Ultra-Diffuse Galaxies study

LSBGs in the *LSST* era as a Big Data challenge.

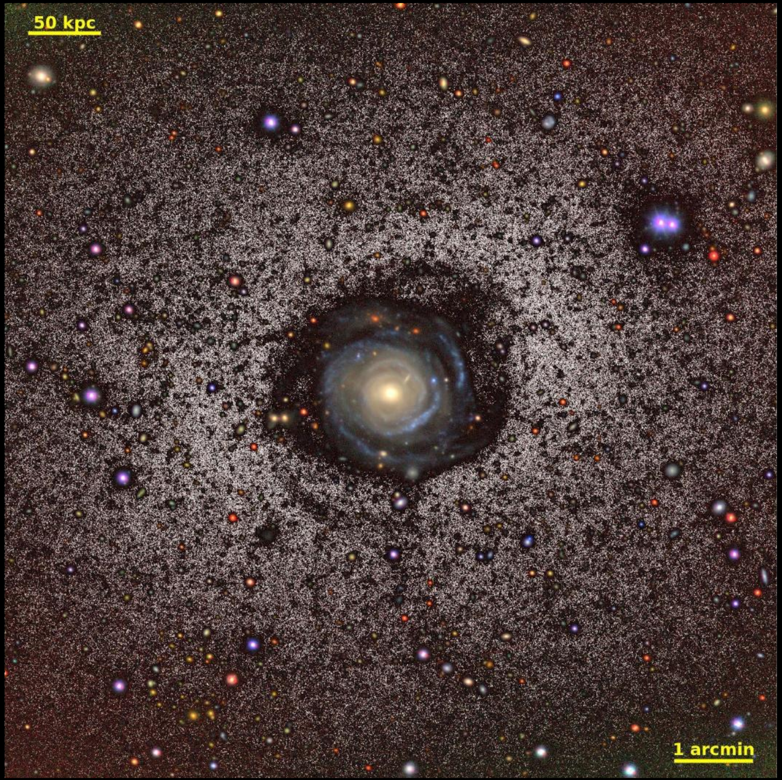
Antonio Vanzanella

Supervisors:
Kasia Malek, Junais

Outline

- Low Surface Brightness Galaxies (LSBGs).
- Ultra Diffuse Galaxies (UDGs).
- Machine Learning (ML).
- Detection of LSBGs/UDGs using ML techniques.
- Results: Spectroscopic follow-up.
- Future works.

Low-Surface Brightness Galaxies



{1}

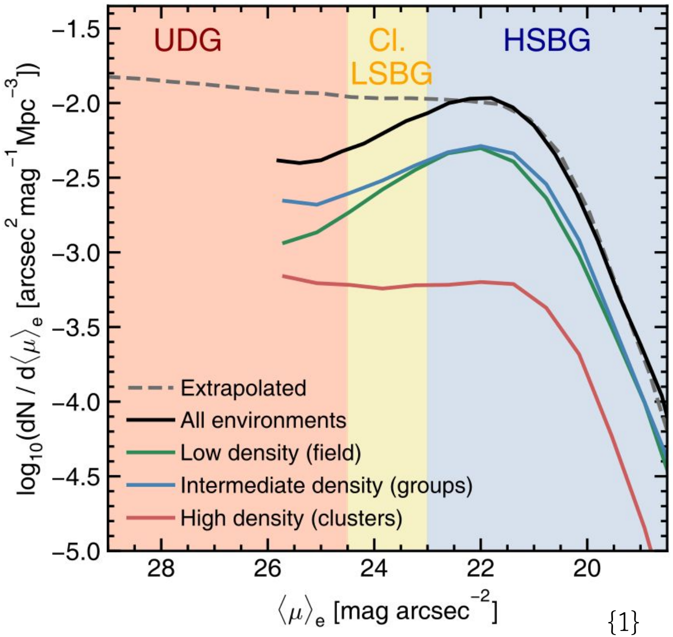
- **LSBGs** are defined as galaxies with an average r-band surface brightness($\boldsymbol{\mu}_r$) below typical level of the night sky. [1]
- $\boldsymbol{\mu}_r$ **>23 mag arcsec^{-2}.**

[1](Martin et al. 2019; Junais et al. 2023){1}(Junais et al. 2025)

Low-Surface Brightness Galaxies

LSBGs in the local universe

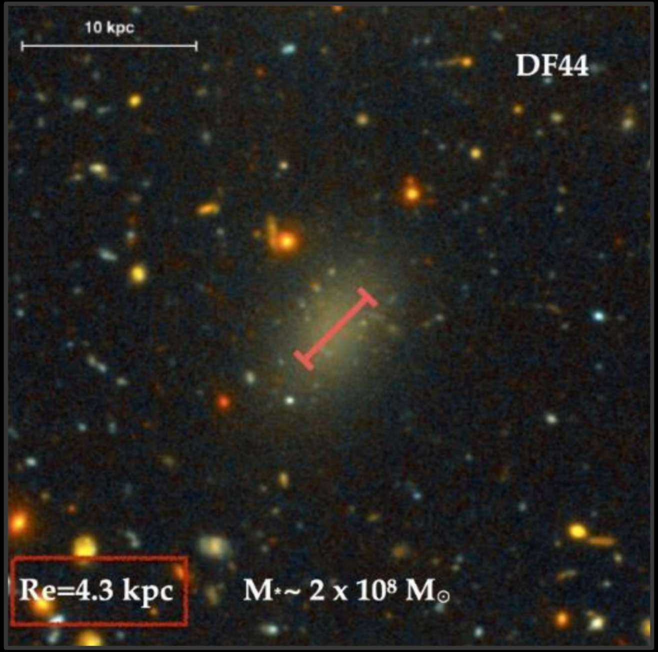
- Simulation *Horizon-AGN* for galaxies with mass 2×10M⊙.[1]
- Instrumental limits for the faint end of the luminosity distribution.
- We are missing 50% of galaxies in our local universe (20% of total mass).



{1}

[1]{1}(Martin et al. 2019)

Ultra-Diffuse Galaxies



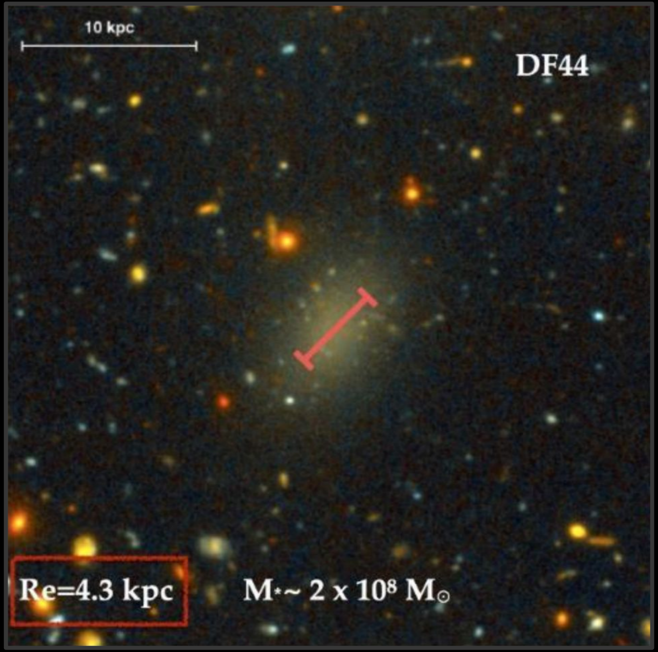
{1}

UDGs are a subclass of LSBGs presenting extended half-light radii $\mathbf{r_{1/2}}$ **>1.5 kpc** and a central surface brightness
$\boldsymbol{\mu_0}$ **> 24 mag arcsec^{-2}** in the g-band.[2]

Re or $\mathbf{r_{1/2}}$ is the radius of the circular aperture that encloses half of the total luminosity of an object.

{1}(Iodice, seminar)[2](van Dokkum et al. 2015)

Ultra-Diffuse Galaxies - Formation

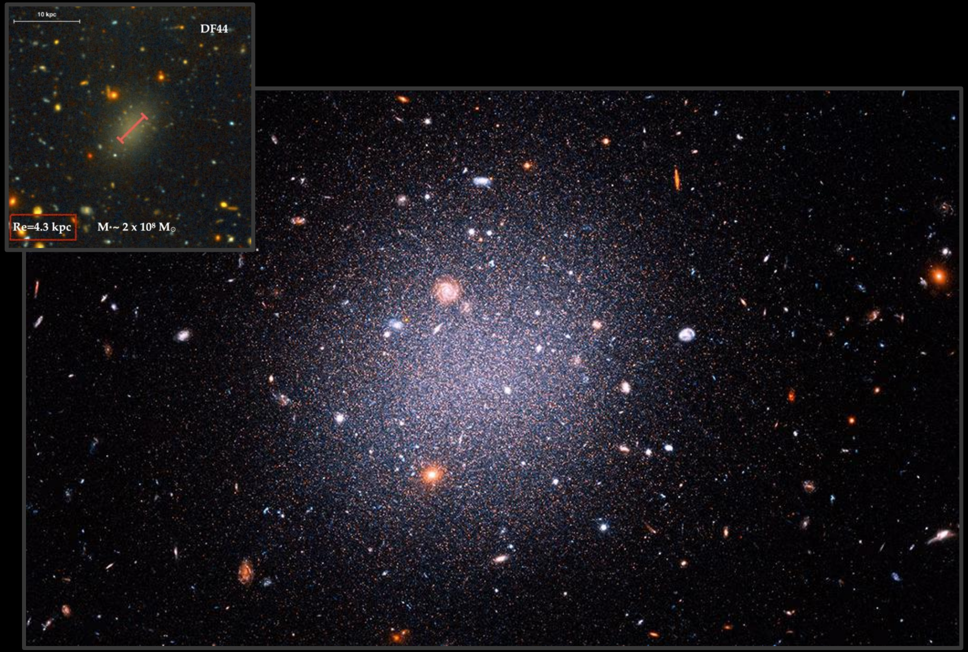


Failed Milky Ways-like Galaxies

- Massive dark matter halos ($\sim 10^{12}\ M_\odot$).[1]
- Early quenced, feedback or environmental effects prevented them from forming many stars.

