Distant galaxies analysis with Deep Neural Networks

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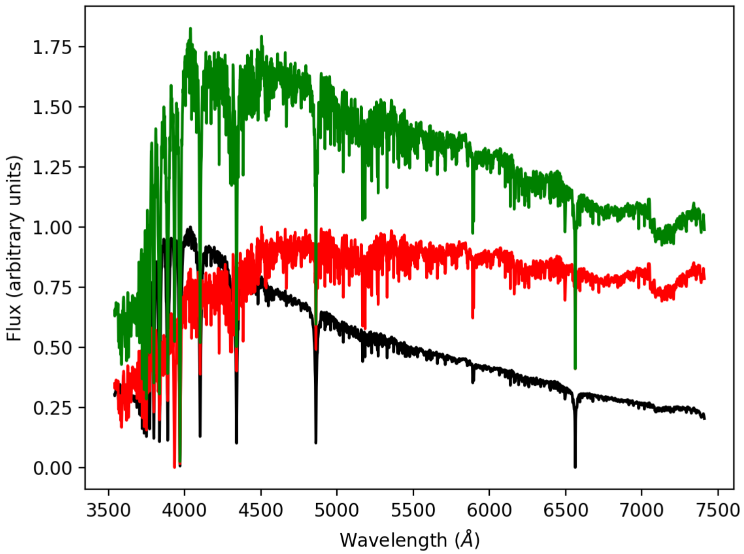
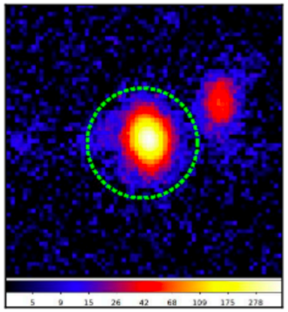
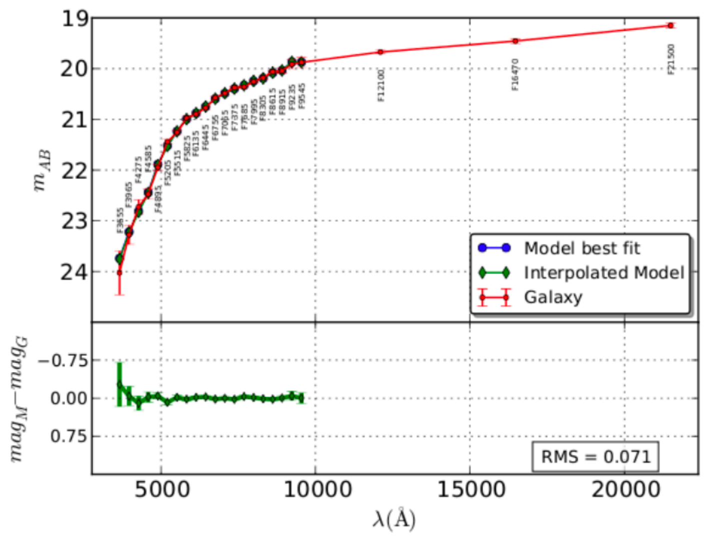
1. Introduction

