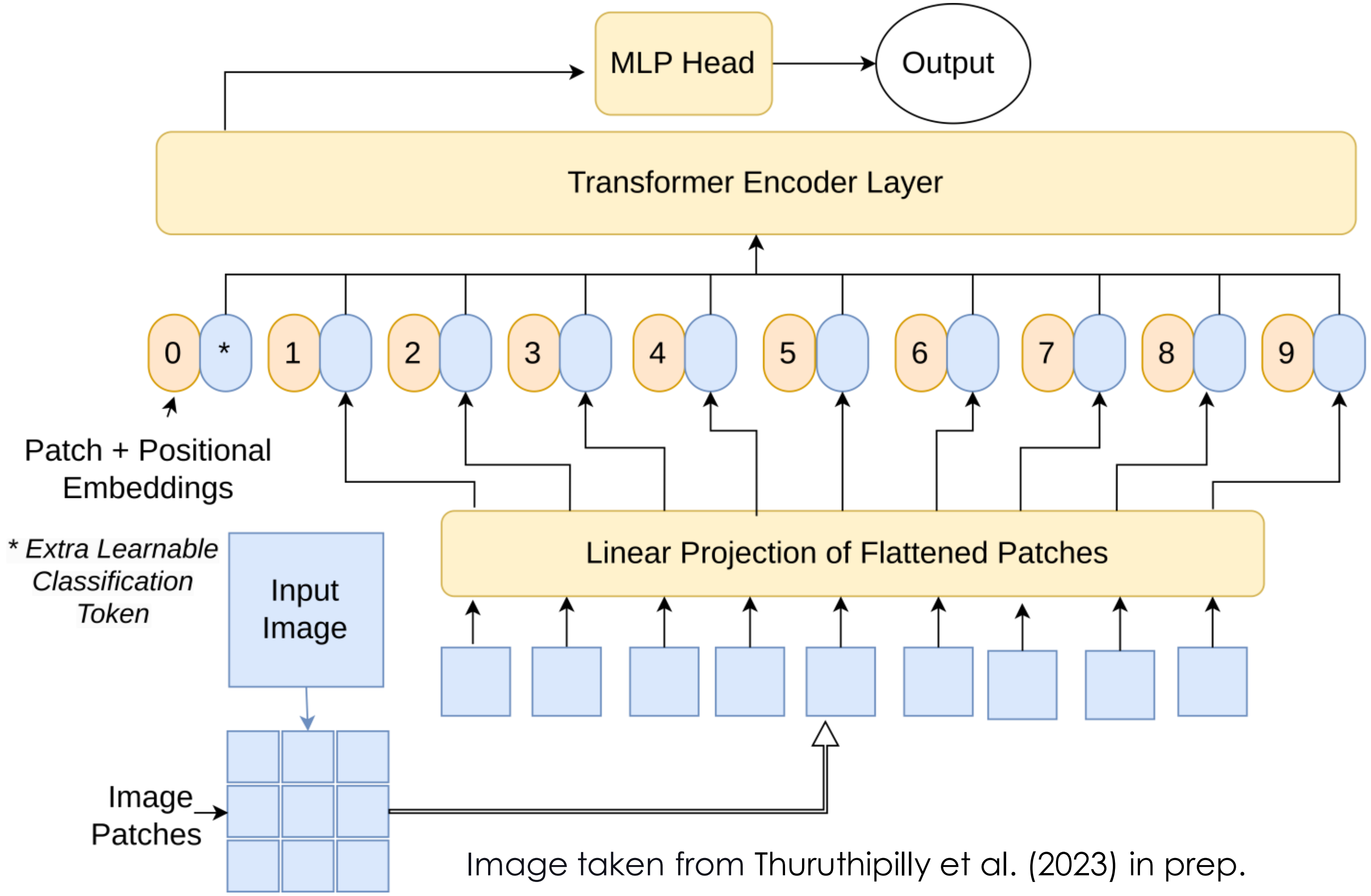


Image taken from Thuruthipilly et al. (2023) in prep.

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Ensemble Models

- Ensemble models in deep learning refer to combining multiple models to create a single model that performs better than the individual models.
- The idea behind ensemble models is to reduce the generalisation error and increase the stability of the system by taking into account multiple sources of information.

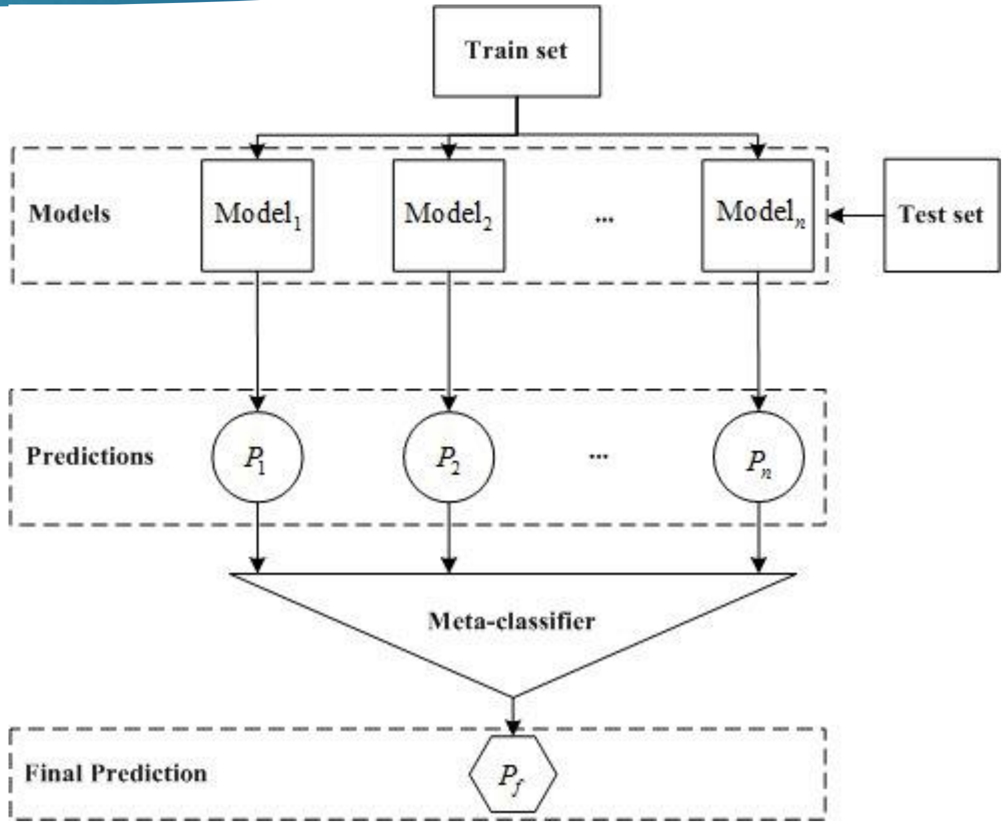
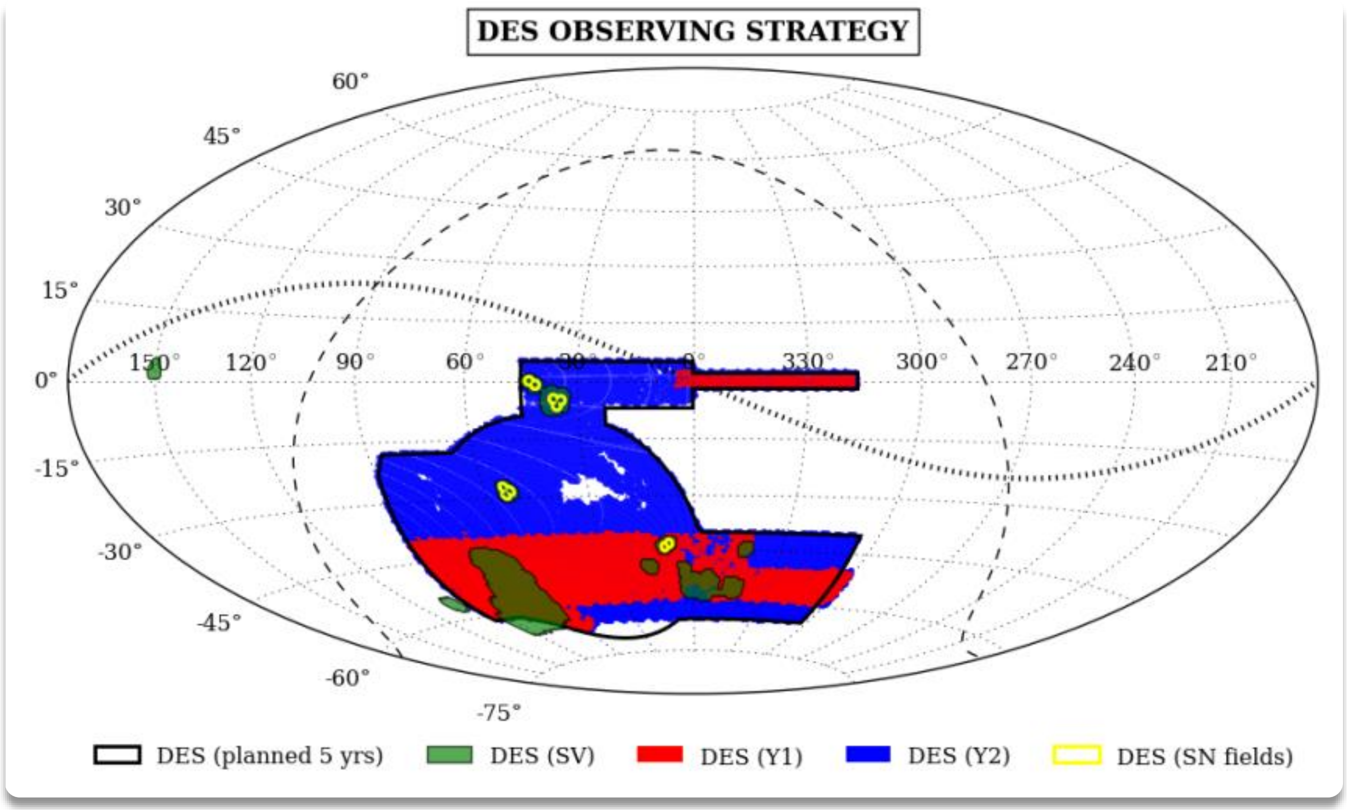


Image taken from W. Jiang et al, (IEEE Access, vol. 7, pp. 120337-120349, 2019)

Back to Astronomy from ML

Or are we ?

