EXPLORING THE SYNERGY OF TEMPLATE AND MACHINE LEARNING METHODS TO IMPROVE PHOTOMETRIC REDSHIFTS

ALSHUAILI ISHAQ YAHYA KHALFAN

UNIVERSITI SAINS MALAYSIA

2024

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by

ALSHUAILI ISHAQ YAHYA KHALFAN

Thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

October 2024

ACKNOWLEDGEMENT

As I near the culmination of my academic journey in pursuit of a doctoral degree, I would like to express my heartfelt gratitude to all those who have contributed to this accomplishment.

First and foremost, I am immensely grateful to my supervisor, Dr. John Soo Yue Han, for his invaluable guidance, support, and expertise throughout the entire research process. His insightful feedback, encouragement, and dedication have been instrumental in shaping this thesis and fostering my growth as a researcher. I am truly fortunate to have had the opportunity to work under his supervision.

I am also deeply thankful to my co-supervisor, Prof. Mohd. Zubir Mat Jafri, for his unwavering guidance, mentorship, and commitment during the research process. Additionally, I extend my sincere thanks to the Dean of the College, Prof. Abdul Razak Ibrahim, as well as the faculty and staff of the School of Physics, whose academic resources and facilities provided a conducive environment for research and learning. Their readiness to support and facilitate my postgraduate administrative tasks has been greatly appreciated.

I would like to express my profound and gratitude and appreciation to my wife, who has supported me throughout every stage of my academic journey, providing constant motivation even during the most challenging times. her encouragement and sacrifices have been a constant source of strength for me.

I also extend my heartfelt thanks to my dear mother for her prayers, boundless love, and unwavering belief in my abilities. Her continuous support has been a driving force in my academic endeavours.

I would also like to express my gratitude to the Oman Astronomical Society, especially its president, Mr. Ali Al-Shaibani, for the support, resources, and opportunities they provided throughout my thesis research. Their commitment to the field of astronomy has been truly inspiring.

My heartfelt appreciation goes to my brothers, sisters, and friends for their unwavering love, and encouragement. Their presence and support have been a constant source of motivation, providing me with the strength to overcome challenges and persevere.

In closing, I want to acknowledge the countless others who, directly or indirectly, played a role in this thesis. Your support and encouragement have been invaluable, and I deeply appreciate every contribution, no matter how small. Thank you all for being part of this academic journey and for your unwavering support in helping me achieve this milestone.

TABLE OF CONTENTS

ACKNOWLEDGEMENT .... **ii**

TABLE OF CONTENTS .... **iv**

LIST OF TABLES .... **vii**

LIST OF FIGURES .... **ix**

LIST OF ABBREVIATIONS .... **xii**

ABSTRAK .... **xiv**

ABSTRACT .... **xvi**

CHAPTER 1 INTRODUCTION **1**

1.2 Problem Statement 2

1.3 Research Objective 4

1.4 Thesis contribution 5

1.5 Outline of the thesis 6

CHAPTER 2 LITERATURE REVIEW **7**

2.1 Introduction 7

2.2 Galaxies 8

2.3 Cosmological Redshifts 10

2.4 Photometric redshift 11

2.5 Template-based Photo-z Methods 13

2.6 Machine learning methods 19

2.7 Template Fitting vs Machine Learning 21

2.8 Review of synergetic methods in photometric redshifts 22

2.8.1 Trees for Photo-z (TPz) 22

2.8.2 Delight 23

2.8.3 Mizuki SED template fitting 24

CHAPTER 3 METHODOLOGY 25

3.1 Introduction 25

3.2 Data samples 27

3.2.1 Sloan Digital Sky Survey (SDSS) 27

3.2.1(a) Luminous Red Galaxies (LRG) 30

3.2.1(b) Boos Galaxy Target Selection 30

3.2.1(c) The Main Galaxy Sample 32

3.2.2 Stripe-82 (S82) Sample 33

3.2.3 Cosmic Evolution Survey 33

3.3 Photometric redshift algorithms 34

3.3.1 ANNz2 35

3.3.2 BPz 36

3.4 SED Templet Sets 37

3.4.1 Brown 38

3.4.2 CWW 38

3.4.3 LePhare 39

3.4.4 COSMOS 39

3.5 Supporting Software 40

3.5.1 TOPCAT 40

3.6 MATLAB 42

3.7 Performance metrics 44

3.7.1 RMS error 44

3.7.2 68^{th} percentile error 44

3.7.3 Outlier fraction 45

3.8 Improving Photometric Redshifts by Merging PDFs from Template-Based and Machine Learning Algorithm 45

3.9 Improving Photometric Redshifts by Training Complementary Features of Galaxy Templates Using Machine Learning 49

CHAPTER 4 RESULTS AND DISCUSSION 51

4.1 Introduction 51

4.2 Improving Photometric Redshifts by Merging PDFs from Template-Based and Machine Learning Algorithm. 52

4.2.1 The Main Galaxy Sample 52

4.2.2 LRG & S82 results 53

4.2.2(a) Photo-zs on the LRG Sample 54

4.2.2(b) Photo-zs on the Stripe-82 Sample 58

4.3 Improving Photometric Redshifts by Training Complementary Features of Galaxy Templates Using Machine Learning 61

4.3.1 Main Galaxy Sample (MGS) 61

4.3.2 The Stripe-82 Sample 62

4.3.3 LOWZ and CMASS Samples 64

4.3.4 The COSMOS Sample 67

4.4 Discussion 69

CHAPTER 5 CONCLUSION AND RECOMMENDATION 72

5.1 Introduction 72

5.2 Conclusion 73

5.2.1 Improving photometric redshifts by merging probability density functions from template-based and machine learning algorithms. 73

5.2.2 Improving photometric redshifts by training complementary features of galaxy templates using machine learning. 74

5.2.3 Develop and compare hybrid methodologies that leverage the strengths of both template and machine learning approaches 74

5.3 Future study recommendation 75

REFERENCES 76

LIST OF TABLES

Page

Table 3-1 LOWZ and CMASS Photometric Samples cuts as (Reid et al., 2016). 32

Table 3-2 Redshift range and number of samples for the data used from the Sloan Digital Sky Survey and COSMOS in this study. 34

Table 3-3 The 5 template sets we used to optimise BPz in this work, they are listed by name, number of templates in the sets and their citation sources. 39

Table 3-4 σRMS and $\sigma 68$ of the photo-zs for both the LRG and Stripe-82 samples during optimisation, showing the different number of interpolations between templates in BPz using the template sets listed in Table 1. (Introduce in chapter 3) 48

Table 4-1 Comparison of σRMS, σRMS and η outlier fraction for ANNz2 and BPz on the MGS samples. 52

Table 4-2 Comparison of σRMS, $\sigma 68$and ηout fraction for ANNz2 and BPz on the LRG and Stripe-82 samples. 53