1. Introduction: Description

- Spectral Synthesis and SED fitting



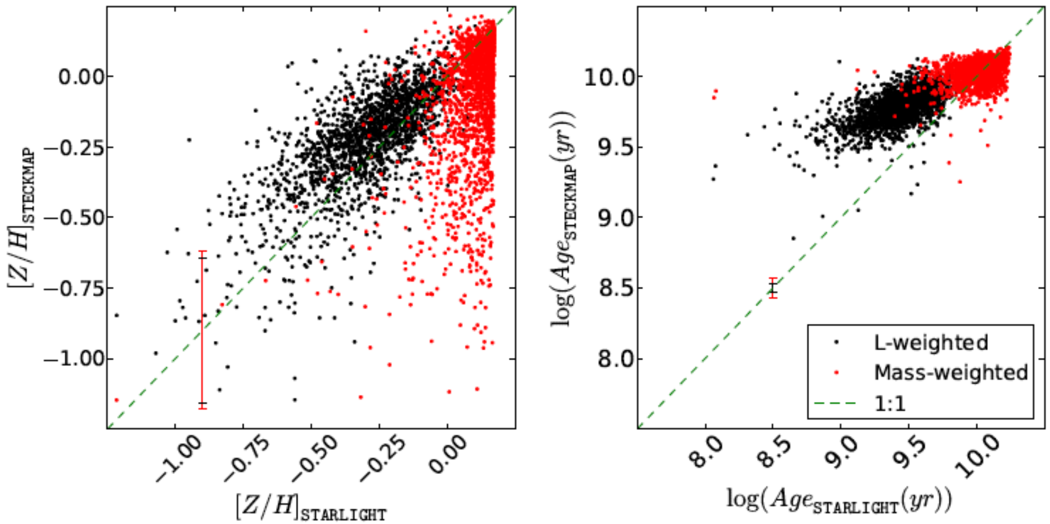




http://www.sedfitting.org/Fitting.html

1. Introduction: Motivation

- Discrepancies among SED Fitting tools



- Machine Learning in Astrophysics (1% of papers in NASA ADS Abstract Service with keyword Machine Learning)

1. Introduction: Goals

- Learn the whole life cycle of data, in particular the capture, the cleaning, the analysis and the visualization.

- Design a tool to calculate photometric redshift and estimate different variables related to distant galaxies (redshift and stellar mass, among others).

- To design, train and test a neural network, capable of accepting the emission of the galaxies in different predefined filters as the input, and returning a reliable array as close as possible to the parameters previously obtained for the galaxy using other techniques

1. Introduction: Methodology

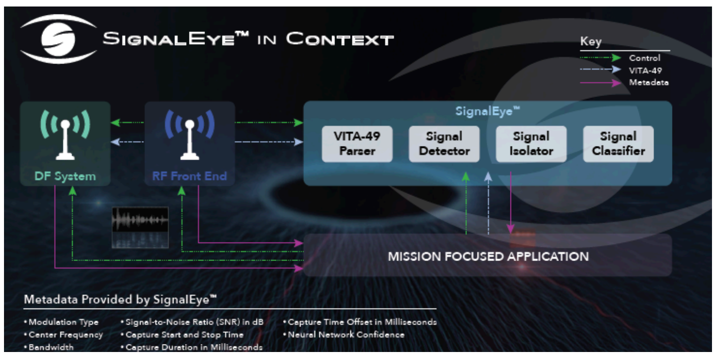
- Deep Neural Networks.

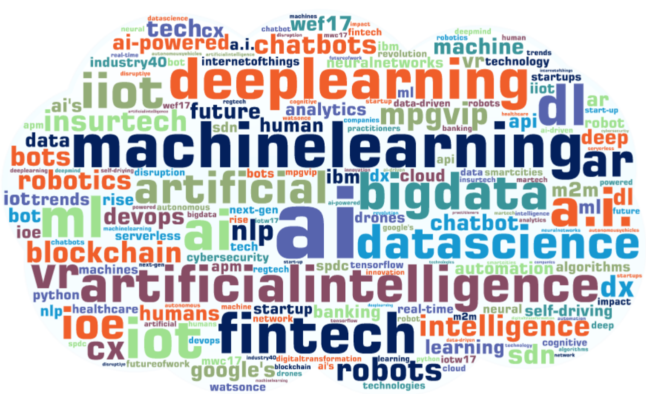
- Python 3.6.6, with the following frameworks and modules installed
    - AstroPY, version 3.2.1
    - iPython, version 6.5.0
    - Keras, version 2.2.4 using TensorFlow backend
    - Matplotlib, version 2.2.2
    - Numpy, version 1.15.2
    - PyAstronomy, version 0.13.0
    - Scipy, version 1.1.0
    - Spectres
    - TensorFlow, version 1.12.0
- ProjectLibre and MSProject, for the planning
- SublimeText, for coding
- TeXworks, using MikTeX backend for writing the report