[1](van Dokkum et al. 2015)

Ultra-Diffuse Galaxies - Formation



{1}

Puffed-up Dwarfs

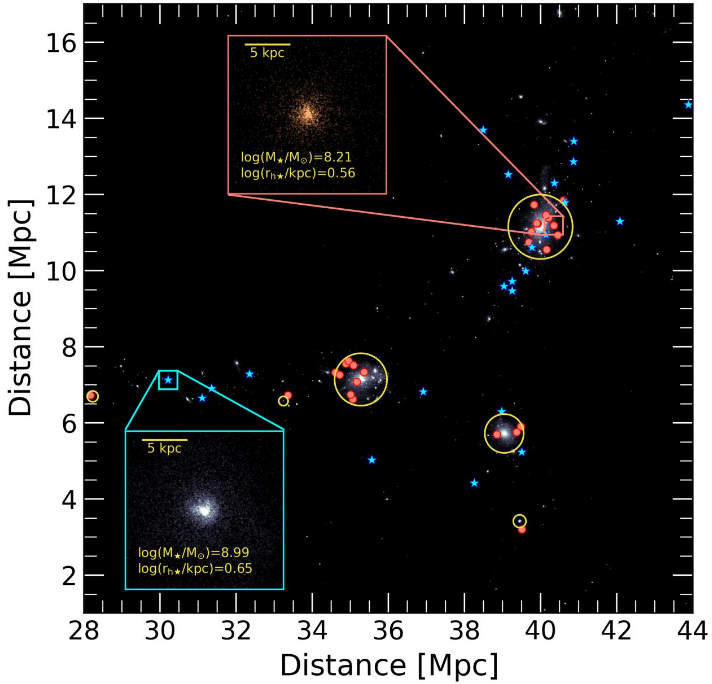
- Dwarf galaxies become extended.
- High angular momentum.
- Supernova feedback or gas outflows caused stars and gas to migrate outward.
- **Low mass dark matter halos.**
- Can exist in several environments.

[1](Yozin & Bekki 2015){1}(Image: NASA, ESA, STScI,Zili Shen (Yale),Pieter van Dokkum (Yale) , Shany Danieli (IAS). Image processing: Alyssa Pagan (STScI))

Ultra-Diffuse Galaxies - Environment

- High density environment.
- Low density environment.
- Instrumental bias.

{1}

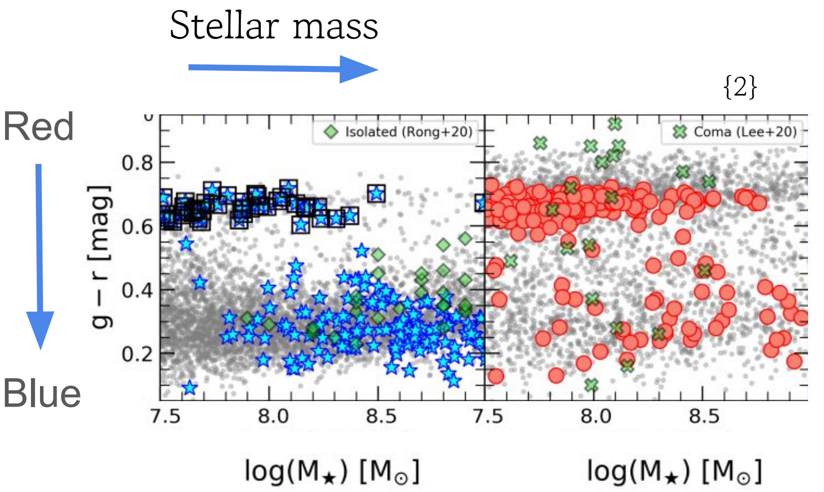


Half mass radius - rh* = 4/3 Reff

{1}(Benavides et al. 2021)

Ultra-Diffuse Galaxies - Environment

- Mostly Red UDGs, quiescent, old galaxies with a low rate of star formation.
- Mostly Blue UDGs, active, young galaxies presenting a high rate of star formation.
- Some exceptions.
  - In the field population, there is a subsample of red, old and quiescent UDGs, which were shown to be backsplash objects.[1]



[1]{2}(Benavides et al. 2021)

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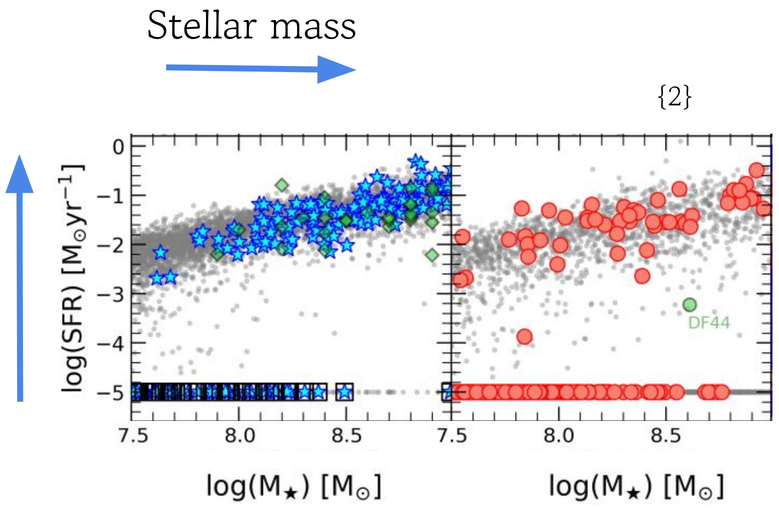

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Ultra-Diffuse Galaxies - Environment

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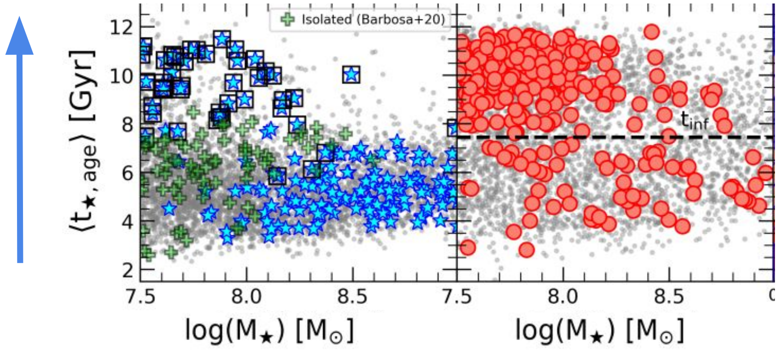
Stellar mass

{2}



[1]{2}(Benavides et al. 2021)

Ultra-Diffuse Galaxies - Formation

Main drivers of the extended sizes in UDGs

- High angular momentum.[1]
- Bursty and prolonged star formation cycles.[2]

Internal processes

[1](Amorisco & Loeb 2016) [2](Di Cintio et al. 2017)

Ultra-Diffuse Galaxies - Formation

Normal dwarf galaxy become larger and more diffuse because of:

- Tidal heating and tidal stripping.[1]
- Non-adiabatic expansion due to gas removal.[2]
- Mergers.[3]
- Stellar dimming after star formation truncation.

Externally-driven processes

[1](Jiang et al. 2019)[2](Safarzadeh et al. 2017)[3](Wright et al. 2021)

Ultra-Diffuse Galaxies - Formation

Found in simulations:

UDG population in group and cluster-like objects consists of the infall of extended dwarfs already “born” UDGs in the field plus the addition of newly formed UDGs due to environmental effects.[1]

Combination of both

[1](Jiang et al. 2019)

Ultra-Diffuse Galaxies

UDG, why they are important:

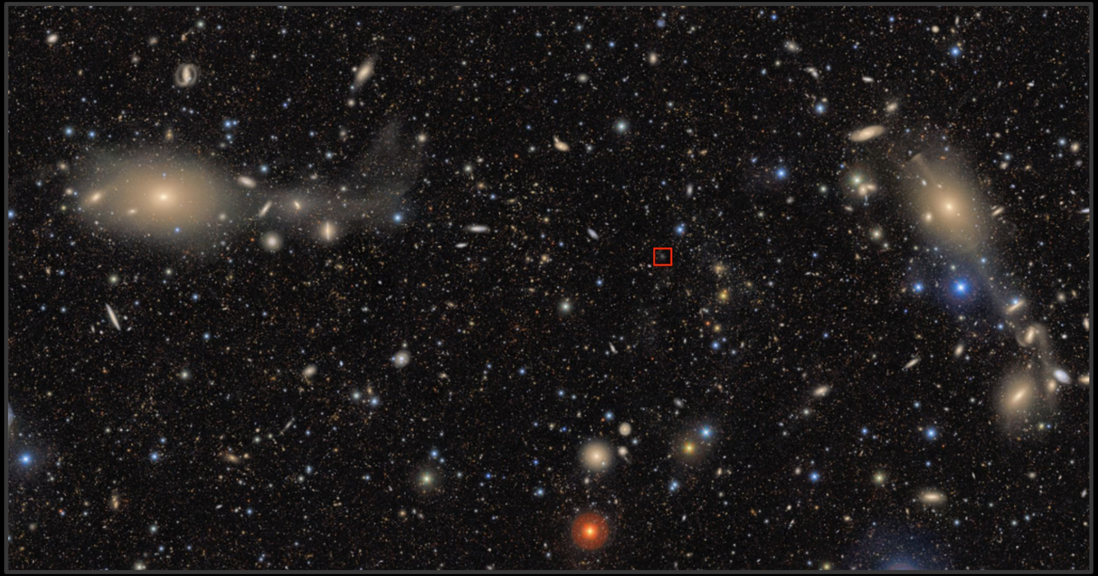
- Missing piece of our knowledge about the evolution and formation of galaxies.
- Dark matter halo formation.
- Environmental Effects.
  - Quenching timescale.