Table 4-3 *Performance of the photo-z as shown in the root-mean-square (σRMS), 68th percentile ($\sigma 68$) errors, and outlier fraction (ηout) when applying the three PDF merging methods for the LRG samples. The results of ANNz2, BPz, (Abdalla et al., 2011) and* (Soo et al., 2018) *) are shown for reference.* 56

Table 4-4 *Performance of the photo-z as shown in the root-mean-square (σRMS) ,68th percentile ($\sigma 68$) errors, and outlier fraction (ηout) when applying the three PDF merging methods for the Strip-82 samples. The results of ANNz2, BPz, Abdalla et al.2011and Sánchez et al. (2014) are shown for reference.* 58

Table 4-5 Performance of photo-z for the MGS Sample, as shown through the root-mean-square (σRMS), 68th percentile ($\sigma 68$) errors, and outlier fraction (η_out) when including $zb$and $tb$from BPz as inputs in ANNz2. The results of ANNz2 and BPz are shown as refer. 61

Table 4-6 Performance of photo-z for the Stripe-82 Sample, as shown through the root-mean-square (σRMS), 68th percentile ($\sigma 68$) errors, and outlier fraction (ηout) when including zb and tb from BPz as inputs in ANNz2. The ANNz2 and BPz are shown as references. 63

Table 4-7 Performance of photo-z for the LOWZ Sample, as shown through σRMS, $\sigma 68$ and ηout when including zb and tb from BPz as inputs in ANNz2. The results of ANNz2, BPz, Meshcheryakov et al., (2015), Brescia et al., (2014) and Soo et al., (2018) are shown as reference.. 65

Table 4-8 Performance of photo-z for the CMASS Sample, as shown through σRMS, $\sigma 68$and η_out when including $zb$and $tb$from BPz as inputs in ANNz2. The results of ANNz2, BPz and Soo et al., 2018 are shown as reference. 66

Table 4-9 Performance of photo-z for the COSMOS Sample, as shown through the σRMS, $\sigma 68$ and $\eta out$when including $zb$and $tb$from BPz as inputs in ANNz2. The results of ANNz2, BPz and Cavuoti et al., (2015) are shown as reference... 68

LIST OF FIGURES

Page

Figure 2-1 Galaxies are categorized using the Hubble tuning fork depending on their morphology. 9

Figure 2-2 An artificial neural network configuration with 5 magnitudes (oneper filter) and redshift as output. 21

Figure 3-1 The flow chart illustrates the data selection sources and the key steps in improving photometric redshifts. 25

Figure 3-2 SDSS Photometric filters are used in this work. 28

Figure 3-3 illustrates the steps we followed in this work to use ANNz2 36

Figure 3-4 The Control Window in TOPCAT. 42

Figure 3-5 User interface in MATLAB. 43

Figure 4-1 Photo-z vs. spec-z plots of ANNz2 (green) and BPz (blue) on the MGS. where the blue lines dictate the boundary of the outliers. 52

Figure 4-2 Photo-z vs. spec-z plots of ANNz2 (green) and BPz (blue) on the LRG and Strip-82 sample. 54

Figure 4-3 Photo-z vs. spec-z plots comparing the performance of ANNz2 (top left) and BPz (bottom left) with the methods we used to improve the photo-zs in the LRG sample. The multiple method gives the best performance as compared to the rest. 55

Figure 4-4 An illustration of 8 randomly selected photo-z PDFs from the LRG sample produced by ANNz2 (green), BPz (red), and when combined using the three methods: averaged (left), weighted (middle) and multiplied (right). The resultant PDFs (blue) showed that all. 57

Figure 4-5 Photo-z vs. spec-z plots comparing the performance of ANNz2 (top left) and BPz (bottom left) with the methods we used to improve the photo-zs in the Stripe-82 sample. The multiplied

PDF gave a better performance when compared to the rest of the methods, as well as those of ANNz2 and BPz. 59

Figure 4-6 An illustration of 8 randomly selected photo-z PDFs from the Stripe-82 sample produced by ANNz2 (green), BPz (red), and when combined using the three methods: averaged (left), weighted (middle) and multiplied (right). Row 7 shows how the multiplied PDF show the multiplied PDF outperforms the other methods by suppressing the anomalous photo-z peak of BPz, successfully giving a photo-z closer to the original spec-z of the object. 60

Figure 4-7 Photo-z vs. spec-z, comparing the performance of ANNz2 (top left), BPz (top right) with the methods we used to improve the photo-zs in the MGS Sample, i.e. adding zb (bottom middle), tb (bottom left) and both $zb$and tb (bottom right) as inputs for ANNz2. 62

Figure 4-8 Photo-z vs. spec-z, comparing the performance of ANNz2 (top left), BPz (top right) with the methods we used to improve the photo-zs in the Stripe-82 Sample, i.e. adding tb (bottom left), zb (bottom middle) and both $zb$and tb (bottom right) as inputs for ANNz2. For this sample, can be seen that adding zb alone gives the best performance as compared to the rest. 64

Figure 4-9 Photo-z vs. spec-z, comparing the performance of ANNz2 (top left), BPz (top right) with the methods we used to improve the photo-zs in the LOWZ Sample (bottom, similar arrangement as in Figure 4.8). 65

Figure 4-10 Photo-z vs. spec-z comparing the performance of ANNz2 (top left), BPz (top right) with the methods we used to improve the photo-zs in the CMASS Sample (bottom, similar arrangement as in Figure 4.8). 67

Figure 4-11 Photo-z vs. spec-z comparing the performance of ANNz2 (top left), BPz (top right) with the methods we used to improve the *photo-zs in the COSMOS Sample (bottom, similar arrangement as in Figure (4.8).* 68

LIST OF ABBREVIATIONS

BAO	baryon acoustic oscillation
BOSS	Baryon Oscillation Spectroscopic Survey
BPz	Bayesian Photometric Redshift
CfA	Centre for Astrophysics Redshift Survey
CFHTLS	CFHT Legacy Survey
CMASS	Constant Mass Sample
CMB	Cosmic Microwave Background Radiation
COSMOS	Cosmic Evolution Survey
CWW	Coleman, Wu and Weedman
Delight	Deep Learning Identification of Galaxy Hosts of Transients
DES	Dark Energy Survey
GALEX	Galaxy Evolution Explorer
HSC	Hyper Suprime-Cam Survey
HST	Hubble Space Telescope
IMF	Initial Mass Function
JWST	James Webb Space Telescope
LOWZ	Low Redshift
LRG	Luminous Red Galaxies sample
LSST	Legacy Survey of Space and Time
MATLAB	MATrix LABoratory
MGS	Main Galaxy Sample
Pan-STARRS	The Panoramic Survey Telescope and Rapid Response System
PDF	Probability Density Function
S/N	signal-to-noise ratio
S82	Stripe 82
SED	Spectral Energy Distribution
SED	Template Spectral Energy Distribution
SOM	self-organizing maps
SPS	Stellar Population Synthesis
TMVA	Multivariate Data Analysis
TPz	Trees for Photo-z