Dark Energy Survey



- The Dark Energy Survey (DES) is a six-year observing program (2013-2019) covering ~ 5000 deg^2 of the sky.
- The DES has observed the sky in grizY photometric bands.
- Detected around **319 million** objects.
- Tanoglidis et al. (2021) identified **23,790** LSBGs from DES.

DeepShadows

DeepShadows is a CNN created by Tanoglidis et al. (2021b) to separate between LSBGs and artefacts.

DeepShadows achieved TP = **94**% and an accuracy **92**%.

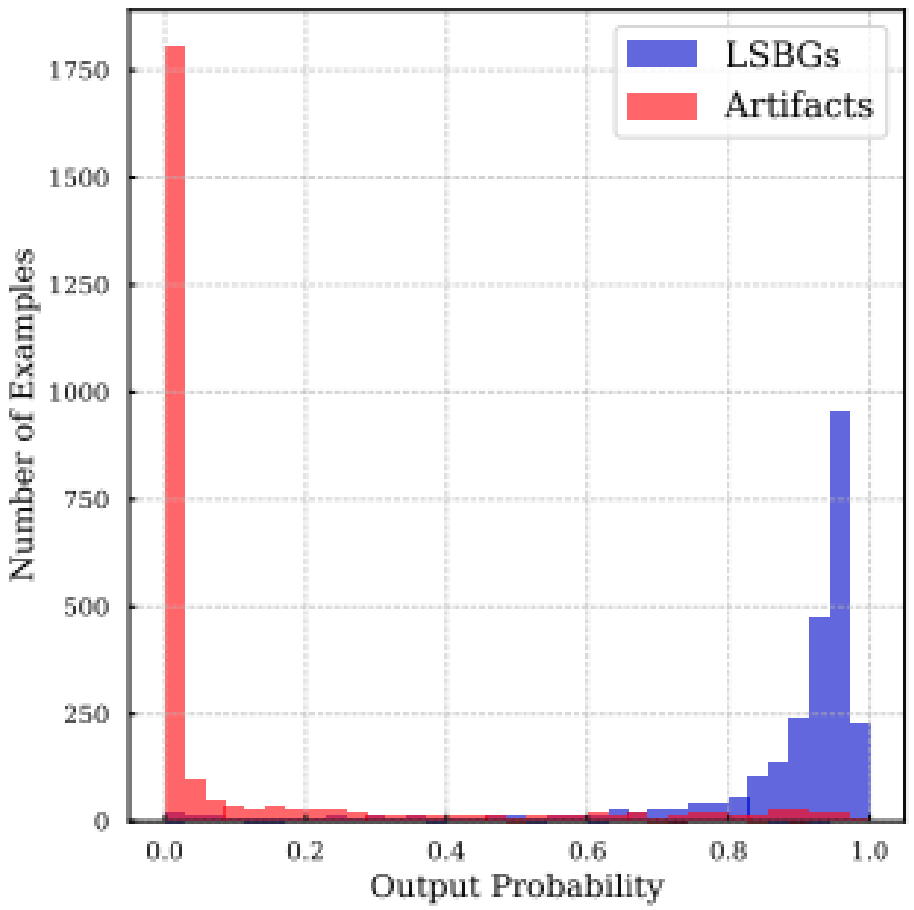


Figure 5: Output probabilities from the *DeepShadows* CNN for the LSBGs and artifacts in the test set.

Image taken from Tanoglidis et al. (2021b)

LSBG Detection 2.0

Thuruthipilly et al (2023) submitted in collaboration for reviewing.

Results on Labelled Dataset - I

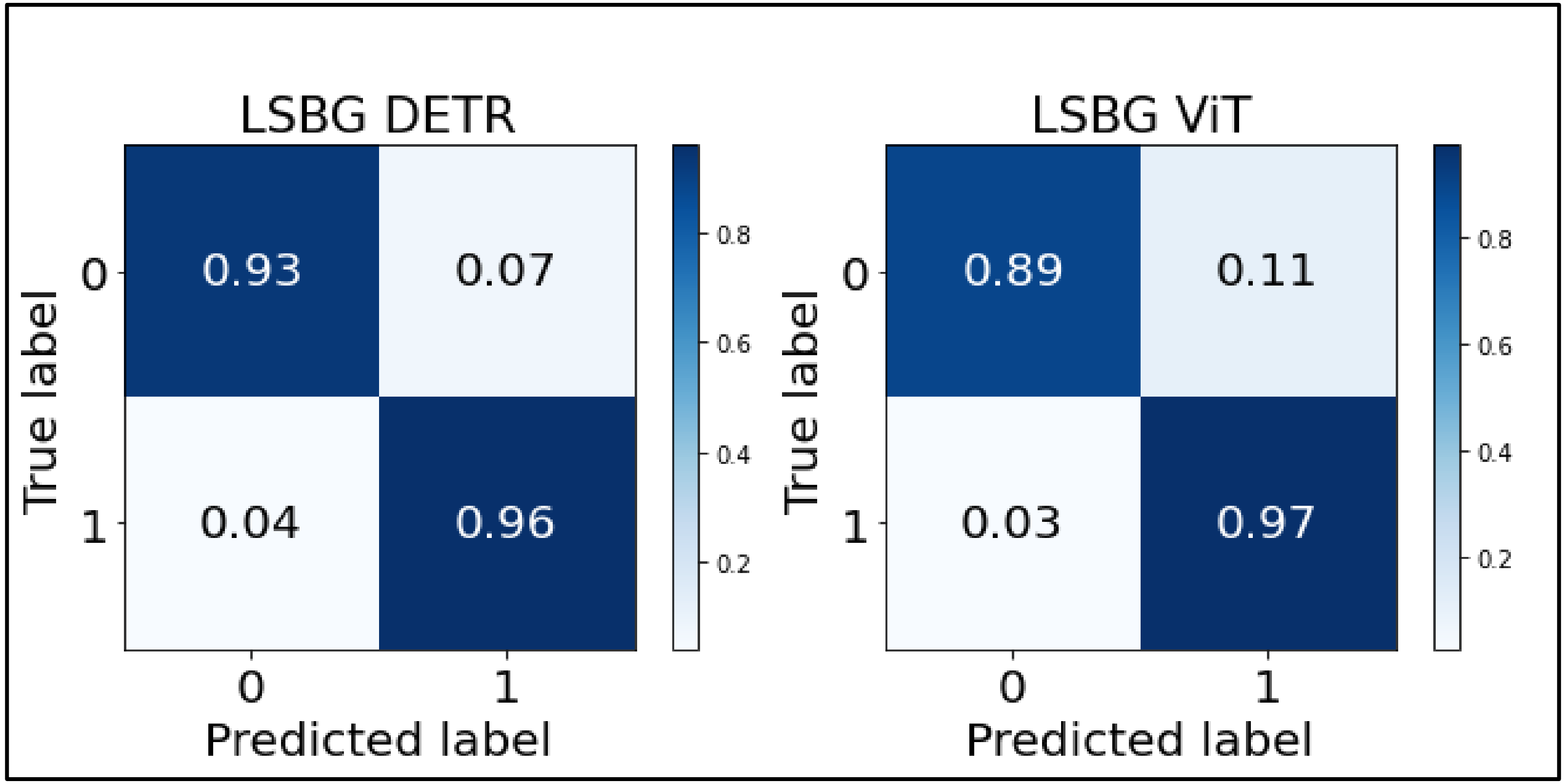
Model name	Accuracy (%)
LSBG VISION 1	93.55
LSBG VISION 2	93.79
LSBG VISION 3	93.47
LSBG VISION 4	93.51
LSBG VISION Ensemble	**93.75**
LSBG DETR 1	94.36
LSBG DETR 2	94.28
LSBG DETR 3	94.36
LSBG DETR 4	94.24
LSBG DETR Ensemble	**94.60**

Accuracy of DeepShadows CNN = **92.00%**

+2.5 % accuracy for LSST means ≈

- +**2,000** additional LSBGs (CNN).
- +**8,000** additional LSBGs (non-computer vision).
- -**4,000** artefacts during visual inspection (CNN).
- -**50,000** artefacts during visual inspection (non-computer vision).