Detection of LSBG/UDGs

{1}

{1}Vera C. Rubin Observatory LSST, Virgo cluster image.

Detection of LSBG/UDGs

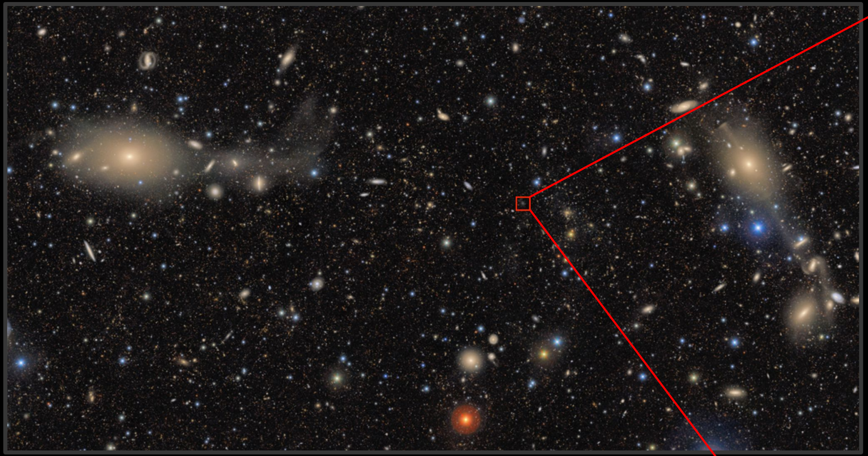


{1}

UDG (VCC 487)

{1}Vera C. Rubin Observatory LSST, Virgo cluster image.

Detection of LSBG/UDGs



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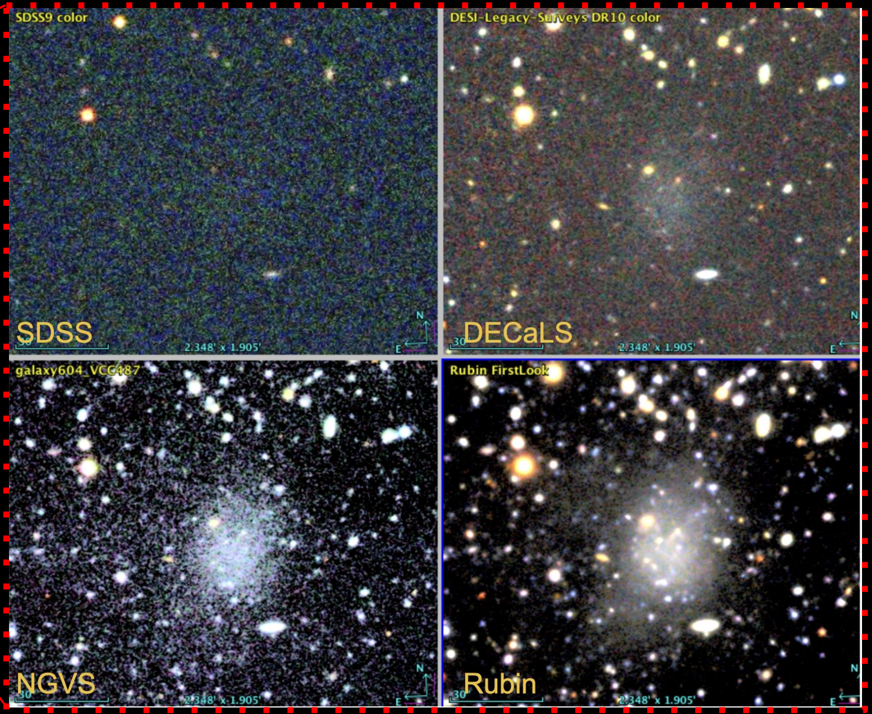
UDG (VCC 487)



{2}

{1}Vera C. Rubin Observatory LSST, Virgo cluster image. {2}(Junais et al. 2022)

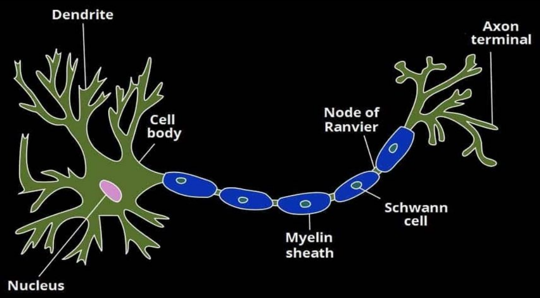
Machine Learning

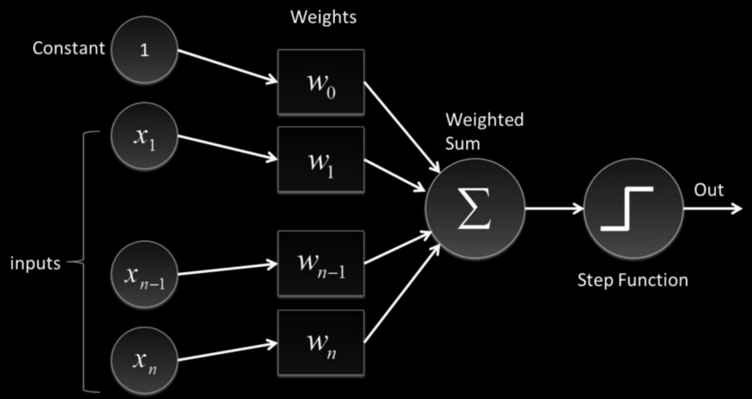
"The field of study that gives computers the ability to learn without being explicitly programmed".

A. Samuel

- Learning from Examples:
  - **Supervised**
  - Unsupervised
  - Reinforcement

Machine Learning





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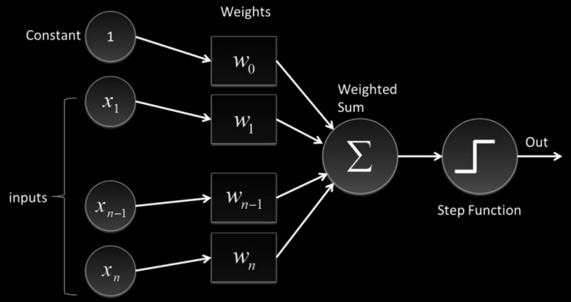
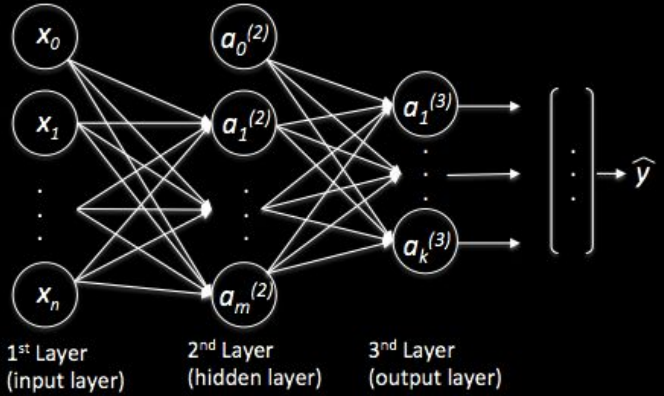
Machine Learning





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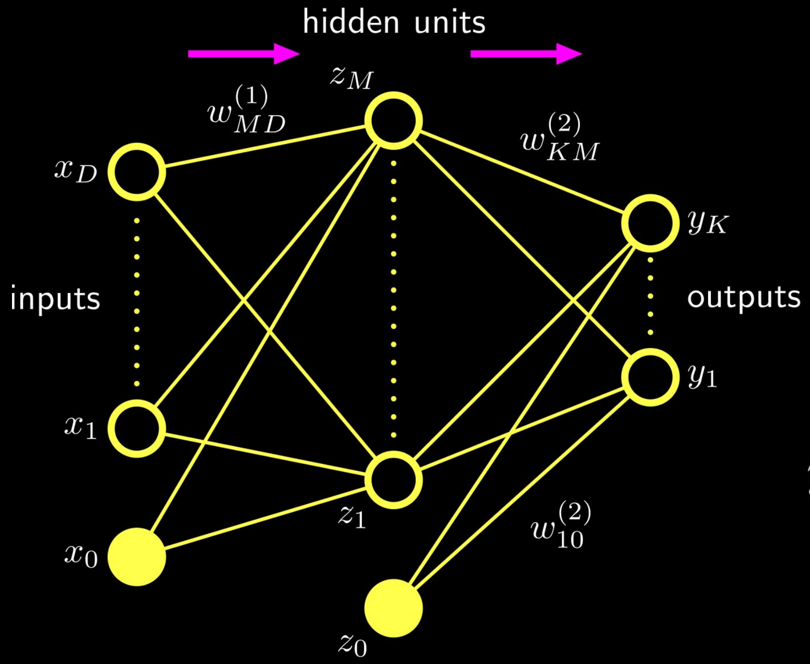
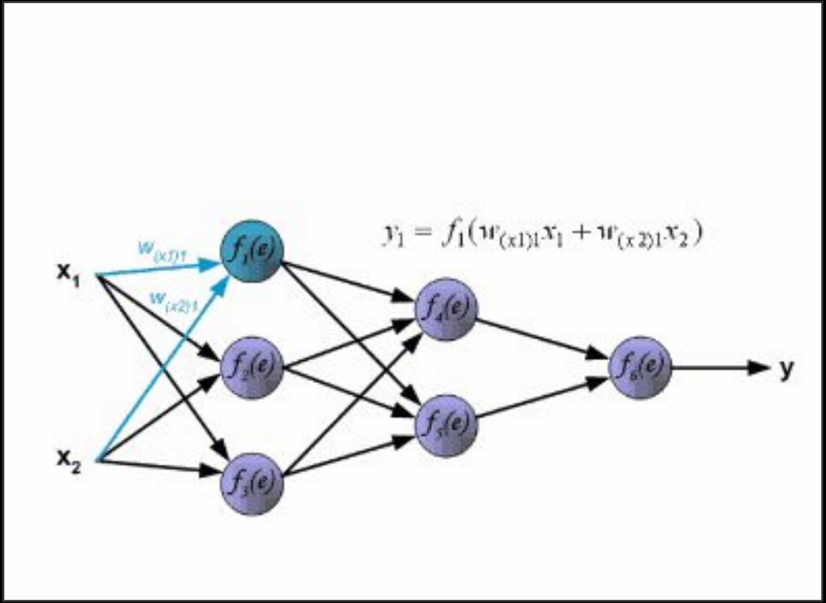


Information is forwarded through the network.