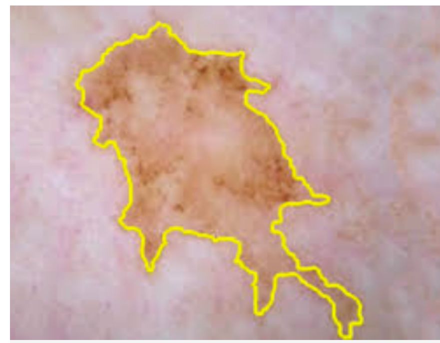
2. State of the art

2. State of the Art: Signal Processing

- Computer Vision —> Trend technology
- Signal Processing

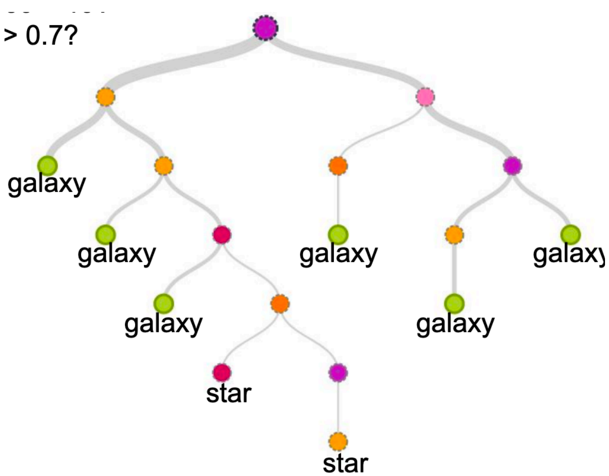


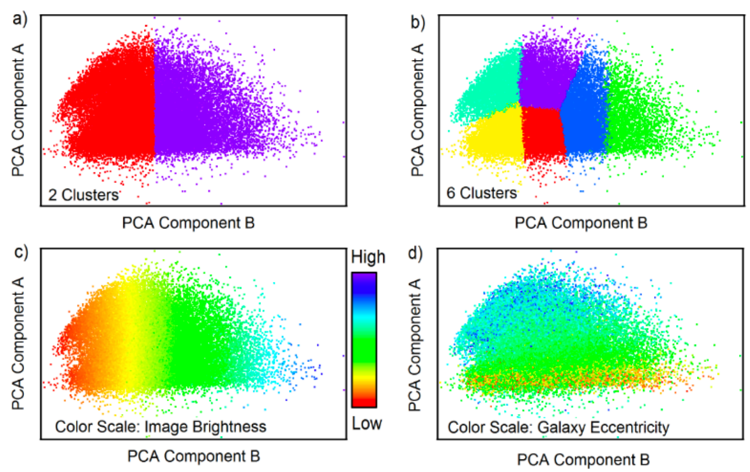


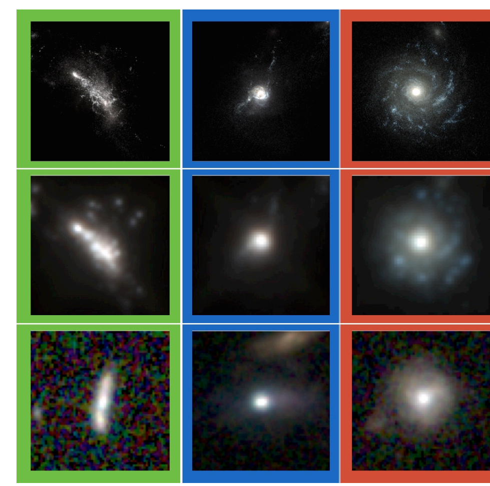


2. State of the Art: ML in Astrophysics

- Star-galaxy classification with random forest (Costa-Duarte *et al.* 2018)
- Galaxy morphology Gauthier *et al.* 2016)
- Data augmentation (Huertas-Company *et al.* 2018)