Results on Labelled Dataset - II



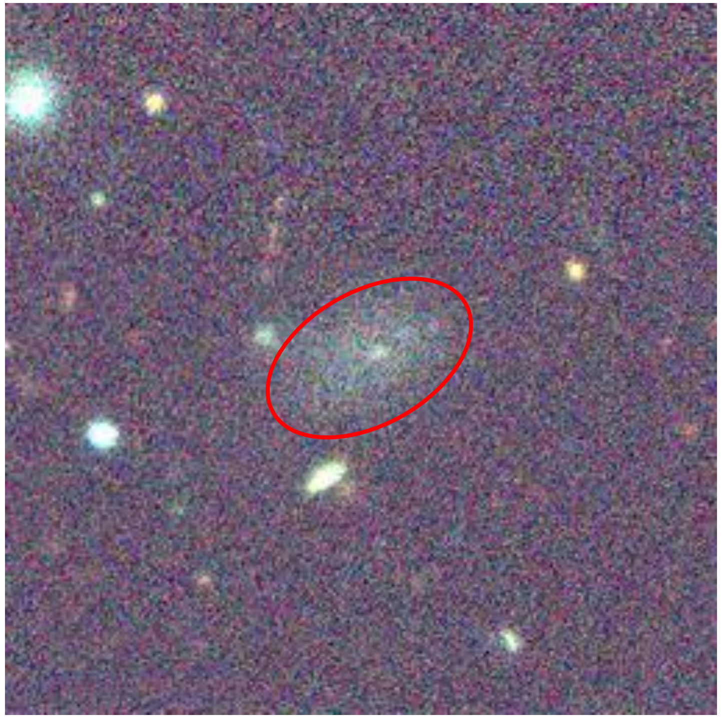
Transformer Models

False Negatives of Transformers

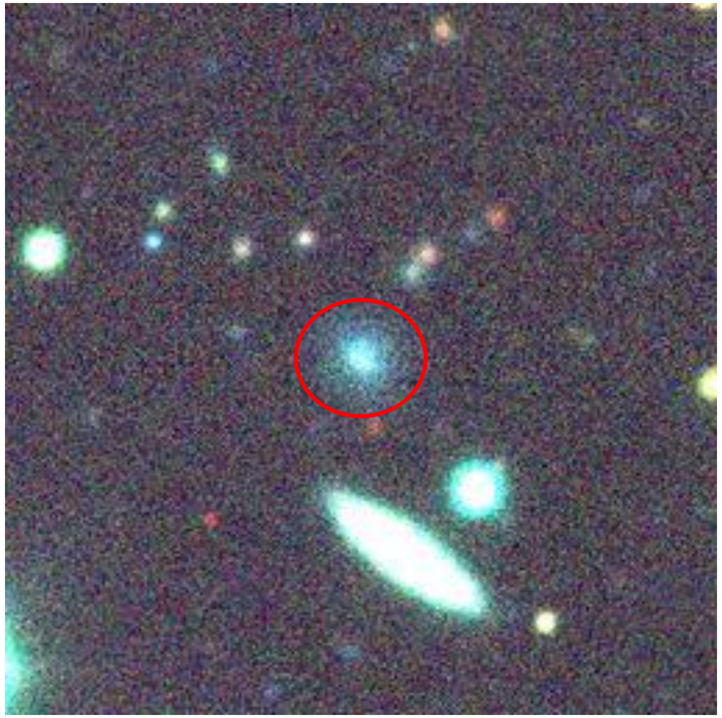
Presence of a bright artefact nearby

Too faint to be observed

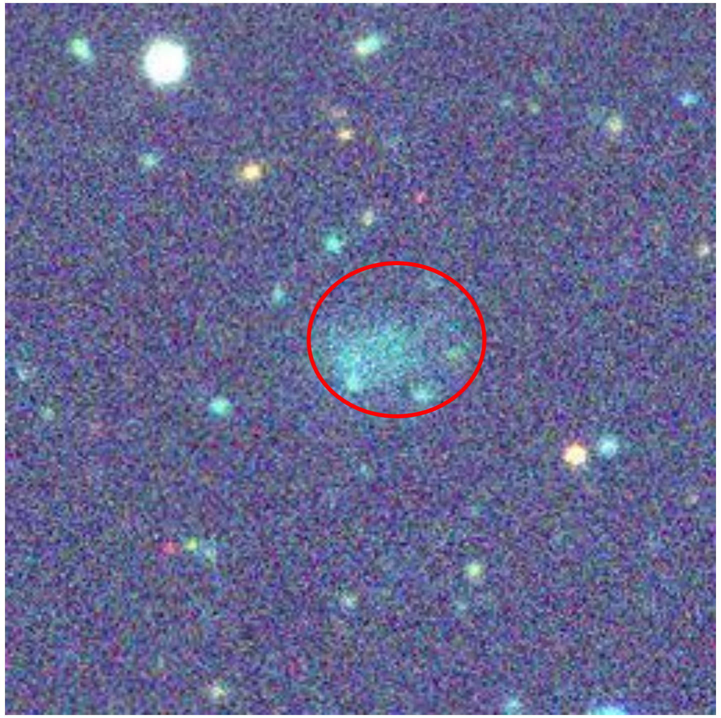
False Positives of Transformers



Difficult to classify

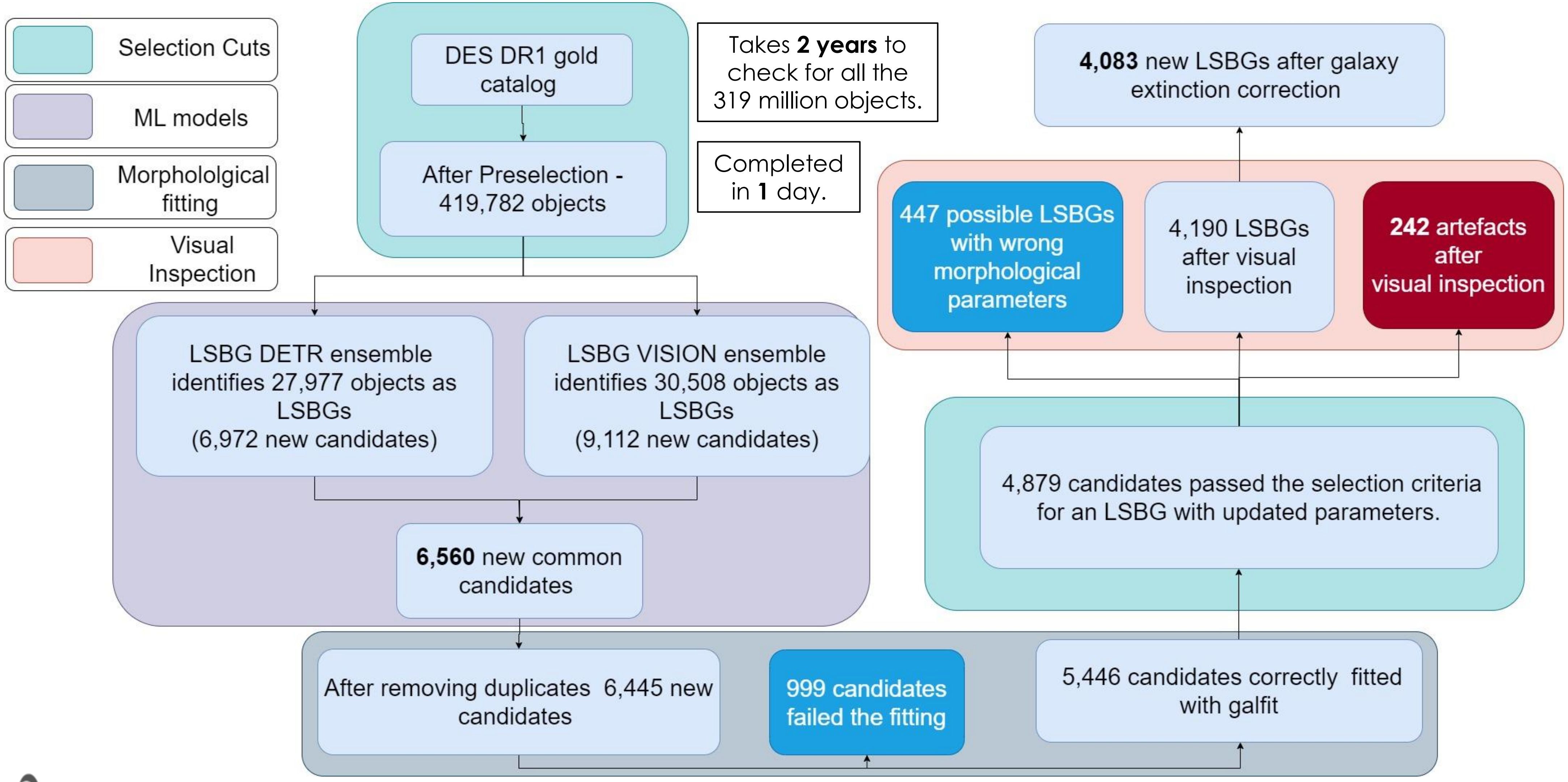


Mislabelled LSBG



Blended objects

Search for New LSBGs from DES DR1

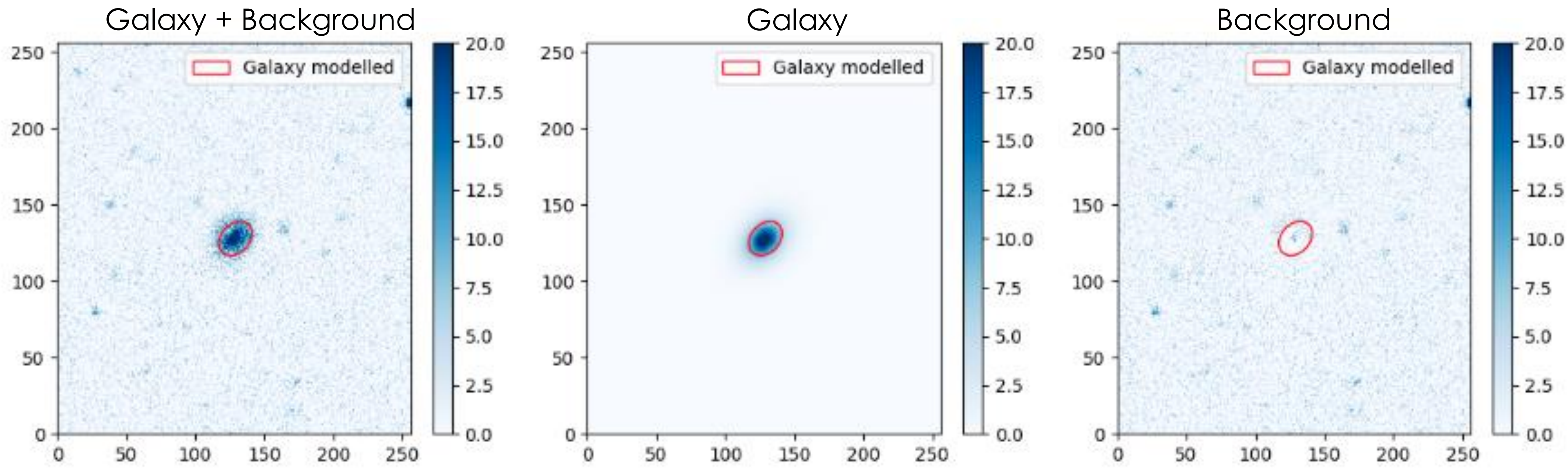


4% artefacts

~ **5,000** artefacts in LSST with Transformers.

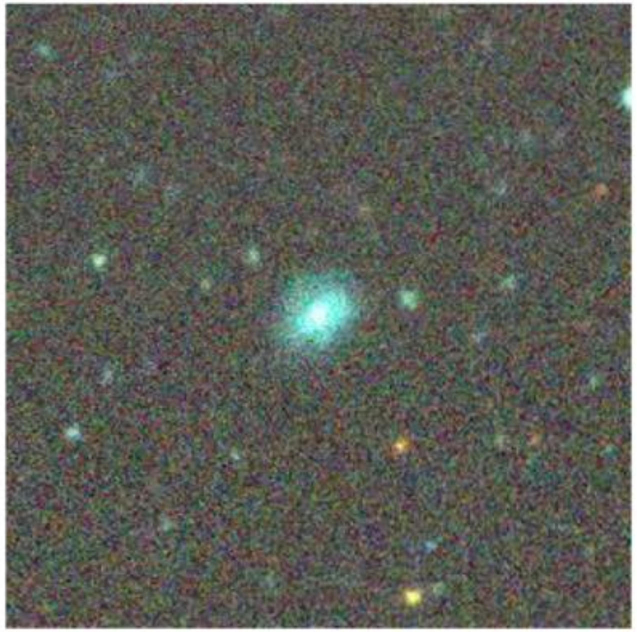