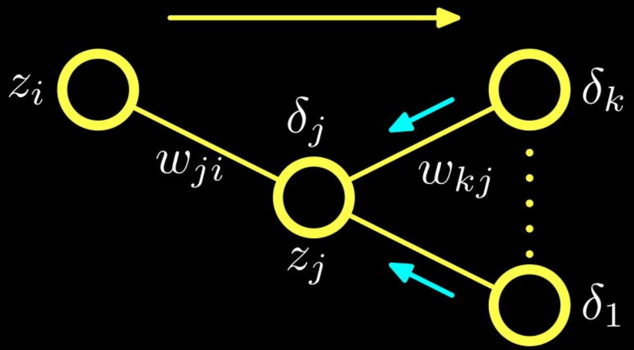
$$y_k(\mathbf{x}, \mathbf{w}) = \sigma\left(\sum_{j=0}^{M} w_{kj}^{(2)} h\left(\sum_{i=0}^{D} w_{ji}^{(1)} x_i\right)\right)$$

Images and equations from: Pattern Recognition and Machine Learning, C. Bishop, 2006.

Machine Learning



Machine Learning



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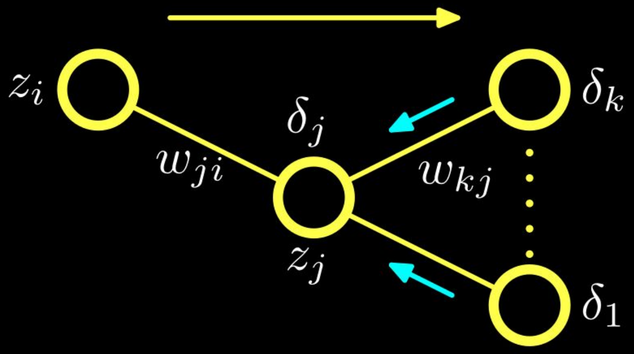
Machine Learning



$$E(\mathbf{w}) = \sum_{n=1}^{N} E_n(\mathbf{w})$$

$$y_k = \sum_i w_{ki} x_i$$

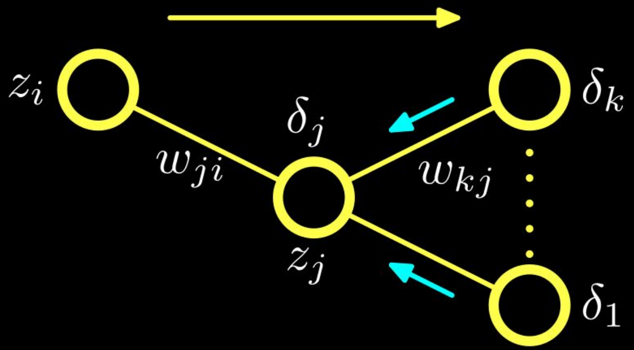
$$E_n = \frac{1}{2} \sum_k (y_{nk} - t_{nk})^2$$

$$\frac{\partial E_n}{\partial w_{ji}} = (y_{nj} - t_{nj}) x_{ni}$$

$$\delta_k = y_k - t_k$$

Images and equations from: Pattern Recognition and Machine Learning, C. Bishop, 2006.

Machine Learning



$$a_j = \sum_i w_{ji} z_i \qquad z_j = h(a_j)$$

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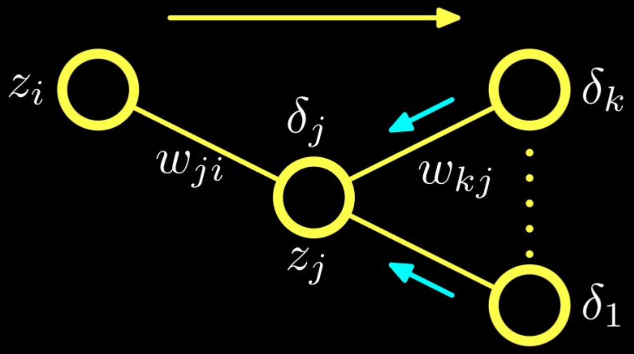
Machine Learning



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$$\frac{\partial E_n}{\partial w_{ji}} = \frac{\partial E_n}{\partial a_j} \frac{\partial a_j}{\partial w_{ji}}$$

$$\delta_j \equiv \frac{\partial E_n}{\partial a_j}$$

$$\frac{\partial a_j}{\partial w_{ji}} = z_i$$

$$\frac{\partial E_n}{\partial w_{ji}} = \delta_j z_i$$

$$\boxed{\delta_k = y_k - t_k}$$

$$\delta_j \equiv \frac{\partial E_n}{\partial a_j} = \sum_k \frac{\partial E_n}{\partial a_k} \frac{\partial a_k}{\partial a_j} \qquad \delta_j = h'(a_j) \sum_k w_{kj} \delta_k$$

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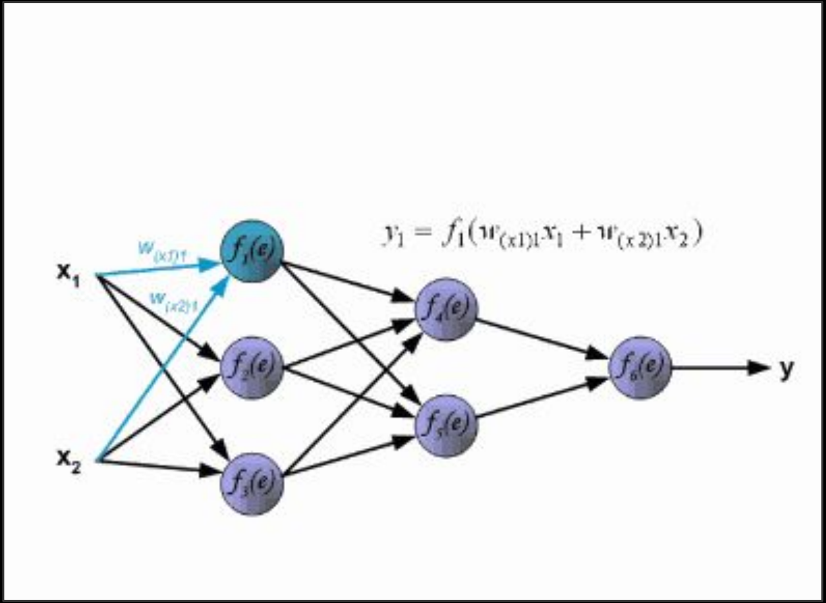
Machine Learning



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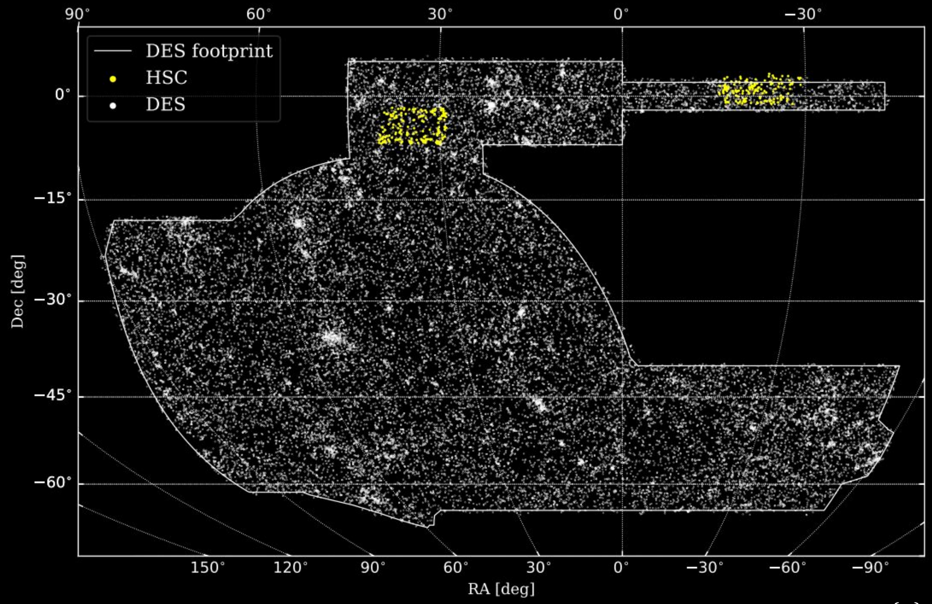