UKIDSS	Infrared Deep Sky Survey
UKIRT	United Kingdom Infrared Telescope
VVDS	VIMOS-VLT Deep *Survey*
$\mathrm{t_b}$	Best-Fitting Template
$\mathrm{z_b}$	Best-Fitting Redshift
η_{out}	outlier fraction rate
σ_{68}	68th percentile error

MENEROKA KAEDAH TEMPLAT SINERGI DAN PEMBELAJARAN MESIN UNTUK MENAMBAH BAIK FOTOMETRIK

ABSTRAK

Tesis ini meneroka penggunaan berasaskan templat dan pembelajaran mesin untuk meningkatkan ketepatan anggaran anjakan merah fotometri galaksi. Kaedah pertama melibatkan penggunaan templat padananan untuk membuat model taburan tenaga spektrum galaksi dan menganggarkan anjakan merahnya. Kaedah kedua menggunakan algoritma pembelajaran mesin untuk mempelajari hubungan diantara ciri-ciri fotometri galaksi dan anjakan merahnya, berdasarkan set latihan pengukuran anjakan merah spektroskopik. Tesis ini juga bertujuan untuk menyiasat potensi sinergi diantara kedua-dua kaedah ini dengan menggabungkan pelbagai cara dan membandingkan keputusan yang diperoleh pada setiap kaedah secara individu. Mencari sinergi antara kedua-dua kaedah ini bukanlah keutamaan pada masa lalu, tetapi kini, kuasa pemprosesan komputer dan ketepatan cerapan telah ditambah baik, kami menganggapnya wajar untuk dikaji. Kami membandingkan dua kaedah untuk meningkatkan anggaran anjakan merah fotometri galaksi dengan menggunakan algoritma ANNz2 dan BPz pada sampel fotometrik dan spektroskopik daripada Sloan Digital Sky Survey (SDSS). Kami mendapati bahawa prestasi anjakan merah fotometri ANNz2 (pembelajaran mesin) adalah lebih baik daripada BPz (templat galaksi), dan dengan menggunakan teknik gabungan yang kami perkenalkan, kami melihat bahawa terdapat peningkatan pada foto-z sehingga [0.0265 & 0.0222] σ_RMS dan σ_68 dalam sampel (LRG) apabila kedua-dua strategi disatukan dan [0.0471 & 0.0471] pada sampel Stripe-82. Dalam kaedah yang berbeza, kami memperkenalkan teknik penghasilan foto-z berasaskan templat (jenis templat paling

sesuai dan foto-z) ditambah sebagai input kepada ANNz2, dan kami melihat bahawa terdapat peningkatan dalam [σ_RMS , σ_68] memberikan nilai serendah [0.0590, 0.0242] dalam sampel Tinjauan Evolusi Kosmik (COSMOS), juga memberikan nilai [0.0474, 0.0471], [0.0368, 0.0253] dan [0.0213, 0.0168] dalam SDSS Stripe-82 , Constant Mass Sample (CMASS) dan Low Redshift Sample (LOWZ). Tesis ini dapat menyumbang kepada perningkatan penggunaan dalam tinjauan langit samar dan tinjauan angkasa luar sekali gus membuka ufuk yang lebih luas untuk membangunkan kaedah ini dan mencari kaedah yang lebih baik untuk mengukur foto-z galaksi.

EXPLORING THE SYNERGY OF TEMPLATE AND MACHINE LEARNING METHODS TO IMPROVE PHOTOMETRIC REDSHIFTS

ABSTRACT

This thesis explores the use of both template-based and machine learning methods to improve the accuracy of galaxy photometric redshift estimation. The first method involves using template fitting to model the spectral energy distribution of a galaxy and estimate its redshift. The second method uses machine learning algorithms to learn the relationship between a galaxy's photometric properties and its redshift, based on a training set of spectroscopic redshift measurements. This thesis also aims to investigates the potential synergy between these two methods by combining them in various ways and comparing the results to those obtained using each method individually. Finding the synergy between these two methods was not a high priority in the past, but now that our computer processing power and observational accuracy have improved, we deem it worth investigating. We compared two methods to improve galaxy photometric redshift estimations by using the algorithms ANNz2 and BPz on different photometric and spectroscopic samples from the Sloan Digital Sky Survey. We find that the photometric redshift performance of ANNz2 (a machine learning methods) surpasses that of BPz (a galaxy template method), Furthermore, by employing the merging technique we introduced, we observe a significant improvement in photo-z when the two strategies are combined, resulting in enhancements in $\boldsymbol{\sigma_{\mathrm{RMS}}}$ and $\boldsymbol{\sigma_{68}}$ up to [0.0265 & 0.0222] for the (LRG) sample and [0.0471 & 0.0471] for the Stripe-82 sample. Additionally, developed a method where the outputs of the template-based photo-z (specifically the best-fit template type and photo-z) are used as inputs to ANNz2. This approach

shows improvements in [$\boldsymbol{\sigma}_{\mathbf{RMS}}$ and $\boldsymbol{\sigma}_{\mathbf{68}}$], with values as low as [0.0590, 0.0242] in the Cosmic Evolution Survey (COSMOS) sample, and [0.0474, 0.0471], [0.0368, 0.0253], and [0.0213, 0.0168] in the SDSS Stripe-82, Constant Mass Sample (CMASS), and Low Redshift (LOWZ) samples, respectively. This thesis contributes to advancing the application of these techniques in fainter and deeper sky surveys, paving the way for further development of these methods and the discovery of improved techniques for measuring galaxy photo-zs.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Photometric redshifts are a technique used in astrophysics and cosmology to estimate the redshift of distant objects, such as galaxies and quasars, based on their observed photometric properties. Redshift measures the extent to which the light from an object is stretched towards longer wavelengths due to the expansion of the universe. This is a crucial parameter for studying the large-scale structure of the universe, galaxy evolution, and the nature of dark energy. As the universe expands, the light from distant astronomical objects, such as galaxies, is stretched, causing the wavelength to shift towards longer wavelengths. By measuring an object's redshift, astronomers can calculate its distance from Earth and determine its location within the vast cosmic web.

Modern astronomy relies heavily on the measurement of galaxy redshifts to enhance our understanding of the nature and evolution of the cosmos. Comprehending a galaxy's creation, evolution, and grouping requires knowledge of its velocity, distance, and other cosmic properties, all determinable from its redshift. Hubble demonstrated the link between the redshift of galaxies and their distance, now known as Hubble's law, in his 1929 paper, "A relation between distance and radial velocity among extra-galactic nebulae," (E. P. Hubble, 1929). The observation of galaxy redshifts played a crucial role in establishing the Big Bang theory of the universe. The Big Bang Theory foresaw the cosmic microwave background radiation (CMB), which was discovered in 1964 by Penzias and Wilson. The CMB redshift is consistent with the universe's expansion. Redshifts enable the study of phenomena as a function of time and distance, allowing for the identification of structure formations like galaxy clusters and the measurement of distance-dependent quantities such as luminosities and masses. Additionally, redshifts are also necessary to differentiate large-scale structures and galaxies along the line of sight (Alshuaili et al., 2022). Measurements of galaxy redshifts have also been used to study the characteristics of supermassive black holes in the centres of galaxies. For instance, millions of quasars, which are very brilliant objects propelled by supermassive black holes, have been found by the Sloan Digital Sky Survey. Furthermore, the properties of gamma-ray bursts, among the most energetic events in the universe, have been investigated using galaxy redshift measurements. The Swift Gamma-Ray Burst Mission (Gehrels et al., 2014) has measured the redshifts of hundreds of gamma-ray bursts, providing valuable insights into their origin and properties.