~ **9,000** artefacts in LSST with CNNs.

~ **55,000** artefacts in LSST with traditional methods.



Enter score, -1 for failed fitting, 0 for non-LSBS, 1 for LSBS and s to stop

RGB



DESI

Visual Inspection

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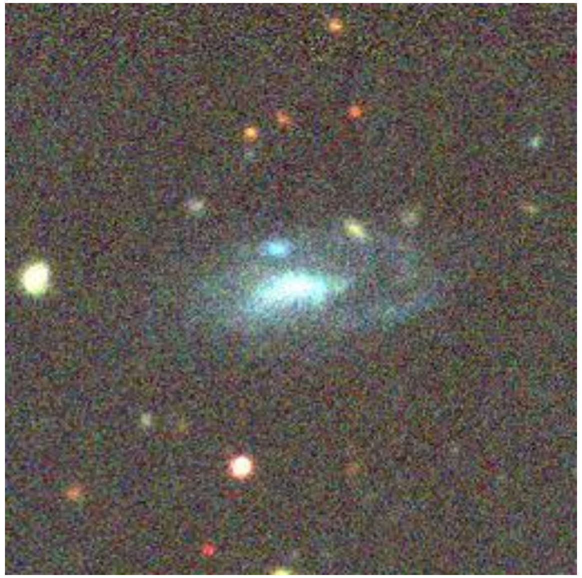
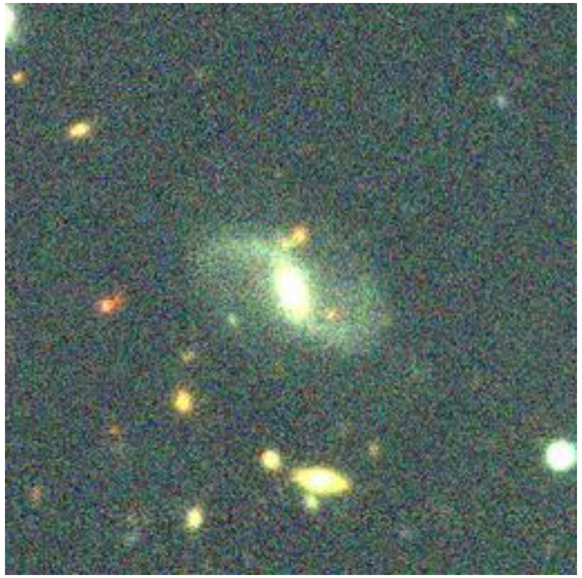
New LSBGs Identified



Coadd Object ID : 70739980



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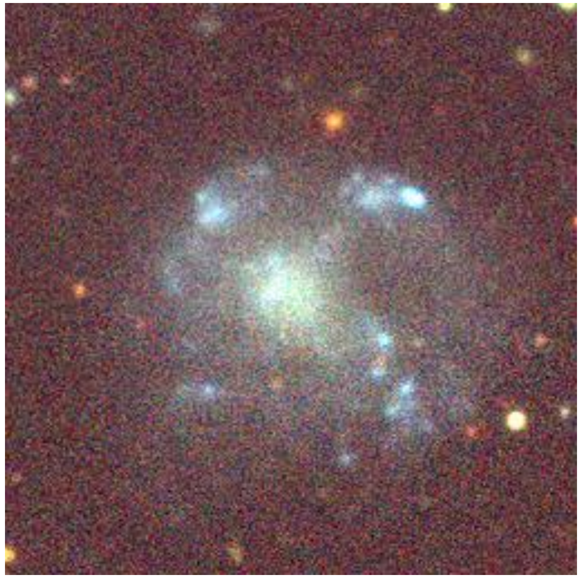

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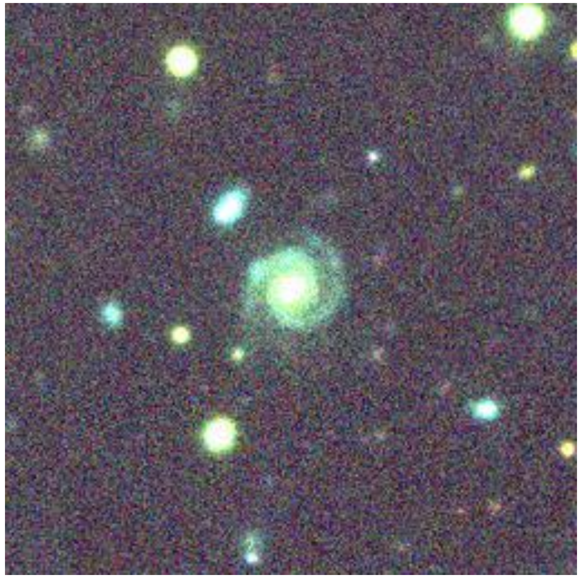