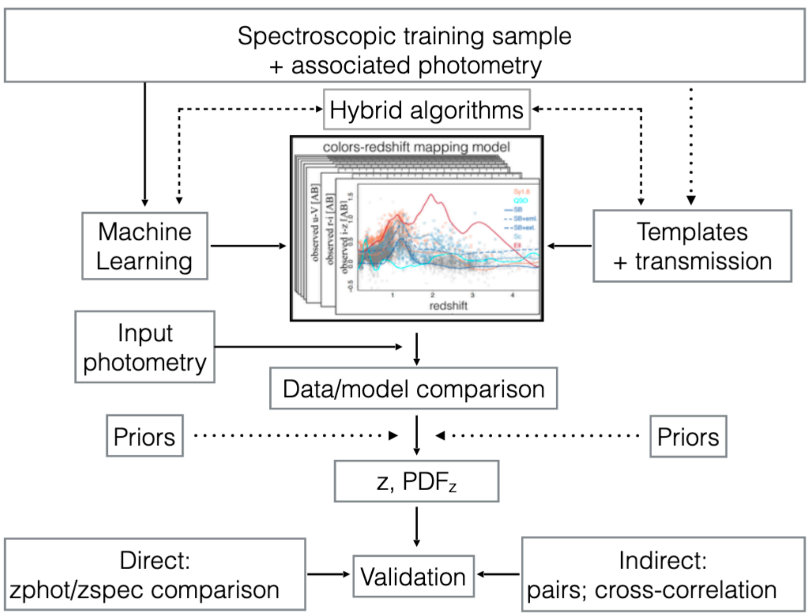


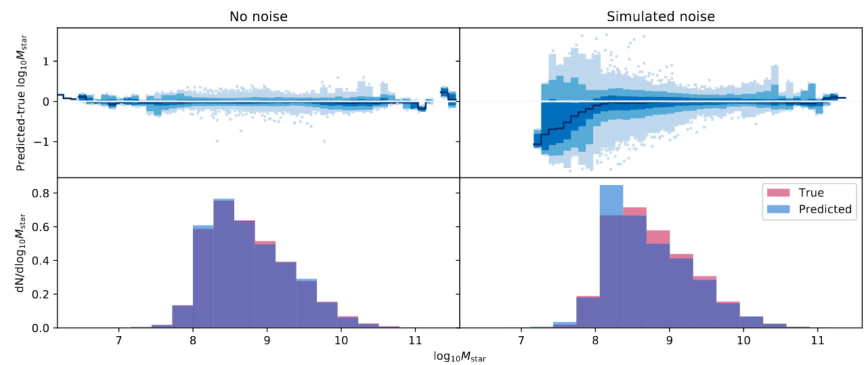


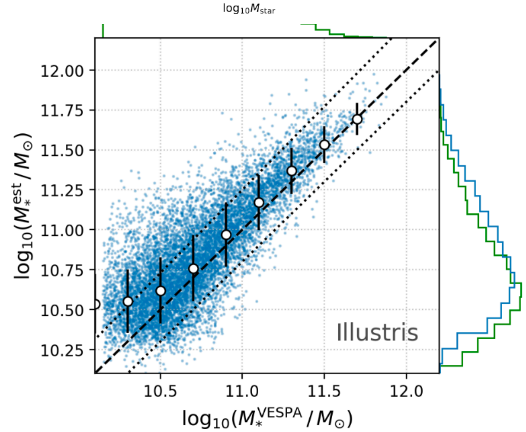


2. State of the Art: SED Fitting

- Photometric redshift (Salvato *et al.* 2018).
- Stellar mass, stellar metallicity, and average star formation rate (Simet *et al.* 2019, Lovell *et al.* 2019).