1.2 Problem Statement

Photometric redshifts are calculated based on the observed properties of celestial objects, such as their fluxes in different filters or bands. However, the estimation process is susceptible to uncertainties and limitations due to various factors, including measurement errors, degenerations in the observed data, and the complex relationship between photometric properties and redshift.

Template-based methods rely on comparing observed photometric data with a library of template spectral energy distributions (SEDs) to find the best-fitting redshift. However, they often encounter challenges in accurately capturing the complex relationships between photometric characteristics and redshift due to uncertainties and degeneracies in the data.

On the other hand, machine learning methods, such as artificial neural networks (ANN), can capture intricate patterns and nonlinear relationships in large datasets. By training on a set of objects with known spectroscopic redshifts, neural networks can learn the complex mapping between photometric features and redshifts, allowing for more robust redshift estimation. The exploit the synergies between template and machine learning approaches to improve the accuracy and reliability of photometric redshift estimation. By combining the strengths of both methods, it is anticipated that the accuracy of redshift predictions can be enhanced, leading to more precise distance measurements and a deeper understanding of the observed celestial objects.

Previous studies have shown an increase in the values of Root Mean Square Error (σ_RMS) and 68th percentile error. For instance, Abdullah et al. (2011) and John (2019) found values of 0.03 and 0.35 for the LRG sample, and 0.03 and 0.5 for the Stripe 82 sample, respectively, Maxwell found values of 0.02 and 0.05 for the CMASS sample. Is it possible to use these approaches to lower these values by about 10% so that redshift estimates for these samples are more accurate?

The proposed methodology seeks to improve and minimize the typical deviations of point estimates from their true values, reduce the frequency of outliers, provide a conservative range of possibilities for the redshift of an object and create PDFs that do a better statistical definition. It can be said that the methods used in this study have their novelty within other previous methods and significantly improve the accuracy of the redshifts of galaxies.

1.3 Research Objective

This study aims to improve the photometric redshift of galaxies via exploring the synergy of two methods: templates and machine learning. Prior attempts to improve the optical redshift focused on one method, either machine learning or templates as their only strategy. Here, in this work, we reveal the possibility of combining the two methods and comparing the extent of improvement in measuring the redshift. We also add parameters from BPz to ANNz2 with the aim of improving performance and benefiting from strengths in both methods. However, there are several research objectives to be achieved in the study:

1- To estimate galaxy redshifts by integrating the photometric probability density functions (PDFs) generated by the two approaches template fitting and machine learning across two separate galaxy samples using the photo-z algorithms, BPz and ANNz2, with data from the Sloan Digital Sky Survey.

2- To minimize uncertainties in photometric redshifts by using ANNz2 while exploring the impact of combining template-based models with machine learning algorithms. This approach involves training a neural network on a trained using a dataset with known spectroscopic redshifts, allowing it to learn the complex relationship between photometric properties and redshift.

3- To develop and compare hybrid methodologies that leverage the strengths of both template -based and machine learning approaches, aiming to create a unified framework that optimally harnesses spectral information, non-linear feature extraction, and model adaptation for more accurate and generalizable predictions of photometric redshifts in cosmological surveys.

This work could provide fresh ideas for enhancing the photometric redshift measurements of galaxies. Additionally, it will expand this sector and enhance contemporary measuring techniques.

1.4 Thesis contribution

Template-based methods, such as BPz, utilize a library of template spectral energy distributions to compare and match the observed photometric data. These methods provide a robust foundation for redshift estimation but may have limitations in capturing complex relationships between photometric features and redshifts.

To overcome these limitations, we present how we can improve the photometric redshift of galaxies by exploring the synergy of two methods: template and machine learning. By integrating the photo-z PDF obtained from both methods in diverse ways to improve the overall galaxy redshift estimation and by combining the template-based and machine learning approaches, we aim to leverage the strengths of each method. The best-fitting template and redshift estimate obtained from template-based methods like BPz are utilized as additional inputs to the ANNz2 framework. These parameters provide valuable information and insights into the photometric properties and estimated redshifts of objects.

The synergy between template-based methods and machine learning techniques has significant potential to improve the accuracy and reliability of photometric redshift estimation. This study seeks to demonstrate the effectiveness of this combined approach and contribute to advancing the field of photometric redshift estimation by leveraging the strengths of both template and machine learning methods.

1.5 Outline of the thesis

Chapter 1 briefly outlines the purpose, method, and contribution of this thesis. also, outlines the concept of galaxies redshifts, gives a general overview of its various methods: machine learning methods, and template fitting.

Chapter 2. explains subjects and explores recent literatures to the thesis. We will discuss galaxy photometry and spectroscopy, and the fundamental principles of photogrammetry's different 3D methods: experimental methods, machine learning methods, and template fitting, with a comparison of the three types and we will review synergistic methods in optical redshift.

Chapter 3 details the research approach, method, data collection, photometric redshift algorithms, SED template sets, supporting software, data file processing, analysis tools, ethical issues, and research limitations associated with this project.

Chapter 4 analyses data and explains the two methods that we used in this study: improving photometric redshifts by merging pdfs from template-based and machine learning algorithms and introduce the samples and improving photometric redshifts by adding template parameters and information into machine learning algorithms, and applied to samples used in this method (LRG, Stripe-82, COSMOS, CMASS, and LOWZ samples), and they are compared the results obtained. with the previous studies.

Chapter 5 is a condensed synopsis of the key ideas explored in this study. So, this brief chapter includes the thesis's conclusion and future recommendations.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter underscores the crucial role of photometric redshift in gaining a deeper understanding of cosmic evolution and estimating the distance and velocity of celestial objects. Traditionally, galaxy redshifts were derived from spectroscopic analysis, comparing observed spectral features to known terrestrial atomic and molecular spectra. However, the current set of spec-zs is insufficient for most current cosmological studies, mainly because spectroscopy is a time-consuming and expensive technique. As such, to produce redshifts ideally for all objects in large galaxy samples and to overcome these challenges, the concept of photometric redshifts (photo-zs) emerged, which can be broadly categorized into two broad categories: the empirical training set method and the fitting of spectral energy distributions (SED) by synthetic or empirical template spectra.