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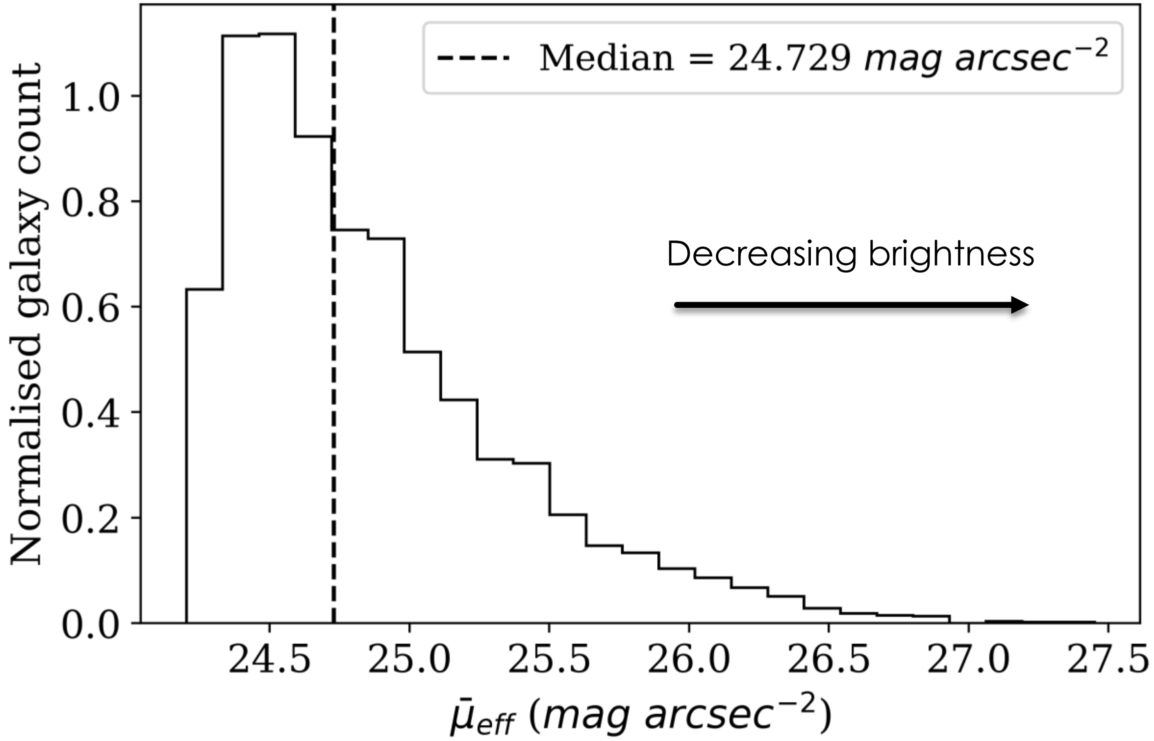
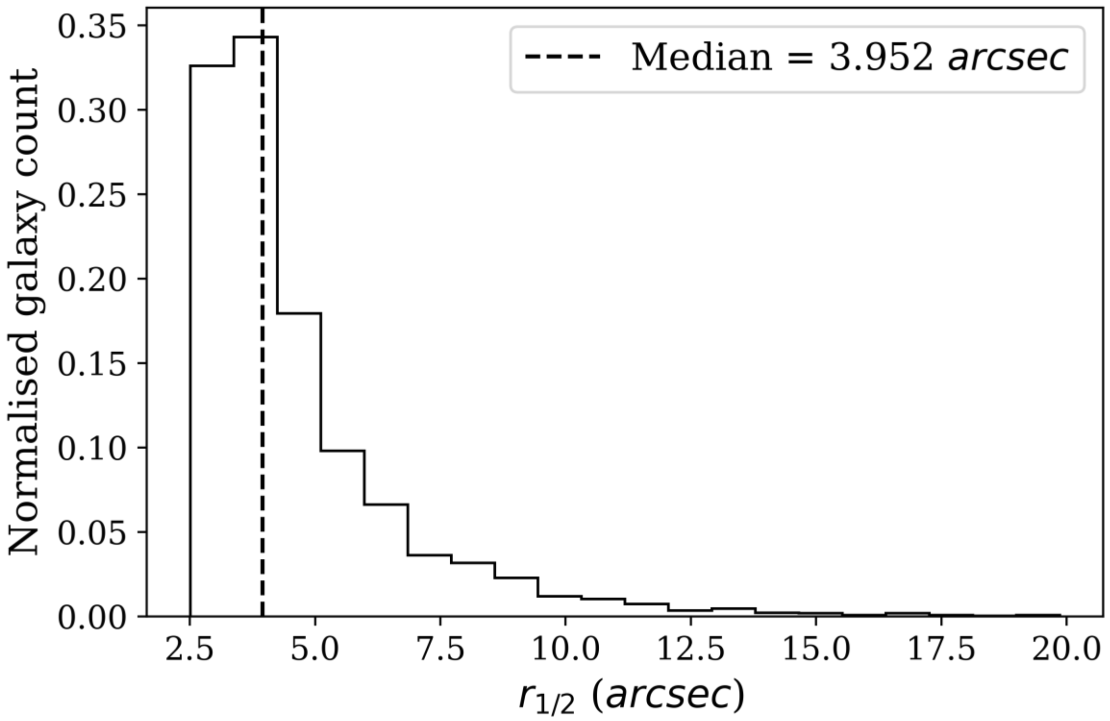
Properties of New LSBGs - I



Mean Surface brightness distribution



Half-light radius distribution

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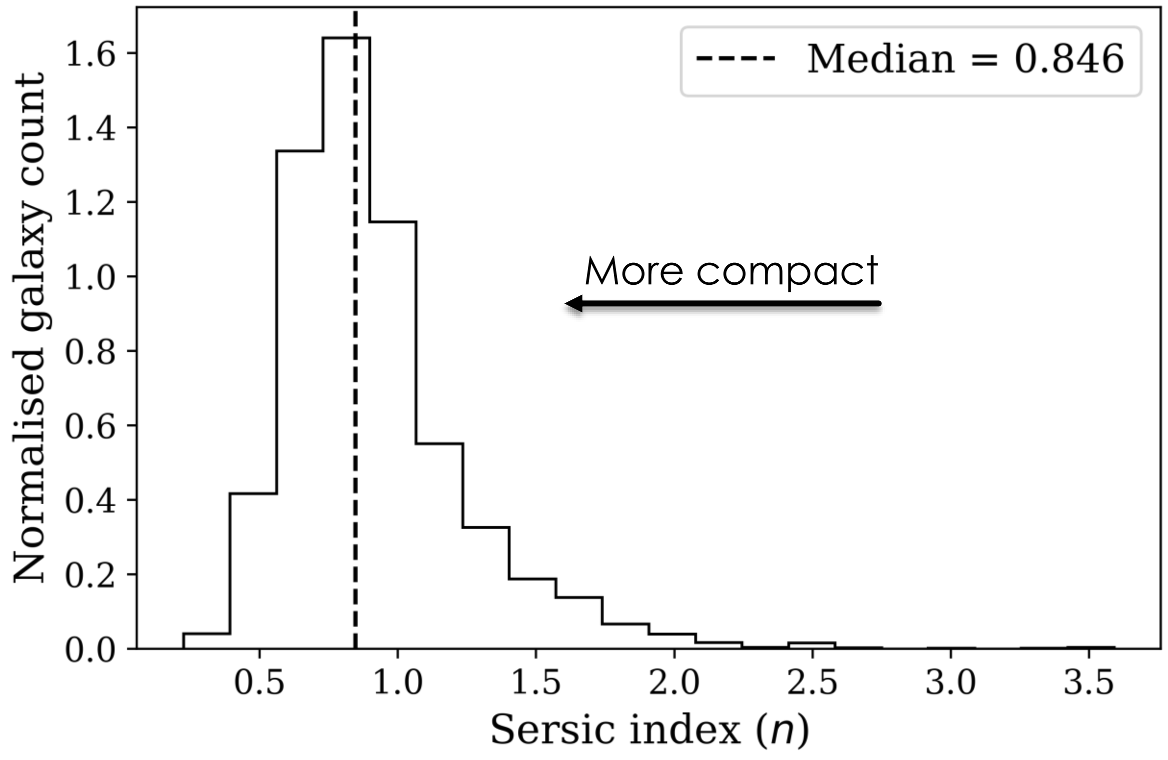
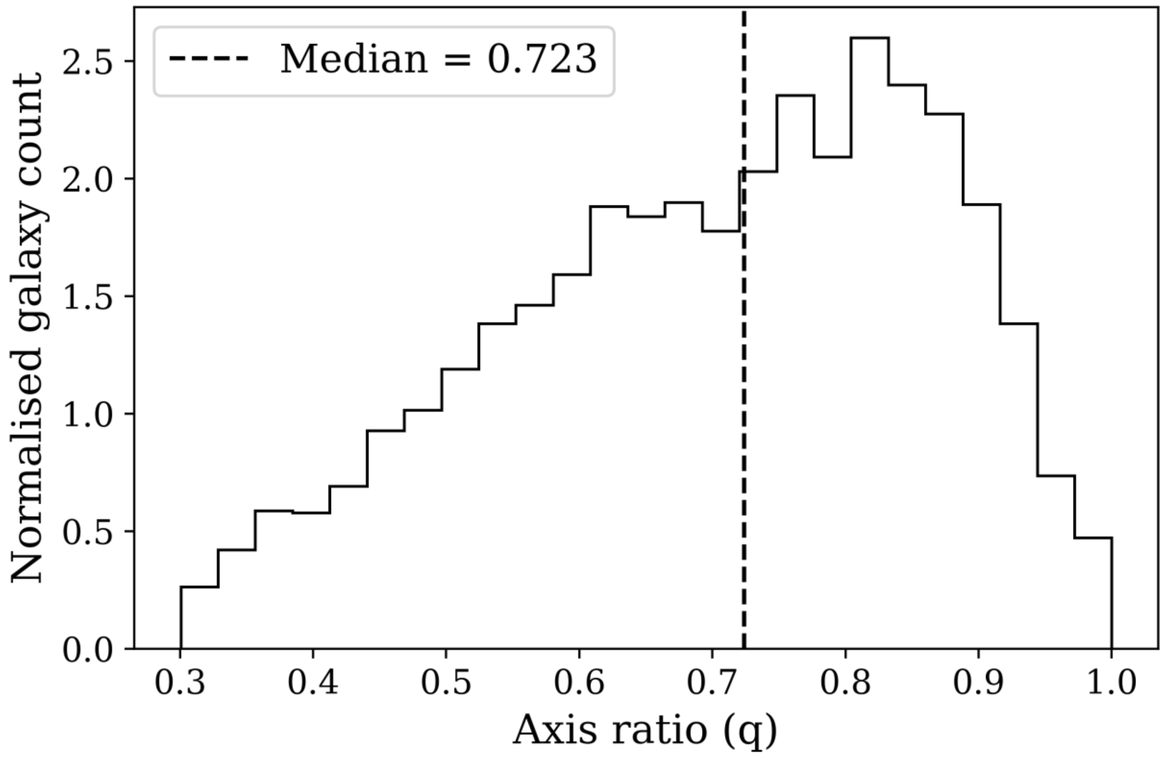
Properties of New LSBGs - II