2. State of the Art: Narrow Band Filter Surveys

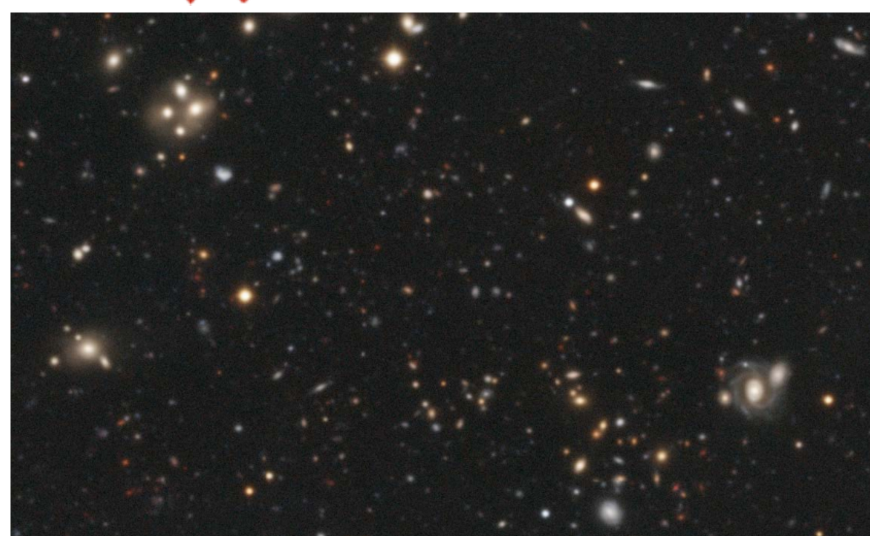
- ALHAMBRA, SHARDS, J-PAS/J-PLUS…

3. Implementation

3. Implementation: Data

- ALHAMBRA Survey
  - Csv file (‘,’ as delimiter) with 446,343 Objects
  - Integers: ID, Field, Pointing, CCD number
  - Float: Sky coordinates, CCD coordinates, *stellarity,* Fluxes, redshift, spectral type
  - String: F814W_Image
- Input: Fluxes in filters
- Outputs:
  - Redshift
  - Stellarity
  - Spectral Type
  - Stellar Mass

ALHAMBRA SURVEY



3. Implementation: Preprocessing

- Pandas dataframe
  - No NaNs
  - Fluxes: -99 if image is saturated; 99 if no detection —> clipping to [0, 27]
  - Stellarity —> categorical value
  - No need for normalization

3. Implementation: Modeling

- 4 different NN
  - 3 for regression: Redshift, Spectral Type, Stellar Mass
  - 1 for classification: Stellarity

	Input	Hidden	Output layer	Optimizer	Loss	Metrics
Redshift	75 Linear	120 Linear	1 neuron Linear	Adam	MSE	R Square
Stellarity	75 ReLu	2, 3 ReLu	2 SoftMax	Adam	Categorical Crossentropy	Accuracy
Spectral Type	75 Linear	20, 10 Linear	1 neuron Linear	RMSprop	MSE	R Square
Stellar Mass	75 Linear	120, 200, 50 Linear	1 neuron Linear	Adam	MSE	R Square