Machine learning methods demonstrate a clear performance advantage, however, both template and machine learning approaches offer unique benefits that can be leveraged together. In this chapter, we explore how these methods can be combined to enhance the accuracy of redshift estimation by capitalizing on their respective strengths. The chapter also reviews synergistic approaches to photometric redshift estimation, such as Mizuki SED template fitting, Delight, and Trees for Photo-z. Finally, we provide a summary of the key knowledge, and contributions presented in this thesis

2.2 Galaxies

The enormous clusters of stars, gas, and dust known as galaxies are fundamental cosmic structures that provide insight into the universe's origin and evolution. These celestial objects exhibit a variety of characteristics, including size, shape, star populations, motion, and more. Understanding the diverse nature of galaxies is crucial for unravelling the mysteries of our cosmos.

The most distinctive feature of current theories of galaxy formation is the mechanism relating the assembly of the galactic potential wells (primarily determined by the dark matter content) to the buildup of the stellar population contained therein (Fontana et al., 2003). For well over a century, astronomers have differentiated or classified galaxies based on their visual appearance (Figure 2-1). The science of galaxy "morphology" matured with Hubble's work (1926 & 1936), nd his famous Hubble Sequence remains a standard technique for studying galaxies today (Jarrett, 2002).

Galaxies have traditionally been categorized based on their morphology using the Hubble sequence (E. Hubble, 1926). Spiral and elliptical galaxies constitute the two primary categories of the Hubble series. Lenticular galaxies are a third type of galaxies that, in terms of their properties, lay between spirals and ellipticals. However, it is worth noting that some galaxies do not conform to this classification scheme.

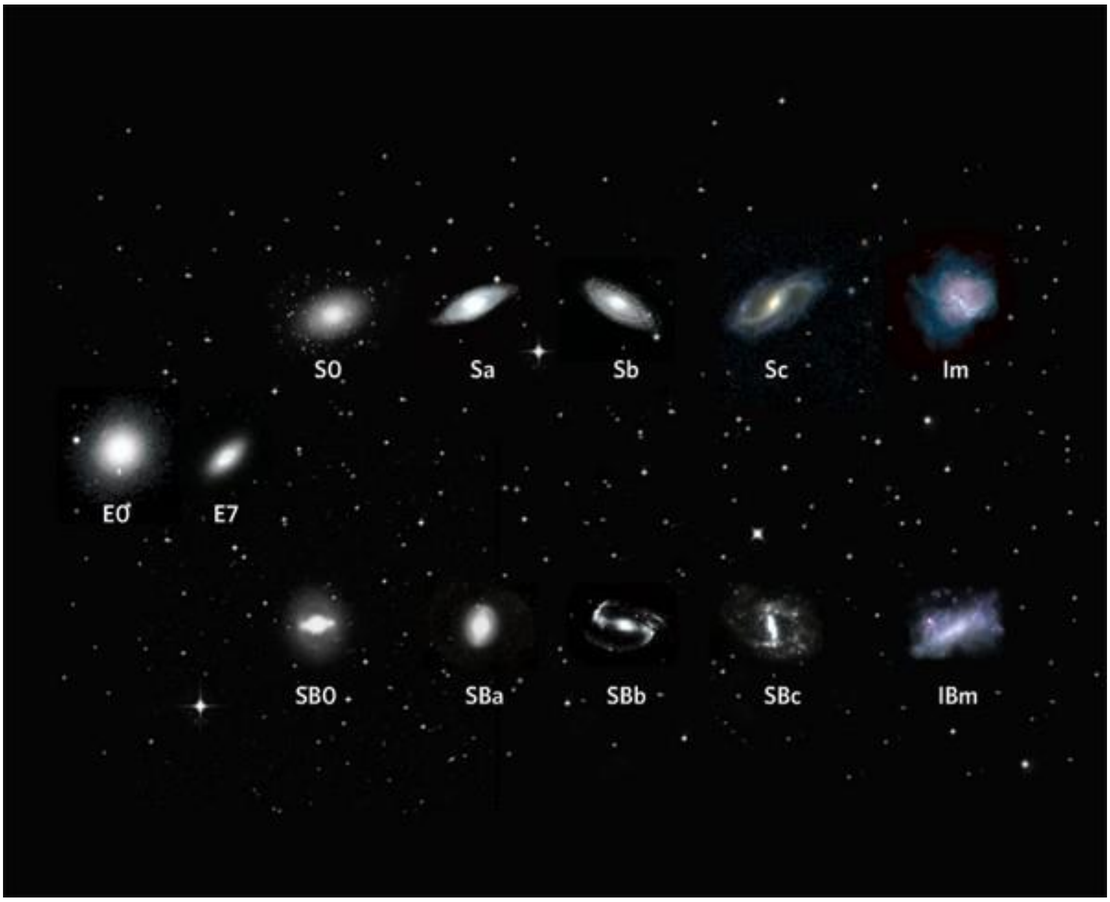

Figure 2-1 Galaxies are categorized using the Hubble tuning fork depending on their morphology.
Source: (Madau & Dickinson, 2014).

Numerous galaxies defy traditional classification. Extremely dwarf galaxies, as well as very big elliptical galaxies, irregularly shaped galaxies without a clear disk structure, and other objects, do not cleanly fit into Hubble's categorization scheme. These atypically shaped galaxies are categorized independently due to their deviation from standard Hubble types.

Through a variety of observational methods, like imaging, spectroscopy, and multi-wavelength surveys, galaxies have been extensively studied. Spectroscopic investigations give thorough details about emission and absorption lines in galaxy spectra, allowing exact measurements of redshifts and other physical characteristics.

The redshift of a galaxy, represented by the letter "z," represents the relative motion of the galaxy concerning Earth and serves as a gauge of the universe's expansion. It is described as the ratio of a spectral line's observed wavelength to its rest wavelength, subtracted by unity. Astronomers utilize the redshift parameter as a proxy for the distance to galaxies to investigate the large-scale structure of the cosmos, the rate of the universe's expansion, and the age of galaxies. In recent years, large-scale surveys, such as the Sloan Digital Sky Survey, Hubble Space Telescope (HST) observations, and the European Space Agency's Gaia mission, have revolutionized our understanding of galaxies. These surveys have provided extensive datasets facilitating the exploration of galaxy populations, their clustering properties, and the cosmic web structure.

2.3 Cosmological Redshifts

Astronomers frequently discover that the spectral lines in an object's spectrum are displaced towards longer wavelengths in comparison to laboratory values when they view light emitted by distant astronomical objects, such as galaxies or quasars. as the universe expands and stretches the wavelengths of light during its journey to us, causing the phenomenon known as redshift.