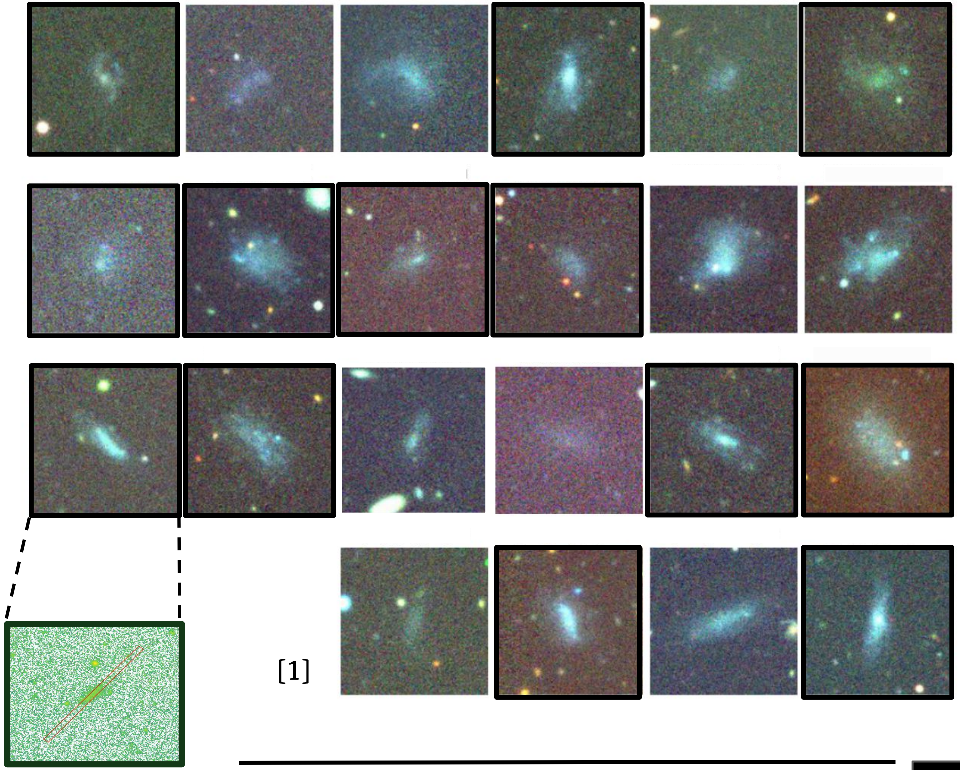
{1}

- Transformers model for classification.
- Dark Energy Survey (DES) samples.
- **Candidates**(~27.000 LSBGs/317 UDGs).[1]

[1]{1}(Thuruthipilly et al. 2024)

Results: spectroscopic follow-up

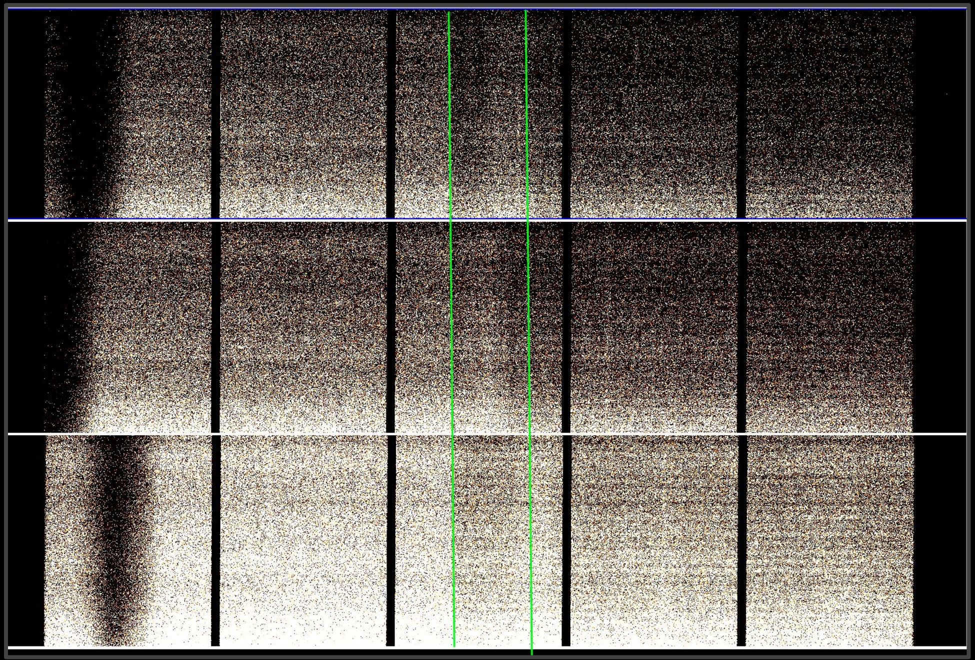
- Proposal **accepted for 22** UDG candidates, **observed** 14.
- Large Binocular Telescope Observatory(**LBT**)/The Multi-Object Double **Spectrographs**(MODS).
- Mostly **Blue UDGs in the field**.
- Relative new objects, just **~40 spectroscopically confirmed in the field,** to date.



[1]

[1](PI: Peter Weilbacher, 2024B LBT cycle)

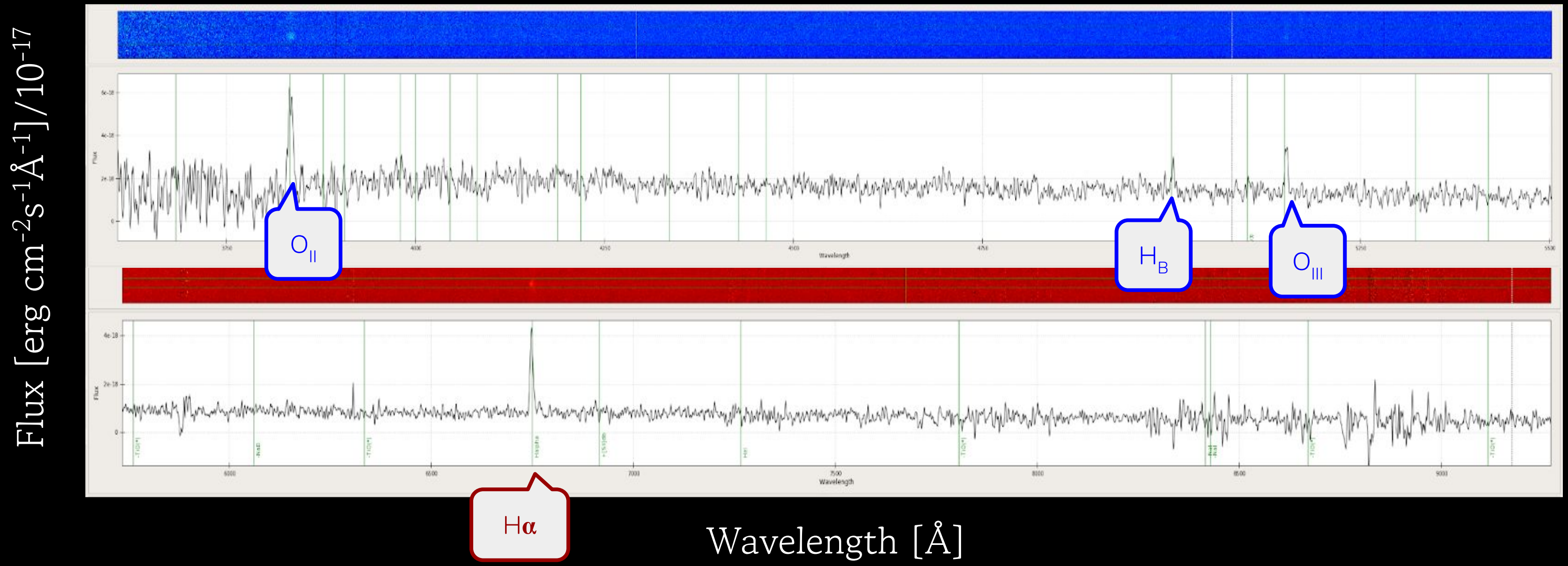
Results: spectroscopic follow-up



{"sipgi: an interactive pipeline for spectroscopic data reduction." A Gargiulo et al. 2022}

Results: spectroscopic follow-up

spectroscopic redshift=0.0289 | **confirm.**:LSB/**UDG** | **SFR:0.0027** | **C.S.BRIGHTNESS: 24.610**

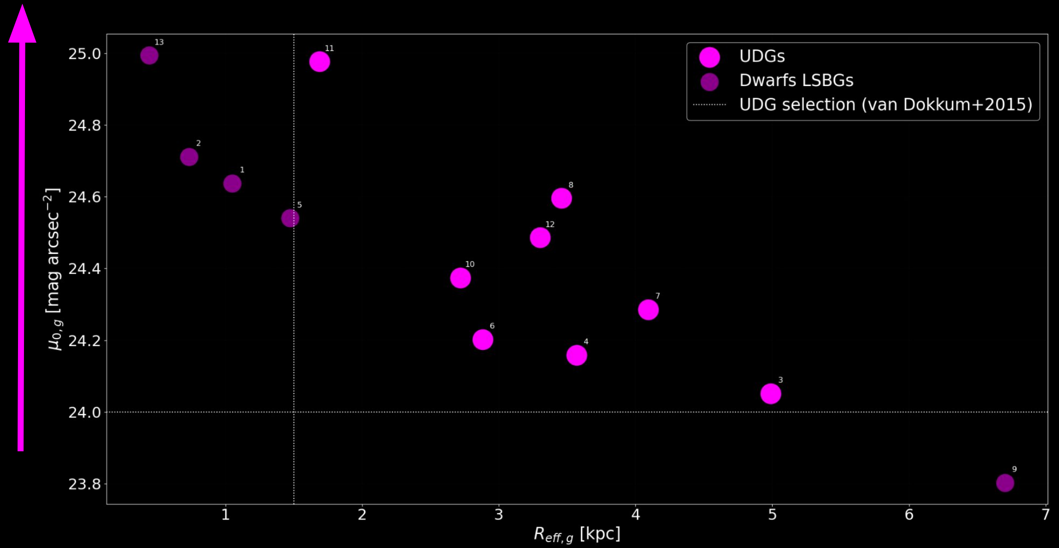


BLUE CHANNEL: 3200-6000 Angstrom **RED CHANNEL: 5000-10000 Angstrom**

{"sipgi: an interactive pipeline for spectroscopic data reduction." A Gargiulo et al. 2022}

Results: spectroscopic follow-up

FAINTNESS



Vanzanella et al.(in prep.)