Sersic index distribution



Axis ratio distribution

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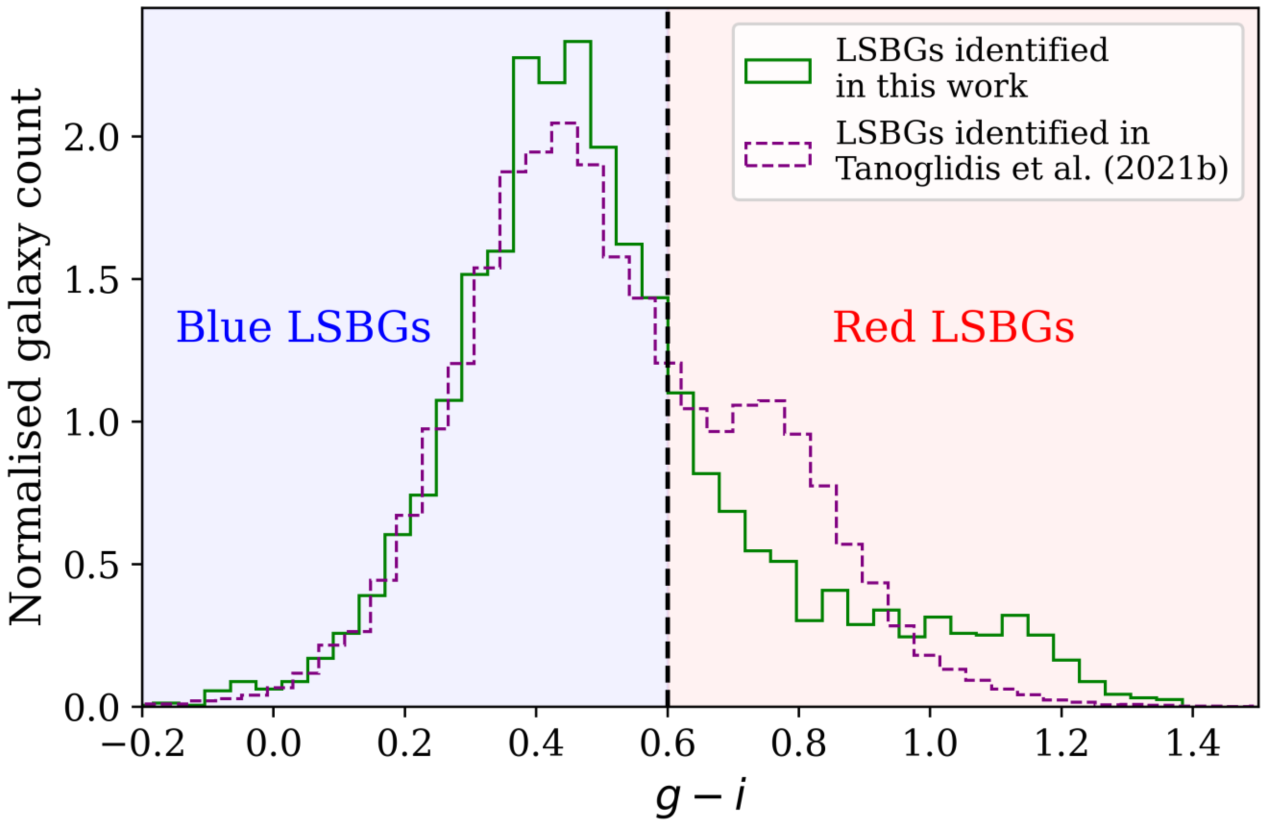
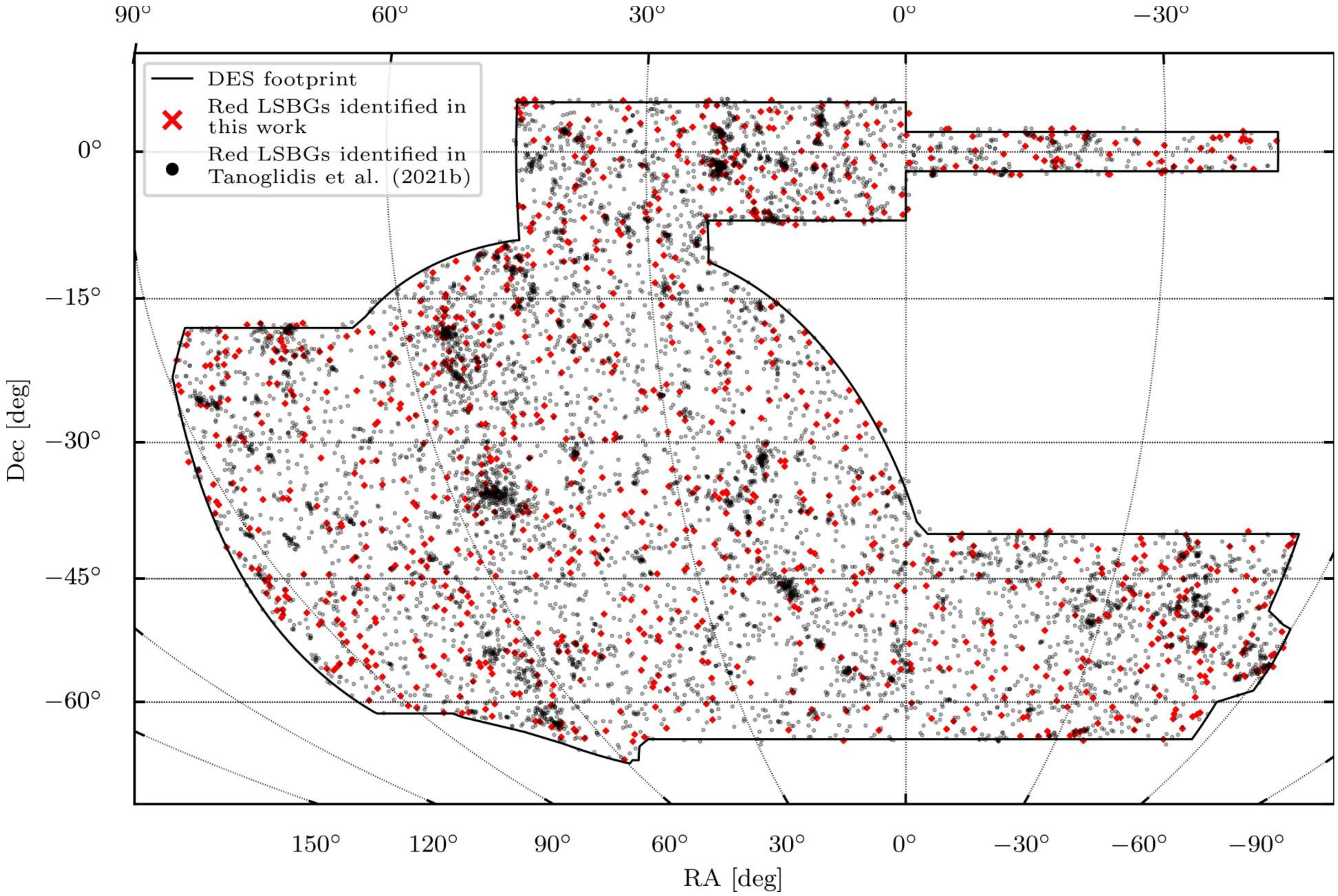
Red and Blue LSBGs

- Blue galaxies are generally actively forming stars and are so named because they emit more light at shorter, bluer wavelengths, which is a hallmark of young, hot stars.