Cosmological redshift differs significantly from the well-known Doppler shift, despite their first similarities. The velocity of the item at the time the photons are released affects the wavelength of radiation emitted in the Doppler shift. The wavelength is moved toward the blue end of the spectrum if the item is traveling toward us and the red end if it is going away. Cosmological redshift, on the other hand, results from the stretching of the radiation's wavelength as it moves across expanding space. Rather than being caused by the velocity of any object, this redshift is the result of space itself expanding. For instance, in a distant binary system, it is theoretically possible to measure both a Doppler shift and a cosmological redshift. The Doppler shift arises from the motion of the individual stars within the binary system, depending on whether they were moving toward or away from us when the photons were emitted. The cosmological redshift, on the other hand, is determined by the distance of the system from us at the time of photon emission. The greater the distance, the longer the photons have travelled through the expanding universe, resulting in a higher cosmological redshift.

An astronomical object's redshift is measured using the redshift parameter, abbreviated "z". It is defined as the ratio of the observed wavelength (λ_{obs}) to the rest wavelength (λ_{rest}) of a spectral line, subtracted by unity:

$$z = \frac{\lambda_{obs} - \lambda_{rest}}{\lambda_{rest}} \qquad 2\text{-}1$$

Redshift facilitates the comparison of distant object distances by astronomers. In 2011, scientists announced they had seen the farthest object ever seen — a gamma-ray burst called GRB 090429B, which emanated from an exploding star. At the time, Scientists calculated at the time that the explosion occurred 13.14 billion years ago. In contrast, 13.8 billion years ago was the time of the Big Bang. Also, the development of observational cosmology was greatly aided by cosmological redshifts. They have offered proof for the existence of dark energy, the expanding cosmos, and the Big Bang theory. Astronomers have been able to map the universe's large-scale structure, research the creation and development of galaxies, and examine the cosmic microwave background radiation thanks to redshift measurements in combination with other observational data.

2.4 Photometric redshift

Traditionally, spectroscopy has been used to measure the redshift of objects by directly observing the characteristic spectral lines in their light. Due to the lengthy exposure times required and the limited multiplexing capabilities of spectroscopic instruments, high-precision spectroscopic redshifts (spec-z's) can only be obtained for a small fraction of the galaxies for which we have imaging data. For example, it will be possible to measure spectroscopic redshifts for less than 1 per cent of the galaxies that will be used in the Rubin Observatory Legacy Survey of Space and Time (LSST)studies of galaxy evolution and cosmology(Dey et al., 2022).

Overall, photometric redshift is a technique in astrophysics and cosmology to estimate the redshift, or the shift in the wavelength of light from distant objects, based on their observed photometric properties. This technique was originally proposed by Baum (1962), who applied it to measure the redshifts of elliptical galaxies in distant clusters (Bolzonella et al., 2000). In recent years, photometric redshifts have been extensively used, particularly in ultra-deep and well-calibrated observations like those from the Hubble Deep Field (Firth et al., 2003). The field of optical redshift estimation has greatly benefited from the vast amount of data provided by numerous surveys, including the Sloan Digital Sky Survey (York et al., 2000,the first extensive multi-band and spectroscopic native digital survey of the sky), Dark Energy Survey (DES, Abbott et al., 2005), Cosmic Evolution Survey (COSMOS, Scoville et al., 2007), (Roman Space Telescope, Green et al., 2012), Hyper Suprime -Cam Survey (HSC, Aihara et al., 2018), Vera C. Rubin Observatory Legacy Survey of Space and Time (LSST, Shemmer et al., 2018) and James Webb Space Telescope (JWST, Kauffmann et al., 2020).

A variety of techniques can predict certain photometric redshifts (Pössel, 2019). These methods for estimating photometric redshifts can be divided into two main categories:

- SED template fitting methods: this method compares the measured photometry of a galaxy to a collection of templates that may be seen, obtained by averaging the spectra of related galaxies, or computed through synthetic spectroscopy, so that the redshift is determined.

- Empirical techniques: This category is defined by machine learning or data-driven approaches that in the case of supervised learning, learn how to map photometric space onto z using the a-priori knowledge supplied by a sub-sample of objects for which precise spectroscopic information is available. Alternatively, one may let the photometric data organize themselves while one finds regions of the parameter space that have comparable traits.

In this work, we will discuss the two methods in more detail in the following chapters and explain precisely how we improved the accuracy of redshift by combining the advantages of each method.

2.5 Template-based Photo-z Methods

In astronomy, template-based photo-z algorithms are frequently used to calculate galaxy redshifts from their observable photometric data. It is a type of photometric redshift estimation that uses a template library of galaxy spectra to a galaxy's redshift based on its observed spectral energy distribution. The template library is typically constructed from high-quality spectra of galaxies with known redshifts. The redshift of an unknown galaxy is determined by identifying the template in the library that best matches the observed SED.

Template-based photo-z methods were first introduced in the 1980s by (Yahil et al.,1986). This technique estimates galaxies redshifts in the Centre for Astrophysics Redshift Survey (CfA) using a library of 10 galaxy templates (Davis et al., 1983).

Over time, template-based photo-z methods have undergone significant advancements. One of the most notable improvements was the development of stellar population synthesis models by Connolly et al., (1995). These models enable the calculation of SEDs of galaxies of varying ages, metallicities, and star formation histories, leading to substantially improved accuracy of template-based photo-z methods. Connolly et al., (1995) also presented one of the first template-based methods for estimating redshifts in the Hubble Deep Field. they employed a database of galaxy spectral templates obtained from observed spectra. This study demonstrated the feasibility of photo-z estimation using template-matching techniques. From the 2000s onwards, many different template-fitting photo-z codes were developed and made publicly available. Hyperz (Bolzonella et al., 2000) was the first of these to be freely available to the astronomy community (Soo et al., 2018), However, BPz (Benitez, 2000) was the first algorithm to propose the use of Bayesian inferences and priors to improve photo-z's estimates, the term "Bayesian statistics" refers to a probabilistic method of data analysis and inference where uncertainties in model parameters and hypotheses are quantified using probabilities. In contrast to conventional frequentist techniques, which yield confidence intervals and point estimates, Bayesian techniques use a "prior" distribution to account for past information or assumptions about a system. Using the Bayes theorem, this prior is updated with fresh data to create a "posterior" distribution, which reflects the updated opinions about the parameters after taking the evidence into account. It involves using Bayes' Theorem to update the probability of a hypothesis as more evidence or information becomes available. This differs from several other interpretations of probability, such as the frequentist interpretation. And therefore, it is considered as one of the pioneering template-based photo-z codes. The BPz method uses a Bayesian statistical framework to derive the most likely redshift distribution for a given set of photometric measurements. It employs prior information on the anticipated redshift distribution of galaxies and accounts for errors in the measured magnitudes. The BPz method generates a probability distribution function (PDF) for the object's redshift by combining likelihood and prior. The PDF's peak or peaks indicate the object's most likely redshift(s), while the breadth of the distribution indicates the degree of estimating uncertainty.