UDGs are a subclass of LSBGs presenting extended half-light radii **$r_{1/2}$ >1.5 kpc** and a central surface brightness
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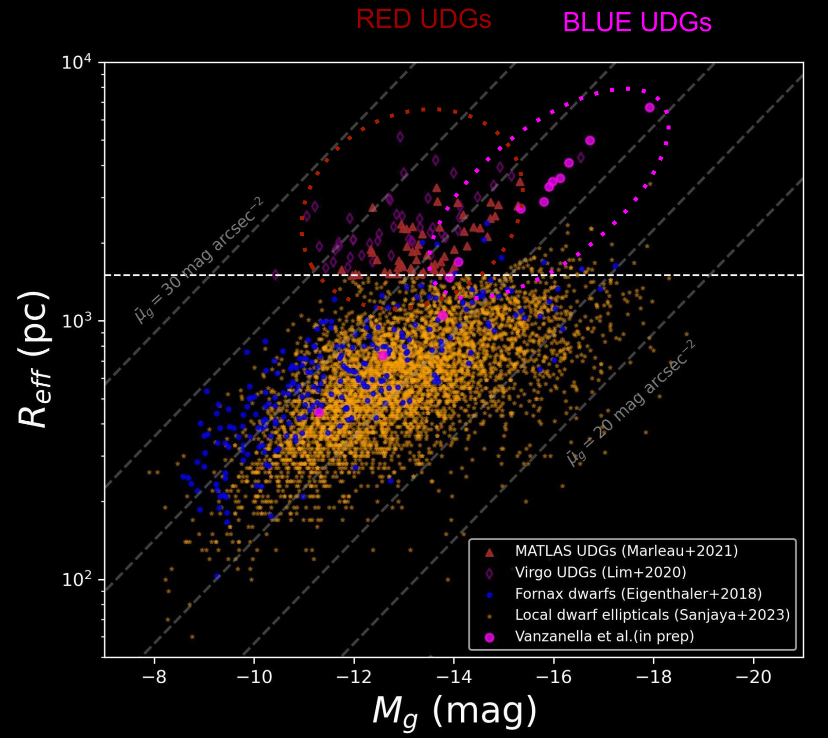

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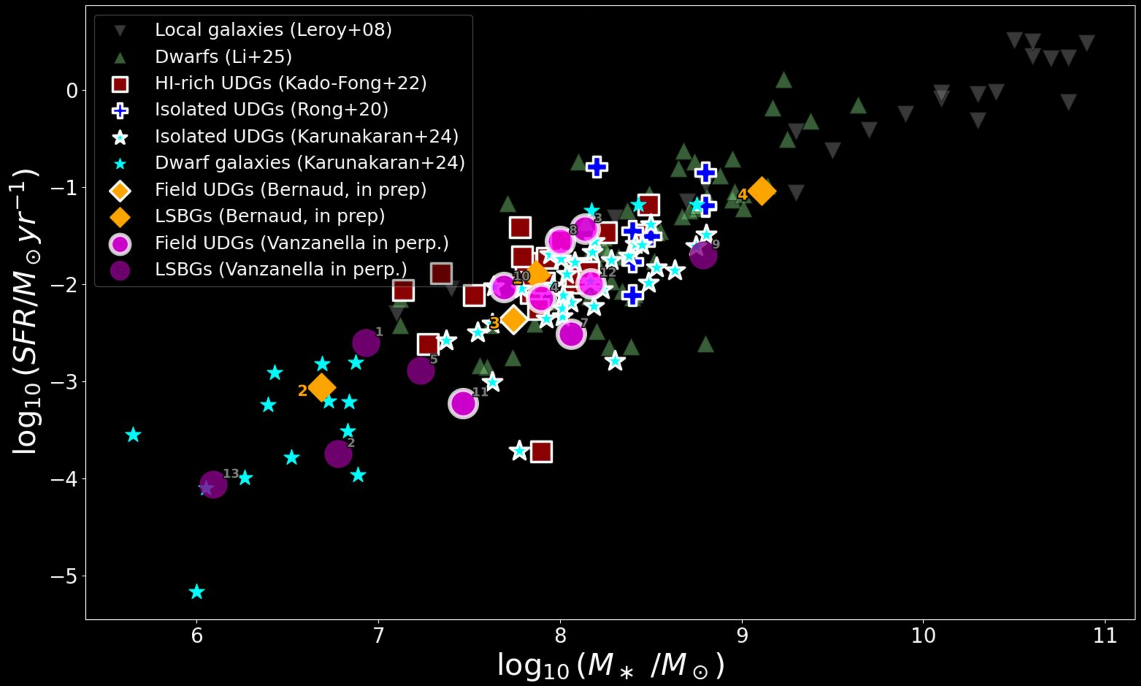


Vanzanella et al.(in prep.)

Future works

- Finalization and publication of the article.
- ML for inferring physical properties of UDGs in high and low-density environments.
- Additional data from LBT Observatory to enlarge the catalog built.

Summary

- UDGs are a subclass of LSBGs presenting extended half-light radii $\mathbf{r}_{1/2}$ >1.5 kpc and a central surface brightness $\mu 0$ > 24 mag arcsec-2 in the g-band.
- We confirm the faint and ultra-diffuse nature of new samples selected using a ML technique - 62% of samples are UDGs.
- The physical properties (SFR and Mstar) extracted from the spectra show these objects are perfectly aligned with local Star Forming Main Sequence.
- Applying new developed ML approaches for the incoming LSST data.

Back up

Table 1: MODS Instrument Configurations

Mode[1]	Channel	Filter(s)[2]	Resolution[3] (0.6″ Slit)	Wavelengths (Å)	CCD Readout[4]
Direct Imaging	Dual	B: SDSS ug R: SDSS riz	n/a	3300-10000	3088×3088
	Blue	SDSS ug	n/a	3300-6000	
	Red	SDSS riz	n/a	5000-10000	
Grating Spectrocopy[5]	Dual	B: Clear R: Clear	B: 1850 R: 2300	3200-10000	8288×3088
	Blue	Clear	1850	3200-6000	
	Red	GG495[6]	2300	5000-1000	
Prism Spectroscopy	Dual	B: Clear R: Clear	B: 420-140 R: 500-200	3200-10000	4096×3088
	Blue	Clear	420-140	3200-6000	
	Red	GG495[6]	500-200	5000-10000	

Basic Parameters:

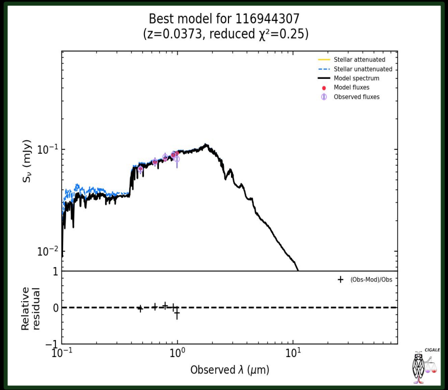
- Optical Design: Seeing-limited, dichroic-split double-beam grating spectrometer
- Wavelength Coverage: 3200 – 10000Å
- Field of View: 6×6-arcminutes (~2900×2900 pixels)

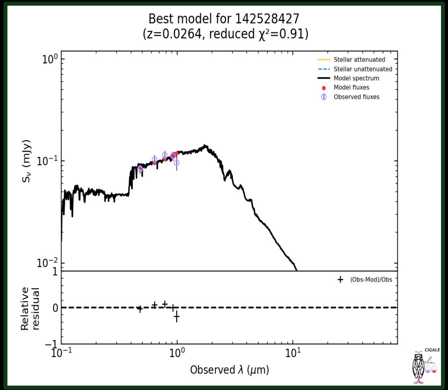
Pixel Scales:

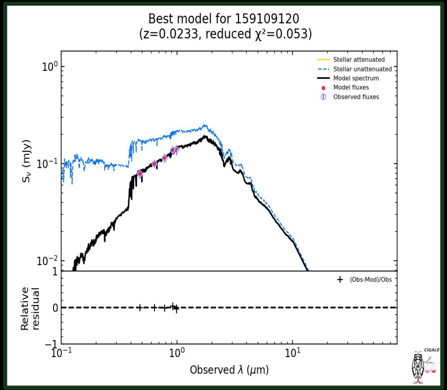
- Blue: 0.120 arcsec/pixel
- Red: 0.123 arcsec/pixel

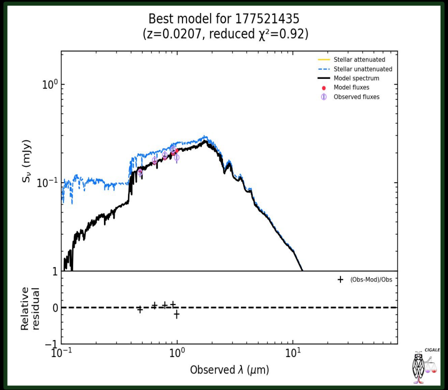
Operating Modes:

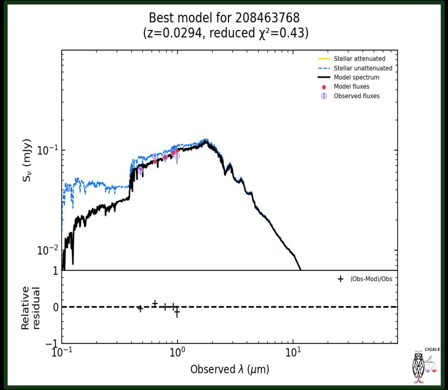
- Direct Imaging: SDSS ugriz filters (ug in Blue, riz in Red)
- Medium-Dispersion Grating Spectroscopy: R≈2000 (0.6-arcsec slit)
- Low-Dispersion Prism Spectroscopy: R=500 – 150
- Slits: Laser-cut spherical slit masks (up to 24 per MODS: 9 fixed + 15 user)
- Calibration: Internal pseudo-pupil projector and integrating sphere
- Pen-Ray® wavelength calibration lamps (Hg, Ne, Ar, Xe, Kr)
- Quartz-Halogen and variable-intensity incandescent continuum lamps
- CCD Detectors: e2v CCD231-68 3072×8192, 15μm Pixels
- Flexure Compensation: Real-time closed-loop IR laser metrology system sending
- collimator-mirror tip/tilt corrections during exposures.
- Acquisition & Guiding: 50×50-arcsec FoV CCD camera, 4 filters
- Active Optics: Off-axis Shack-Hartman wavefront sensor
- Dichroic: Blue-transmit/Red-reflect design, ~5700Å cross-over wavelength.
- Collimators: 3450mm focal length, off-axis paraboloids. Red: Ag, Blue: Al
- Cameras: f/3 decentered Maksutov-Schmidt. Red: BK7, Blue: Fused Silica
- Minimum Exposure Time: 1 second
- Dimensions: ~4.0×2.5 meters
- Mass: 3079 kg


