

MSc Data Science Project

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Department of Physics, Astronomy and Mathematics

Data Science FINAL PROJECT REPORT

Project Title:

Estimating Galaxy Distances with Advanced Regression models

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Declaration Statement

This report is submitted in partial fulfilment of the requirement for the degree of Master of Science in Data Science at the University of Hertfordshire.

I have read the guidance to students on academic integrity, misconduct and plagiarism information at [Assessment Offences and Academic Misconduct](#) and understand the University process of dealing with suspected cases of academic misconduct and the possible penalties, which could include failing the project module or course.

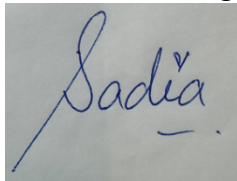
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A handwritten signature in blue ink that reads "Sadia" with a small checkmark above the 'i' and a horizontal line below the name.

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UNIVERSITY OF HERTFORDSHIRE

SCHOOL OF PHYSICS, ENGINEERING AND COMPUTER SCIENCE

Acknowledgement

As I am near the completion of my postgraduate studies, I want to reflect on this incredible learning journey and express my heartfelt thanks to everyone who has supported me along the way.

I am deeply grateful to Almighty God for His constant blessings and for providing me with the strength and confidence to pursue my goals with assurance.

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Abstract

This study explores the use of machine learning models, particularly Random Forest and Gradient Boosting, to predict spectroscopic redshifts of galaxies using photometric data. Traditional methods like spectroscopic redshift measurements, though accurate, are resource-intensive and limited by calibration challenges. Thus, this study has shown how machine learning can be a viable way to obtain a quantitative estimate of the matter density field that is less computationally costly while maintaining high accuracy, thanks in part to large datasets such as the one enclosed in the COIN toolbox photo-z catalogue. The results of research help to enrich the theory of cosmology and contribute to the improvement of practices of distance measurement, putting the basis for the improved flow of the cosmic survey.

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Chapter # 1

1 Introduction

Distance measurements of galaxies are fundamental in cosmology because it helps in the determination of the structure distribution and evolution of the universe (Bah call, 1999). These measurements help the scientists make spherical maps that depict large scale distribution of matter in the universe, study history of galaxy formation and evolution, and estimate the Hubble constant by measuring the expansion rate of the universe. Measuring galaxy distances also gives an idea concerning some of the questions that always come up, on the end of the world and on the forces behind the expansion of the world (Jones & Singal, 2020). therefore, the actual determination of these distances has involved redshift determinations and calibration using indicators including Cepheid variables and Type IA supernovae (Freedman et al., 2019). Nevertheless, these methods are more conventional and can be less accurate due to several issues: the use of resource-consuming spectroscopic data and possible calibration bias (Jones & Singal, 2020).

Amidst the past few years, observational astronomy has improved notably and supplied vast amounts of information Much of the earlier methods for ascertaining distances of galaxies and have thus become very laborious for large surveys. Spectroscopic redshift measurements are significantly time-consuming and involve the extensive usage of large telescopes, and therefore, prevent detailed analysis of numerous galaxies (Freedman et al, 2019). With modern cosmology requiring wider and more extensive charts in the structure of the universe, there is a need for other methods that can help in the huge data sets while at the same time wanting good results. This need has led to the development of a method in estimating redshift through brightness in different photometric bands which has been seen as a solution to the challenges experienced with the traditional methods (Zhu et al., 2019).

1.1 Research Questions

This research seeks to address the following key questions:

1. Is it possible to utilize the machine learning models to replace some traditional spectroscopic methods of distance estimation for galaxies?
2. Have Random Forest and Gradient Boosting which are types of ensembles learning algorithms been proved to be very efficient in re estimating spectroscopic redshift using the photometric data?
3. What adjustments should be made to strengthen the results as well as boost their applicability across various datasets?