In large-scale astronomical surveys, where obtaining spectroscopic redshift measurements for all objects is often constrained by time and resource limitations, the BPz approach has been widely adopted. It gives the ability to easily determination of redshifts for numerous objects and provides valuable data for investigating galaxy evolution, cosmology, and the large-scale structure of the universe. Other instances of some notable template-fitting photo-z codes:

- HYPERZ: HYPERZ (Bolzonella et al., 2000) is a template-fitting code that makes use of artificial template spectra produced by stellar population synthesis models. It uses a χ^2 approach to calculate redshifts. Photometric redshifts are estimated by HYPERZ using a template-fitting technique where a collection of synthetic spectral energy distributions (SEDs), or 'templates,' representing galaxies at various redshifts, is compared to the observed photometric data (such as magnitudes in different filters) of a galaxy. These templates are developed using actual data or theoretical theories. The algorithm identifies the combination of template and redshift that best fits the observed photometry for each galaxy. and this best match is used to estimate the galaxy's redshift. The method of minimization typically involves reducing the difference between the observed and template photometric data—often expressed as chi-squared—to determine the best match. The redshift that provides this optimal fit is taken as the estimated photometric redshift.

- Le Phare: Le Phare (Ilbert et al., 2006) is a software package specifically designed for estimating photometric redshifts in astronomy. It is widely used by researchers in the field of extragalactic astronomy to determine the redshifts of galaxies based on their observed photometric properties. Le Phare primarily employs template fitting, comparing template spectra representing various galaxy types with known redshifts to observed optical data. The software performs a more convenient analysis to select the best-fitting template and determines the target galaxy's redshift. Users typically provided a catalog of the observed sizes or fluxes of target galaxies across a variety of wavelengths (e.g., optical and infrared bands) for z-image estimation using Le Phare. The software utilizes a set of appropriate filters, convolutions, and algorithms to select the most suitable template and associated redshift. While both BPz and Le Phare are frequently used for photometric redshift estimation, their underlying techniques differ. Le Phare focuses on template fitting, but BPz takes a Bayesian technique that incorporates prior knowledge.

- ZEBRA: ZEBRA (Feldmann et al., 2006) is a template-fitting algorithm that utilizes self-organizing maps (SOM) to calculate photometric redshifts (photo-zs). It employs grid cells to determine redshifts by mapping the photometric colors of galaxies onto a two-dimensional grid. ZEBRA leverages Bayesian statistics to estimate photometric redshifts, incorporating prior information about the redshift distribution of galaxies to refine estimates, particularly when dealing with noisy or incomplete data. Like other photometric redshift codes, like other photometric redshift codes, ZEBRA utilizes a template-fitting method, comparing observed photometric data to a set of spectral energy distribution (SED) templates. However, ZEBRA can adapt these templates based on the data, enhancing their flexibility and suitability for specific observations. This adaptability enables ZEBRA to handle variations in galaxy properties more effectively. The code calculates the likelihood of each template fitting the observed data at different redshifts. It combines this likelihood with the prior probability to produce a posterior probability distribution for the redshift of each galaxy. The redshift with the highest posterior probability is considered the best estimate. ZEBRA can iteratively refine its templates and priors using the results of an initial redshift estimation to improve subsequent estimates. This iterative process helps reduce biases and enhance the overall quality of redshift estimates. The algorithm provides not only a single redshift estimate but also a full probability distribution function (PDF) for the redshift, offering a measure of uncertainty and enabling more nuanced analyses. This code has been widely employed in cosmological surveys, such as the COMBO-17 survey, where accurate photometric redshifts are crucial for studying the large-scale structure of the universe, galaxy evolution, and other extragalactic phenomena. Its ability to adapt templates and use Bayesian statistics makes it particularly effective in handling complex datasets

- EAZY: Emission Line Analysis for Redshift (EAZY, Brammer et al., 2008) is another popular template-based software code used for photometric redshift estimation in astronomy. The program is optimized for cases where spectroscopic redshifts are not available or are only available for a biased subset of the galaxies (Hildebrandt et al., 2010). The EAZY code offers a flexible framework for fitting templates to the observed photometry and is built to handle big datasets. It is a collection of model spectra that depict several sorts of known-redshift galaxies. These models cover a variety of galaxy populations with various SEDs and emission line intensities. The observed photometric data, which often spans several wavelength bands, is compared to the template library using the EAZY code. It determines a likelihood function that measures how well each template fits the observed data. EAZY finds the best-fitting template and related redshift for a given galaxy by maximising the likelihood. EAZY also includes several features that take into consideration various aspects of the photometric redshift calculation, such as photometric errors, dust-induced reddening, and emission line fluxes. To increase the precision and robustness of the redshift estimations, it makes use of Bayesian priors and regularization methods.

These are just a few instances of template-fitting photo-z codes; the astronomical community has access to many more. Each code offers unique advantages, limitations, and specific implementation. The research project's unique requirements, the features of the data, and the required level of accuracy and precision for the photo-z estimate all influence the choice of code. In this work, BPz was used to improve the accuracy of redshifts by combining probability density functions and incorporating additional characteristics such as best-fitting template "t_b"" and best-fitting redshift "z_b" from BPz as inputs to ANNz2 to enhance its performance.

2.6 Machine learning methods

Since the advent of computer technology in the late 1990s, machine learning techniques have gained prominence in photometric redshift estimation due to their ability to identify intricate patterns and correlations within large datasets. Numerous machine learning photo-z techniques have been developed and refined over time. Firth et al., (2003) are often pioneers in machine learning photo-z methods. They employed artificial neural networks (ANNs) to obtain photo-z's for approximately 20,000 galaxies from SDSS, achieving a root-mean-square error σ_{RMS} ~ 0.021 for galaxies with redshift z < 0.35 (Soo et al.2018).

Collister & Lahav., (2004) presented a machine learning technique known as ANNz in their paper titled "ANNz: Estimating photometric redshifts using artificial neural networks". This method estimates photometric redshifts from multi-band photometric data using artificial neural networks (ANNs).

There are three type of machine learning techniques: supervised, unsupervised, and semi-supervised. Models under supervision are provided data with labels, such as a list of a group of fruits' attributes and their names. By determining model parameters based on the connections between features and labels, this set is utilised to build the model. It is known as the training set. A loss function, which measures the discrepancy between the output predicted by the model and the anticipated output (the label), is minimized during training.