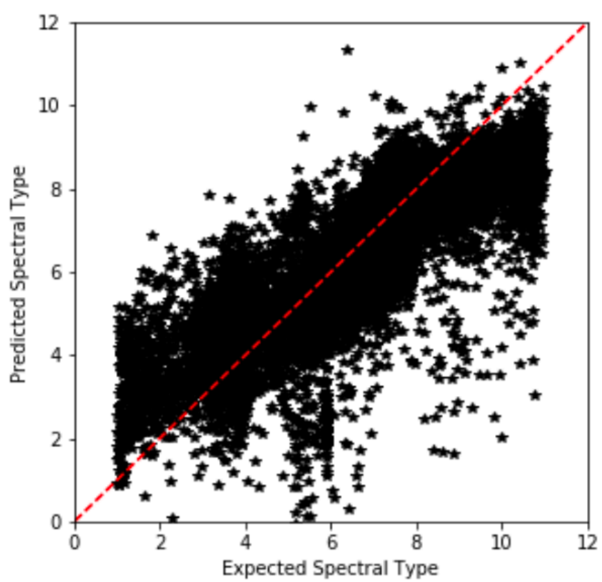
3. Implementation: Training

- Training epochs
  - Subset of data (10% for training, 1% for validation)
  - Training for 500 epochs
  - Loss *vs* epoch and Metrics *vs* epoch

- Optimal training epochs
  - Redshift: 80 epochs
  - Stellarity: 20 epochs
  - Stellar Mass: 7 epochs
  - Spectral Type: 10 epochs

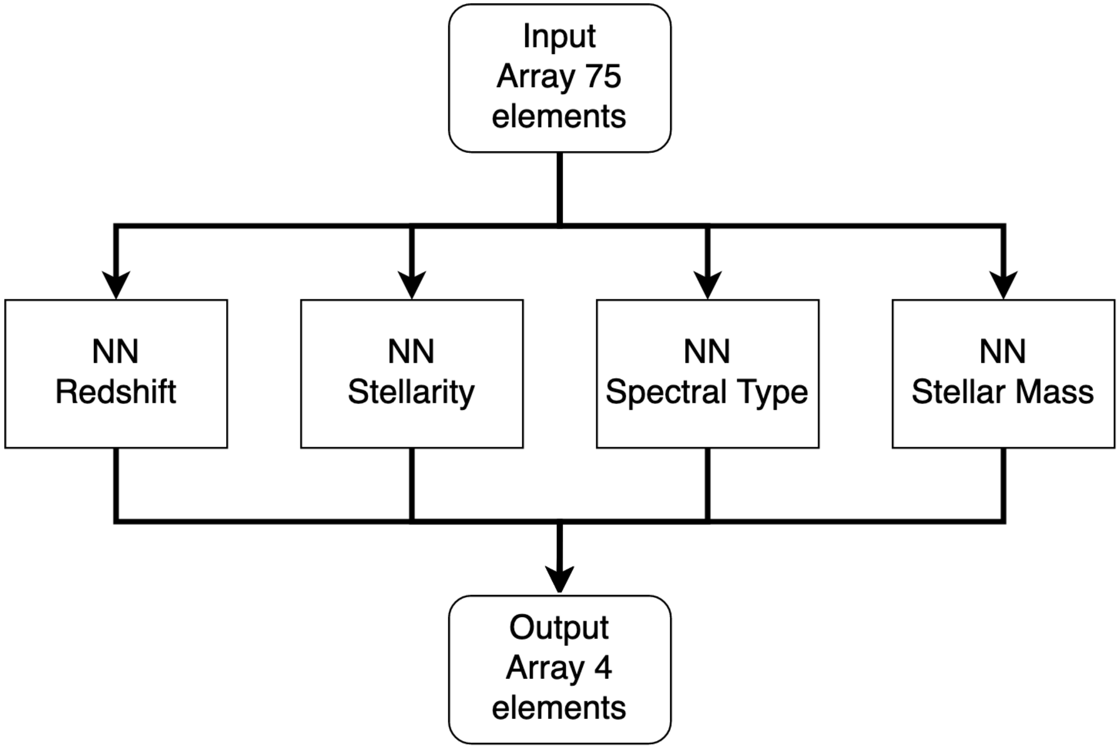
3. Implementation: Postprocessing

- No normalization —> no need for “un-normalization”
- Output *vs* Predicted values:
  - Correlation, but slope is not 1
  - Need for correction
    - Modification of Neural Network (see Future Work)
    - Polynomial Fitting