Best model for 116944307
(z=0.0373, reduced χ²=0.25)
Stellar attenuated
Stellar unattenuated
Model spectrum
Model fluxes
Observed fluxes
(Obs-Mod)/Obs
Sν (mJy)
Relative residual
Observed λ (μm)
CIGALE


Best model for 142528427
(z=0.0264, reduced χ²=0.91)
Stellar attenuated
Stellar unattenuated
Model spectrum
Model fluxes
Observed fluxes
(Obs-Mod)/Obs
Sν (mJy)
Relative residual
Observed λ (μm)
CIGALE


Best model for 159109120
(z=0.0233, reduced χ²=0.053)
Stellar attenuated
Stellar unattenuated
Model spectrum
Model fluxes
Observed fluxes
(Obs-Mod)/Obs
Sν (mJy)
Relative residual
Observed λ (μm)
CIGALE


Best model for 177521435
(z=0.0207, reduced χ²=0.92)
Stellar attenuated
Stellar unattenuated
Model spectrum
Model fluxes
Observed fluxes
(Obs-Mod)/Obs
Sν (mJy)
Relative residual
Observed λ (μm)
CIGALE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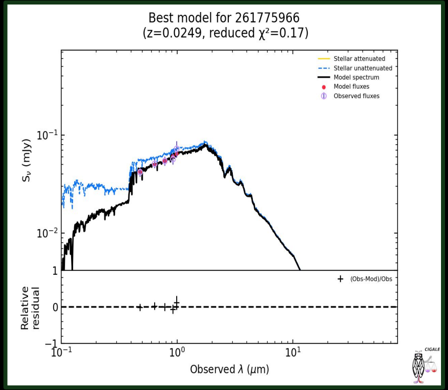
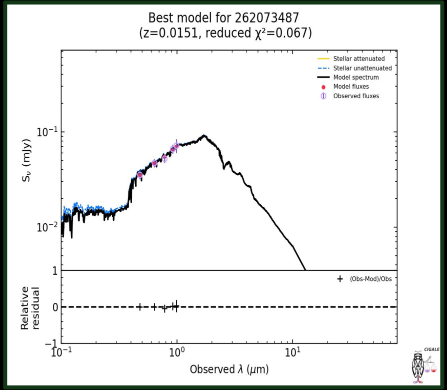
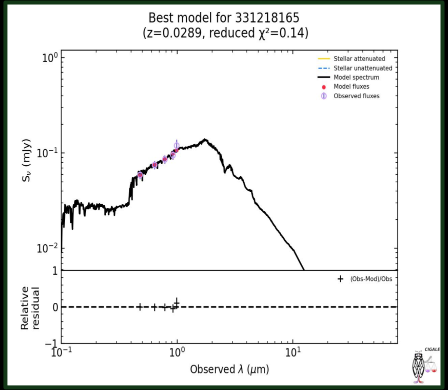
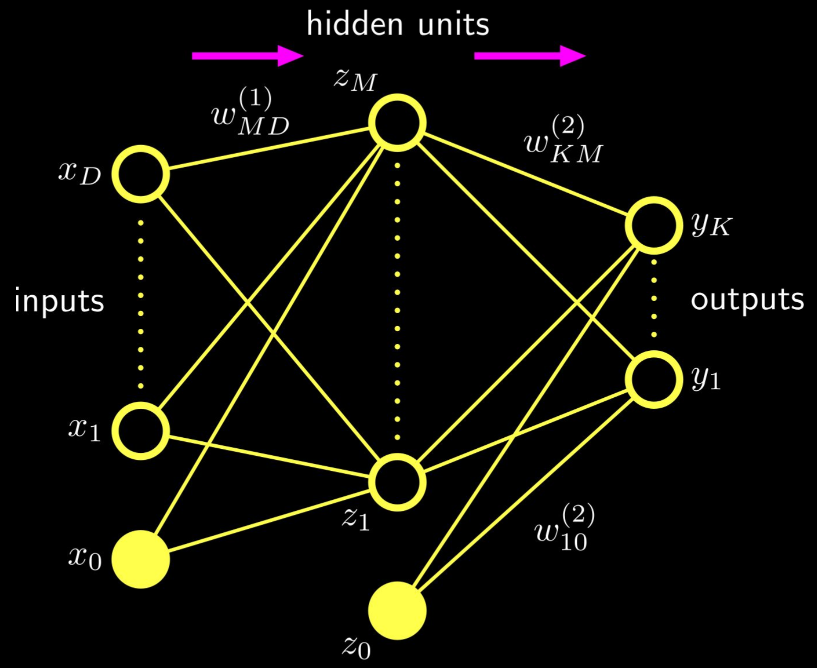
(z=0.0294, reduced χ²=0.43)
Stellar attenuated
Stellar unattenuated
Model spectrum
Model fluxes
Observed fluxes
(Obs-Mod)/Obs
Sν (mJy)
Relative residual
Observed λ (μm)
CIGALE


Best model for 261775966
(z=0.0249, reduced χ²=0.17)
Stellar attenuated
Stellar unattenuated
Model spectrum
Model fluxes
Observed fluxes
(Obs-Mod)/Obs
Sν (mJy)
Relative residual
Observed λ (μm)
CIGALE


Best model for 262073487
(z=0.0151, reduced χ²=0.067)
Stellar attenuated
Stellar unattenuated
Model spectrum
Model fluxes
Observed fluxes
(Obs-Mod)/Obs
Sν (mJy)
Relative residual
Observed λ (μm)
CIGALE

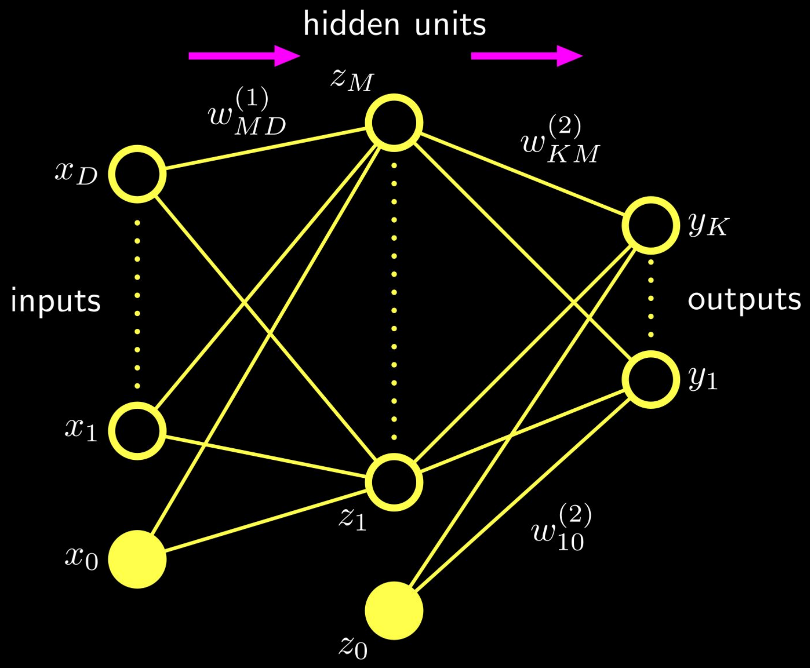

Best model for 331218165
(z=0.0289, reduced χ²=0.14)
Stellar attenuated
Stellar unattenuated
Model spectrum
Model fluxes
Observed fluxes
(Obs-Mod)/Obs
Sν (mJy)
Relative residual
Observed λ (μm)
CIGALE