As training progresses, fitted models are tested on a validation set, an additional labeled data set. This step is used to optimize the pertinent parameters and weights and avoid overfitting, which is when a model fits the training data too closely and fails to generalize to new data. The model is then applied to a fresh collection of labeled data, known as the test set, and its performance is evaluated using a variety of metrics to establish whether it is appropriate for the job at hand. The target set, the dataset containing sample-specific properties for which we want the projected outputs, may then be applied using an appropriate model. Regression and classification are often handled using supervised learning techniques. Unsupervised learning, on the other hand, doesn't need a training set or labelled data. Instead of learning a relationship, these models find relationships between samples based on their characteristics. Unsupervised learning is widely used for tasks like clustering, in which comparable samples are grouped together based on where they are placed in the feature space, and anomaly detection, which involves determining whether any samples are sufficiently unique from the rest of the data. Finally, some techniques include both supervised and unsupervised learning into different model components. This is typically used when there are significant amounts of unlabelled data and scant amounts of labelled data. When a representative training set is available, these methods generally produce accurate redshift results along with acceptable estimates of uncertainty. However, the accuracy of photo-zs varies significantly depending on the method and the specific algorithm used, as well as the size and representativeness of the training set available. There is a wide range of machine learning algorithms. It is important to note that the effectiveness of machine learning algorithms heavily relies on the quality and representativeness of the training data, the choice of algorithm, appropriate feature engineering, and regular monitoring and maintenance of the deployed model. For instance, generally, ANNs fare better with more inputs used, while SVMs require an optimal number of inputs for best performance (Wang et al. 2008b); the versions of boosted decision trees (BDTs) and Gaussian (GPs) are highly dependent on the hyperparameters set, while SVMs do not require complex architecture (Soo et al.2018).

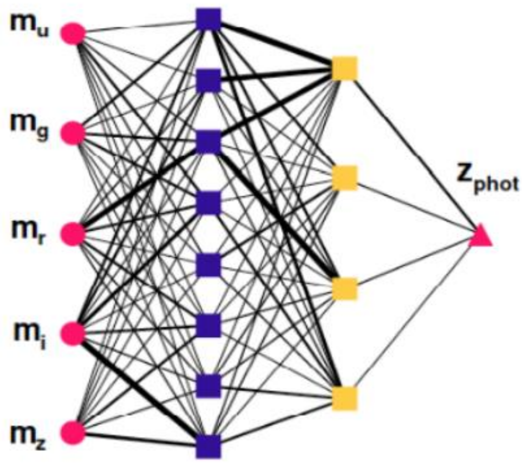

Figure 2-2 An artificial neural network configuration with 5 magnitudes (oneper filter) and redshift as output.

Source: (Sadeh et al., 2016).

2.7 Template Fitting vs Machine Learning

machine learning and template learning approaches each offer distinct advantages, despite estimates of galaxy redshifts showing that machine learning methods have a clear performance and edge. For instance, Template Fitting methods involve comparing observed photometric data to a library of templates (SEDs, Coleman et al., 1980), while machine learning techniques utilize neural networks and computational algorithms to learn the relationship between photometric characteristics and redshifts. Moreover, machine learning approaches offer greater flexibility and adaptability across various galaxy types. In contrast to template fitting approaches, which may face challenges such as template degeneracies and limited template libraries, machine learning techniques can capture complicated, non-linear correlations between photometric characteristics and redshifts.Additionally, with huge datasets or intricate template libraries, template fitting approaches can be computationally costly. Once trained, machine learning methods are scalable for large-scale surveys and can predict redshifts accurately. While machine learning techniques can detect extrapolation, significant variations among neighbours, or insufficient training set coverage, template fitting approaches can identify poor or unlikely template fits as well as broad or multipeaked posterior redshift PDFs (Beck et al., 2017). Thus, taking advantage of the synergy of these two methods can be an opportunity to achieve more accurate results when combined (Alshuaili et al., 2022).

2.8 Review of synergetic methods in photometric redshifts

2.8.1 Trees for Photo-z (TPz)

Trees for Photo-z (TPz; Carrasco Kind & Brunner 2013) is a training-based code that utilizes prediction trees and random forest algorithms(Prat et al., 2018).

TPz can operate in two modes: regression mode or classification mode. The classification mode dividing the redshift distance into several small redshift bins, while the regression mode determines a point estimate of a galaxy's photo-z(Broussard & Gawiser, 2021). Compared to conventional approaches, this method offers better accuracy and flexibility by combining the strengths of template fitting and machine learning.

TPz employs a regression framework where machine learning algorithms, such as artificial neural networks or random forests, are trained to learn the intricate mapping between photometric features and true spectroscopic redshifts. By using large and representative training datasets, TPz models can capture complex relationships and account for various physical factors affecting redshift estimation. In comparison to conventional approaches, this method offers better accuracy and flexibility by combining the strengths of template fitting and machine learning. TPz employs a regression framework, where machine learning algorithms, such as artificial neural networks or random forests, are trained to learn the intricate mapping between photometric features and true spectroscopic redshifts. By using large and representative training datasets, TPz models can capture complex relationships and account for various physical factors affecting redshift estimation. The distinguishing feature of TPz is its ability to incorporate the information contained in template SEDs as additional inputs. These templates are derived from spectroscopic samples and provide valuable insight into the relationships between galaxy types and their redshifts. By combining the advantages of both template fitting and machine learning, TPz aims to enhance the precision and reliability of photo-z estimates.(Kind, 2015).

2.8.2 Delight

Deep Learning Identification of Galaxy Hosts of Transients or Delight (Leistedt & Hogg, 2017) is a hybrid template-based and machine learning photo-*z* algorithm (Soo et al., 2021). The Delight algorithm combines the advantages of machine learning and template fitting methods. It builds a training dataset using a sizable collection of template SEDs. The program then uses a Gaussian process to learn the relationship between observed photometric features and spectroscopic redshifts. Delight differs a little from the standard machine learning approach in that it uses a GP to model the predicted fluxes of a training galaxy at various redshifts with the aid of SED templates, as opposed to directly establishing an empirical relationship between the fluxes and redshifts of the training objects. For each training object, this generates a latent flux redshift template that can be used to compare the best-projected redshift for a particular collection of fluxes in the testing set to a variety of training templates (Soo et al., 2021). It has been successfully applied to various astronomical surveys and datasets, demonstrating its effectiveness in large-scale cosmological studies.

2.8.3 Mizuki SED template fitting

Template-fitting code Mizuki (Tanaka, 2015) The template is a set of features that are known to be present in the dataset, and the code uses these features to find the best fit for the template. The code is named after Mizuki, a Japanese word that means "water drop".

By comparing measured SEDs to a library of model templates, the Mizuki algorithm uses a Bayesian framework to estimate physical parameters like as redshift, stellar population age, stellar mass, star formation rate, and dust attenuation. Based on spectral energy distribution (SED) fitting, MIZUKI calculates photo-zs for objects having clean SDSS CMODEL photometry in at least three bands (inclusive). The algorithm makes use of a collection of templates produced by the stellar population synthesis (SPS) code developed by (Bruzual & Charlot, 2003), assuming the initial mass function (IMF) proposed by Chabrier, (2003), Kawinwanichakij et al., (2021).
The Mizuki code has been used in various research studies and has contributed to our understanding of galaxy properties, stellar populations, and their evolution. It offers a powerful tool for analysing SEDs and extracting valuable astrophysical information.

In this chapter, we discussed the photometric redshift and spectroscopy, and, reviewed synergetic methods in photometric redshifts, and briefly outlined template-based photo-z methods, and machine learning methods. In the next section, we move on to discussing data samples, photometric redshift algorithms, SED template sets, performance metrics, and supporting software.