3. Implementation: Ensemble

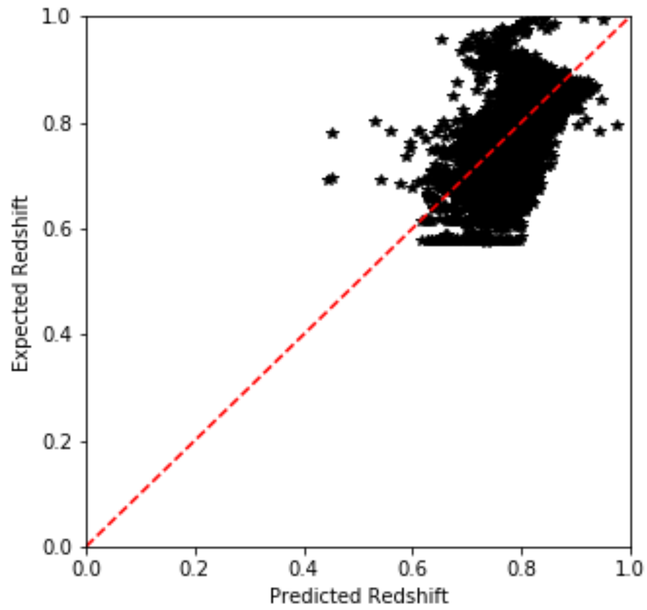
- 4 independent NN



4. Results

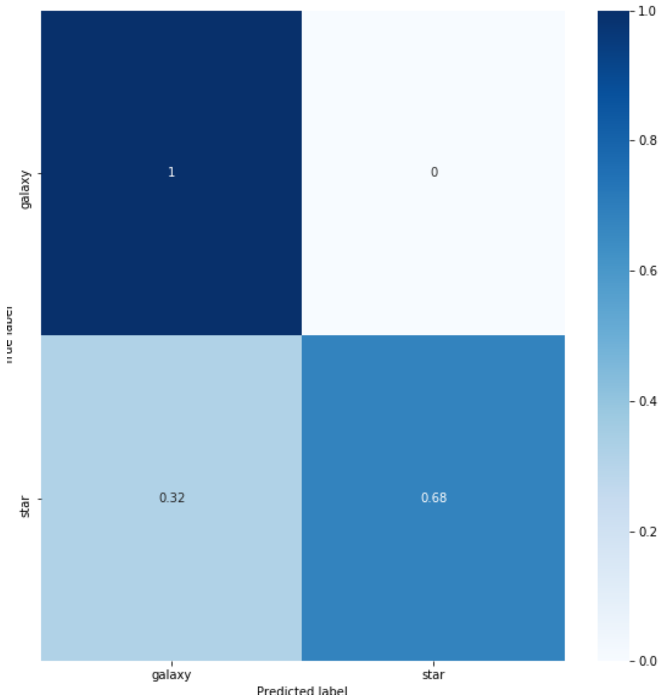
4. Results: Redshift

	Training dataset	Validation dataset
Initial Loss	0.4815	0.1607
Final Loss	0.0027	0.0021
Initial r2	-152.4	-48.8
Final r2	0.2019	0.3760