- Red galaxies, on the other hand, emit more light at longer, redder wavelengths, indicating red galaxies tend to have older, more evolved stars, and are therefore less active in terms of star formation.

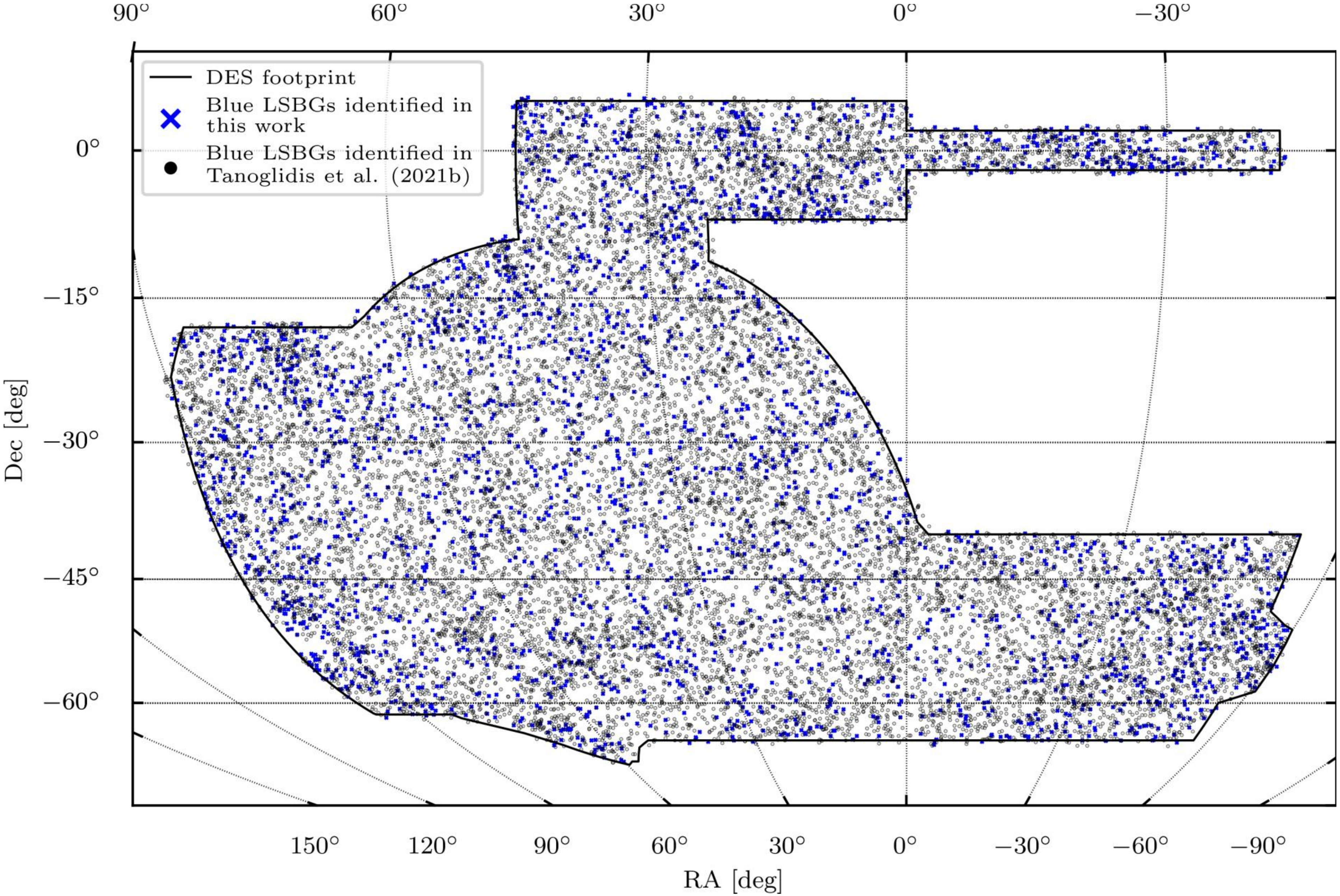


Properties of LSBGs in DES: Clustering - I



Red LSBGs

Properties of LSBGs in DES: Clustering II



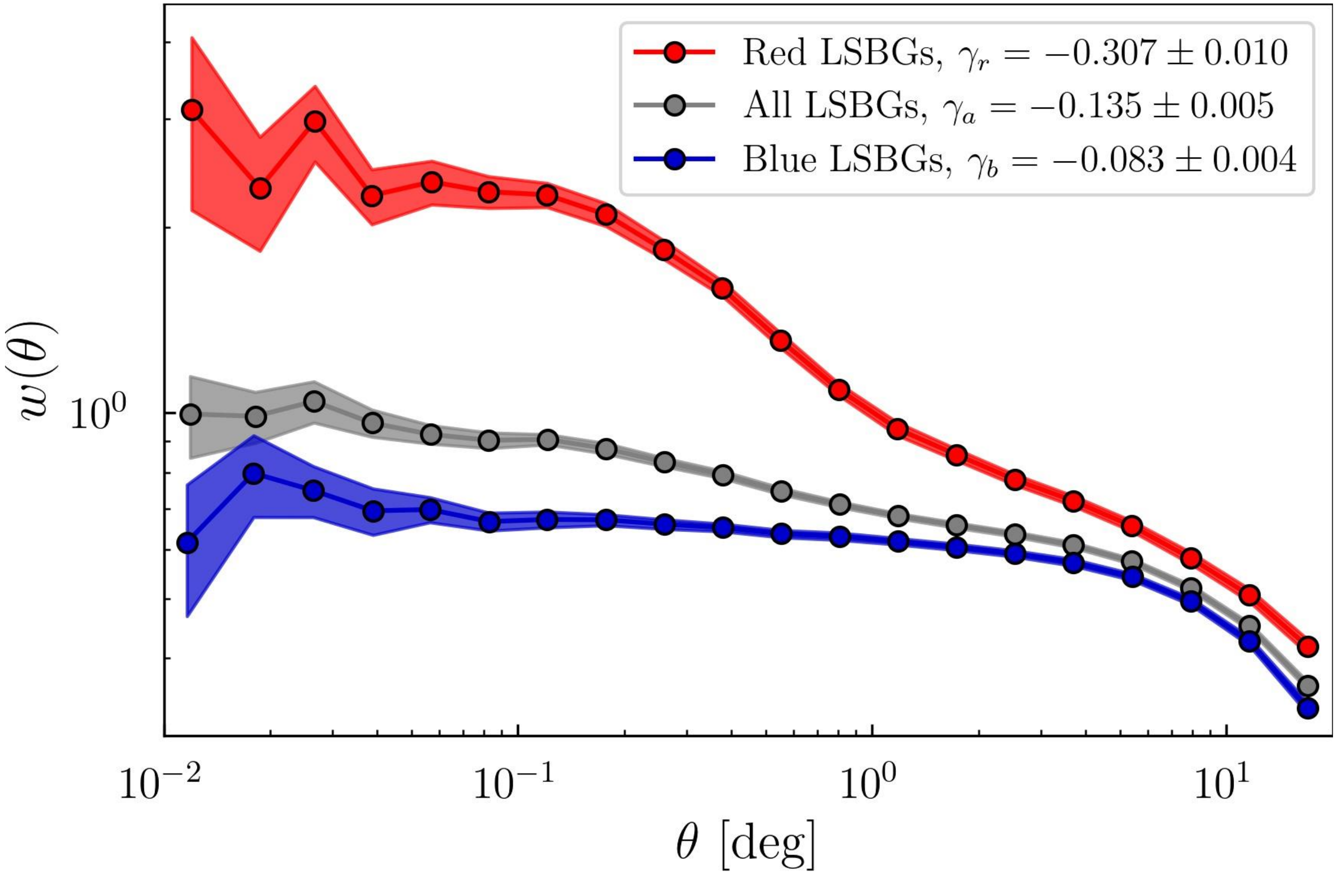
Blue LSBGs

Clustering of LSBGs

To measure the extent of we computed the angular two-point autocorrelation function, ω(θ).

Generally, the angular correlation function for galaxies follows a power-law behavior, $\omega(\theta) \propto \theta^{\gamma}$ where γ represents the strength of the clustering.

Surprisingly, there is a significant difference in the value of γ for LSBGs compared to HSBGs (-0.7 to -0.8).



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Number Density of LSBGs

Greco et al. (2018)	Tanoglidis et al. (2021)	Thuruthipilly et al. (2023)
Number density reported by Greco et al. (2018) ~ **3.9** deg^2 in HSC SSP.	Number density reported by Tanoglidis et al. (2021) ~ **4.5** deg^2 in DES DR1.	New number density ~ **4.9** deg^2 (expected to increase more.)