Machine Learning



$$a_j = \sum_{i=1}^{D} w^{(1)}_{ji} x_i + w^{(1)}_{j0}$$

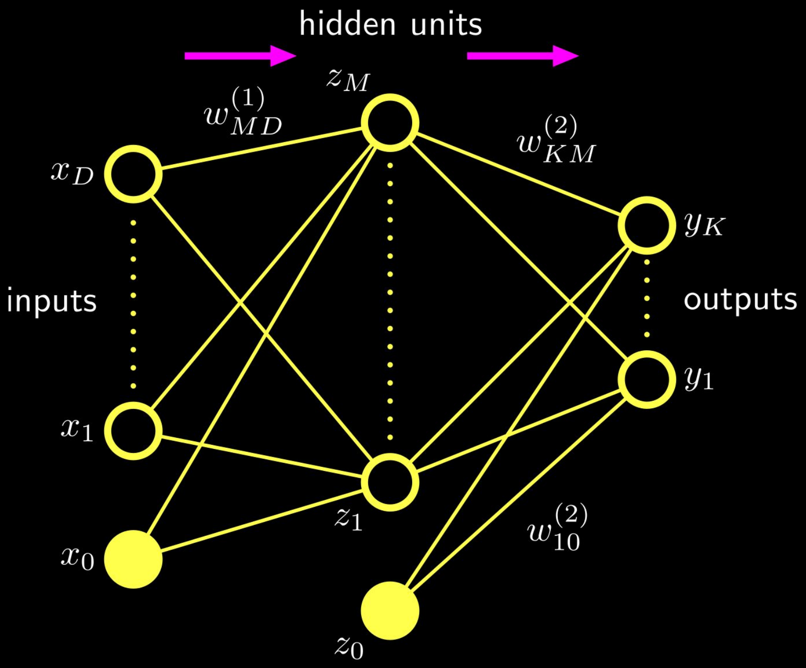
Machine Learning



$$a_j = \sum_{i=1}^{D} w^{(1)}_{ji} x_i + w^{(1)}_{j0}$$

$$z_j = h(a_j)$$

Machine Learning

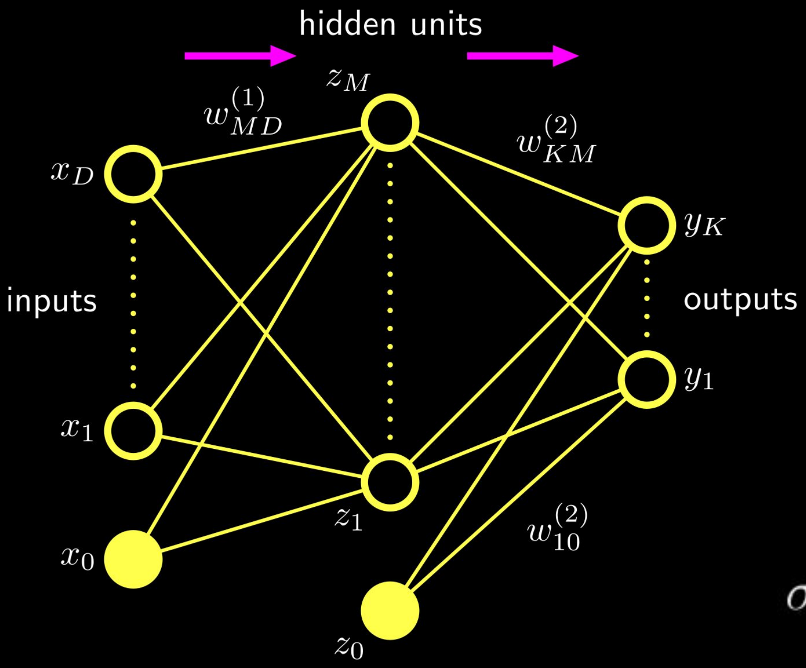


$$a_j = \sum_{i=1}^{D} w_{ji}^{(1)} x_i + w_{j0}^{(1)}$$

$$z_j = h(a_j)$$

$$a_k = \sum_{j=1}^{M} w_{kj}^{(2)} z_j + w_{k0}^{(2)}$$

Machine Learning



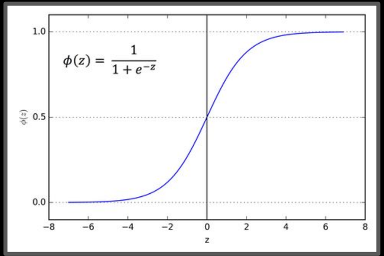
$$a_j = \sum_{i=1}^{D} w^{(1)}_{ji} x_i + w^{(1)}_{j0}$$

$$z_j = h(a_j)$$

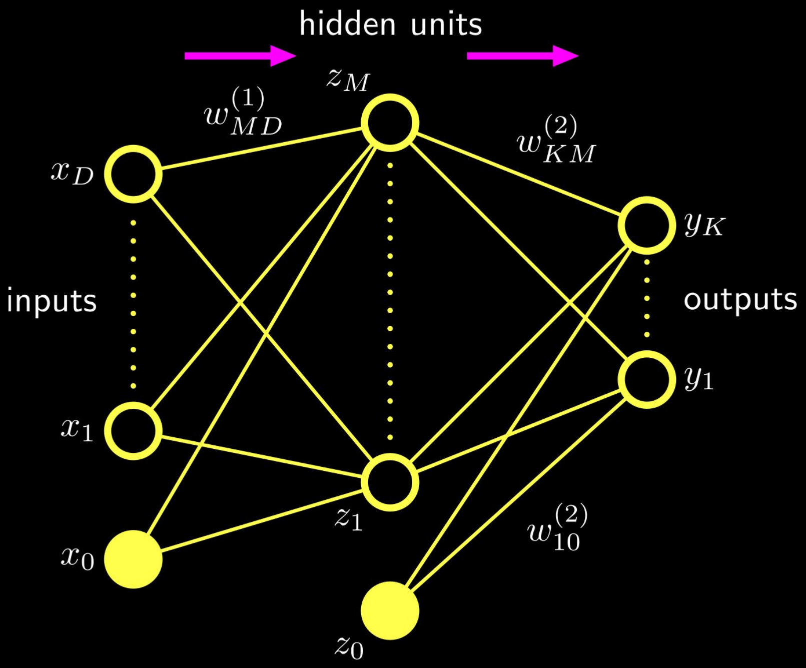
$$a_k = \sum_{j=1}^{M} w^{(2)}_{kj} z_j + w^{(2)}_{k0}$$

$$y_k = \sigma(a_k)$$

$$\sigma(a) = \frac{1}{1+\exp(-a)}$$



Machine Learning



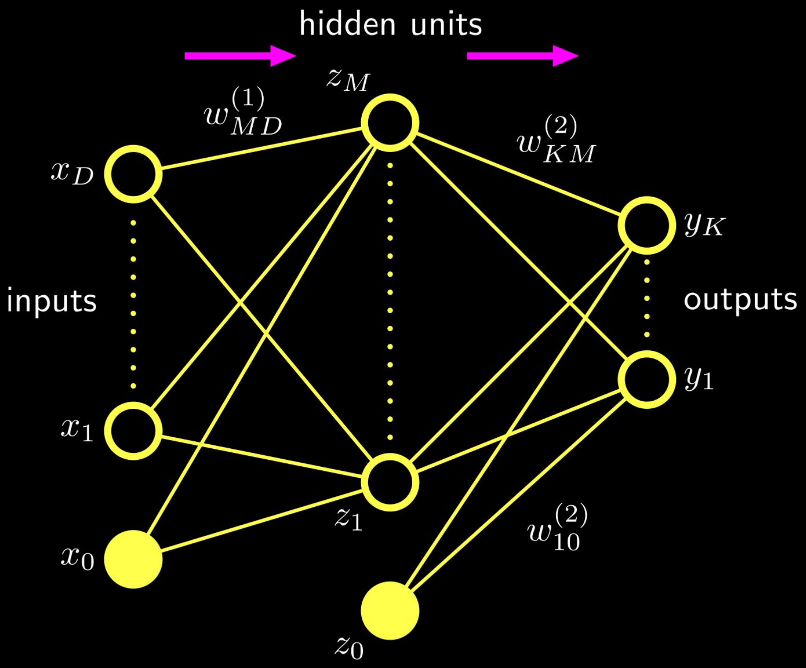
$$a_j = \sum_{i=1}^{D} w_{ji}^{(1)} x_i + w_{j0}^{(1)}$$

$$z_j = h(a_j) \qquad a_k = \sum_{j=1}^{M} w_{kj}^{(2)} z_j + w_{k0}^{(2)}$$

$$y_k = \sigma(a_k) \qquad \sigma(a) = \frac{1}{1+\exp(-a)}$$

$$y_k(\mathbf{x}, \mathbf{w}) = \sigma\left(\sum_{j=1}^{M} w_{kj}^{(2)} h\left(\sum_{i=1}^{D} w_{ji}^{(1)} x_i + w_{j0}^{(1)}\right) + w_{k0}^{(2)}\right)$$

Machine Learning



$$a_j = \sum_{i=1}^{D} w_{ji}^{(1)} x_i + w_{j0}^{(1)}$$

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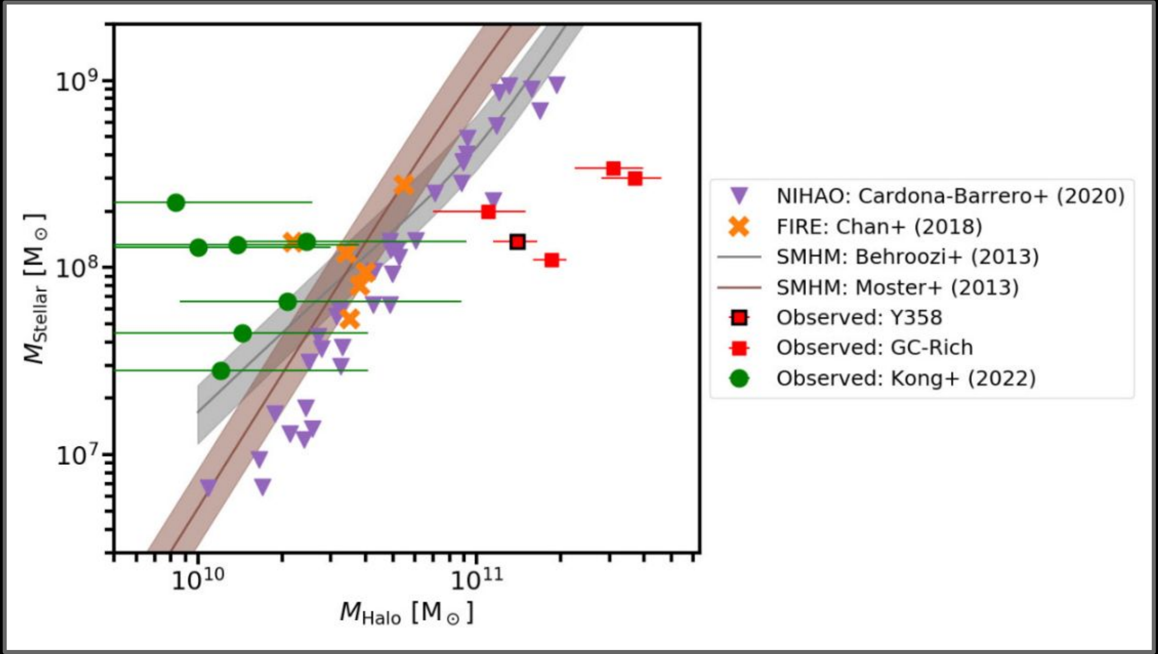
$$y_k = \sigma(a_k) \qquad \sigma(a) = \frac{1}{1 + \exp(-a)}$$

$$y_k(\mathbf{x}, \mathbf{w}) = \sigma\left(\sum_{j=1}^{M} w_{kj}^{(2)} h\left(\sum_{i=1}^{D} w_{ji}^{(1)} x_i + w_{j0}^{(1)}\right) + w_{k0}^{(2)}\right)$$

$$y_k(\mathbf{x}, \mathbf{w}) = \sigma\left(\sum_{j=0}^{M} w_{kj}^{(2)} h\left(\sum_{i=0}^{D} w_{ji}^{(1)} x_i\right)\right)$$



[1]{1}(Gannon et al. 2023)