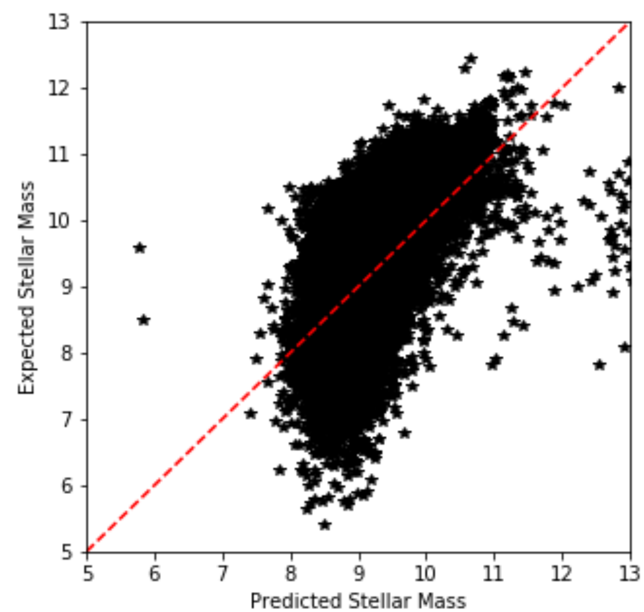
4. Results: Stellarity

	Training dataset	Validation dataset
Initial Loss	0.1111	0.1084
Final Loss	0.0446	0.0494
Initial accuracy	97.40%	97.24%
Final accuracy	98.33%	98.32%



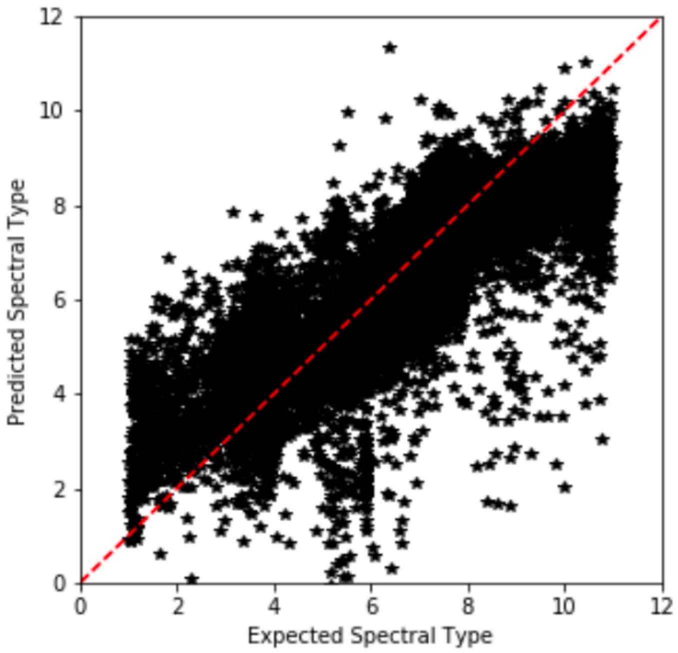
4. Results: Stellar Mass

	Training dataset	Validation dataset
Initial Loss	1.2458	0.5330
Final Loss	0.5310	0.5124
Initial r2	-0.5766	0.3251
Final r2	0.3240	0.3552



4. Results: Spectral Type

	Training dataset	Validation dataset
Initial Loss	2.6171	1.3255
Final Loss	1.1477	1.2242
Initial r2	0.1708	0.5957
Final r2	0.6399	0.6246



5. Discusion

5. Discussion: Summary

- Design and training of 4 different neural networks
- Prediction of Redshift, Stellarity, Stellar Mass and Spectral Type of galaxies
- Data from Alhambra Survey
- Comparison of Predicted and Expected output

5. Discusion: Conclusions

- Life cycle of data: Capture, exploratory analysis, cleaning, analysis and visualization
- Desing and training of 4 models to predict different types of varibles in observed objects
- Solution for a complex problem in Astrophysics
- Star-Galaxy Classification
- High accurate results:
  - $\frac{\Delta z}{1+z} = 0.03 \rightarrow \frac{\Delta z}{1+z} \leq 0.006$
  - Star-Galaxy precision = 98%
  - Stellar Mass: $\Delta M_{stellar} = 0.14$
  - Spectral Type: $\Delta ST = 0.2$

5. Discussion: Future Work

- Improve Neural networks: Include slope correction for predicted values
- Scalability of model for other photometric surveys
- Prediction of the spectrum of the object
- Improve model to accept spectra instead of photmetric data
- Implement calculation of uncertainties using MC simulations

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