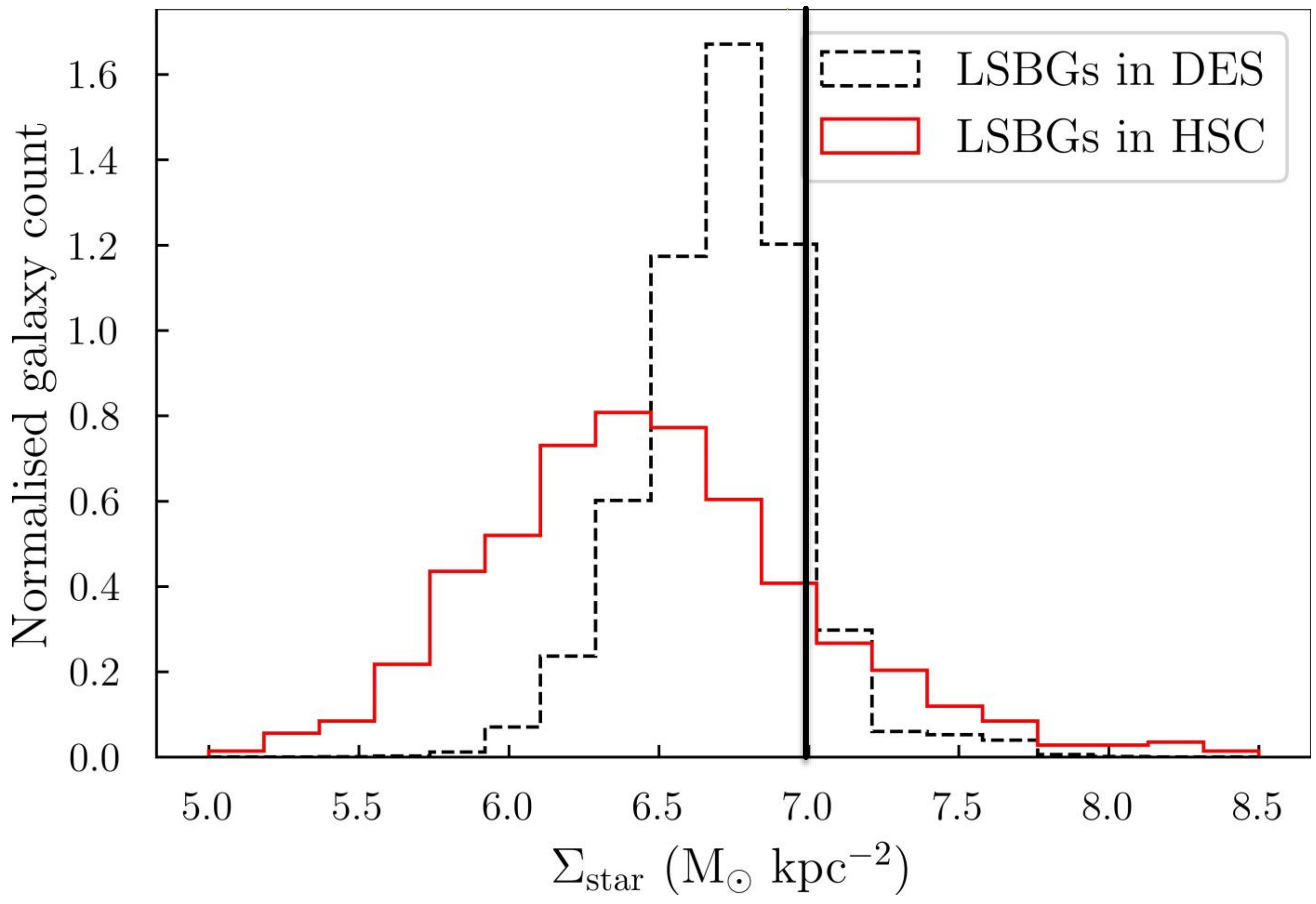
Total Sky area is 41,253 degree^2 and increase in 0.4 in number density ~ +16500 LSBGs. Making LSBGs a potential candidate for the missing baryon problem.

What is an LSBG ?

Definitions of an LSBGs are based on the surface brightness magnitudes, which is an observation-dependent quantity leading to discrepancies.

One possible solution is to define an LSBG based on the stellar mass density of the galaxy*.

$$\Sigma_{star} \lesssim 10^7\ M_\odot\ kpc^{-2}$$



10 % of LSBGs from DES and 15 % of LSBGs from HSC will be eliminated with the new definition.

(*Carleton et al. 2023)

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Methodology

Future ?

Bonus Sample of 3913 candidates remains + 1260 candidates needed to be refitted.

Number density ~ **6** deg^2 forecasting around **120,000** new LSBGs from LSST.

Transfer learning to HSC SSP survey to look for new LSBGs in different part of the sky.

Search for LSBGs in DES DR2.

Problems ?

Visual Inspection impossible for confirmation.

Solutions ?

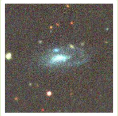
- Crowd Science for confirmation.
- Accept a small number of FP in the data.

Scientific Perspective

- H1 spectroscopic follow up of the identified LSBGs to estimate redshift.
- Analyze the clustering of LSBGs and its difference with HSBGs.
- Spectroscopic follow up of LSBG clusters without any nearby massive counterparts.
- **Definition** of an LSBG based on better statistics.

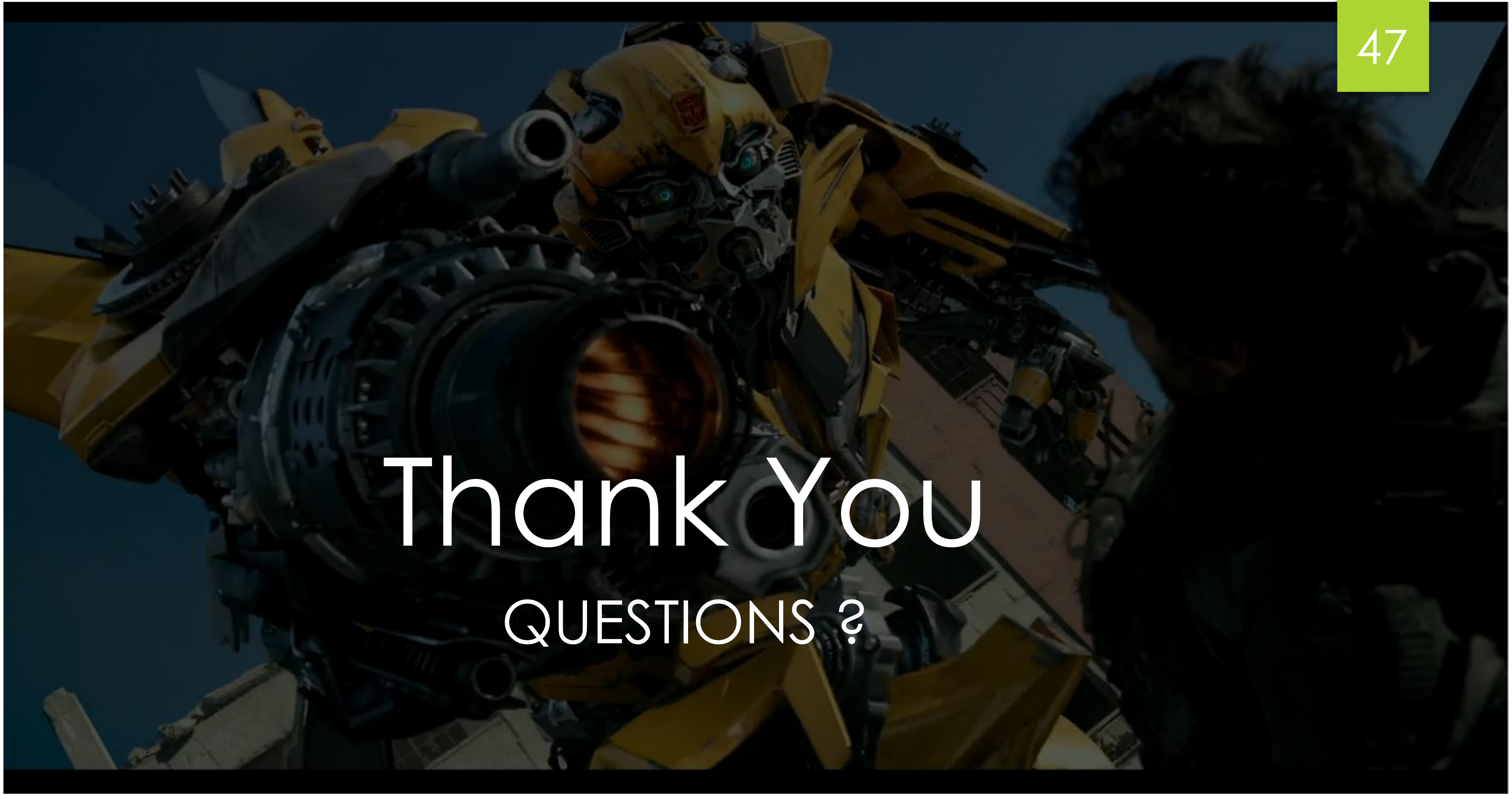
Summary

Transformer models can effectively identify LSBs from the current and the upcoming large scale surveys.



We have identified 4083 new LSBGs from DES DR1 increasing the numbers of LSBGs in DES by ~17%.

Increased number density of LSBGs to 5.5 per deg^2



Thank You

QUESTIONS ?

Back UP

Completeness of Survey

- The LSBGs found are local since the value of the slope ~ 0.6.
- Surveys with better completeness will increase the angular number density of the LSBGs further.