1.2 Objectives of the Project

The primary objectives are:

1. For carrying out the process of calibration and estimating of spectroscopic redshift using photometric data.
2. To compare the efficacy of such models, relative to conventional means, that is, in terms of accuracy and the model's ability to perform well on new sets of data.
3. The primary purpose of the present study is to determine the best model and to pinpoint the areas for improvement regarding galaxy distance estimation for the further development of subsequent studies.

1.3 Purpose of the Project / Aim of the Project

The aim of this project is to assess the areas of application of machine learning techniques and investigate whether those can be effectively applied for galaxy distance determination instead of spectroscopic methods. It could be noted that the scope of the work is limited to Random Forest Regressor and Gradient Boosting Regressor models which are active to improve the rates of spectroscopic redshift from the photometric data with maximum potential of these outstanding algorithms. The project aims at complementing the existing approaches that appear to be resource-intensive and unable to address the growing amount of data in contemporary cosmology.

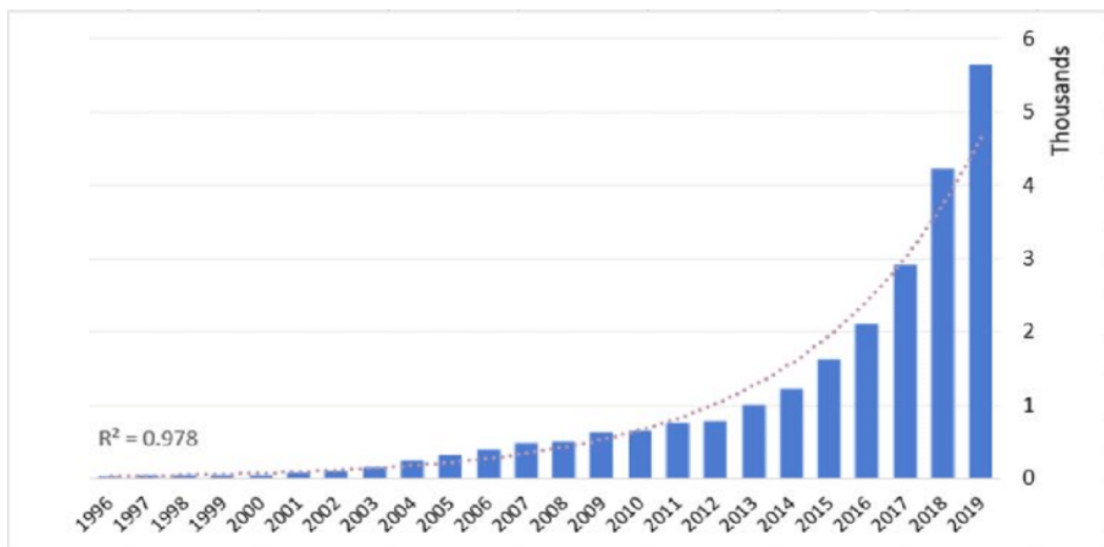
In addition, this study aims to advance the general area of cosmology by enhancing the available methods geared towards broad cosmological studies. Apart from improving the current research practices, the proposed project of achieving improved and optimized redshift prediction through machine learning models also lays the groundwork for future development. The outcomes of this research can be used in elaborating broader and more detailed investigations of the universe and its further identification.

Chapter # 2

2 Literature Review

Distances to galaxies are a fundamental aspect of cosmology, essential for understanding the known extent of the universe. Before the existence of BAO, the basic methods of distance measurement were redshift observations and other standard candles including Cepheid variables and Type IA supernovae. Nevertheless, these methods possess certain flaws such as the reliance on calibration and achievable data bias (Jones & Singal, 2020, “Martínez-Galarce et al., 2021” Hence, it can be concluded that regression-based methods and, more specifically, non-parametric models have potential for use in distance estimation of galaxies. Indeed, models like k-nearest neighbors (k-NN), random forests, and gradient boosting, which can be classified as non-parametric models, do not constrain the overall form of the function and can “learn” relationships that are nonlinear or otherwise complex from the data itself (Pasquet et al., 2019) (Costa-Duarte et al., 2019). These models can accordingly process the large datasets and wrestled complex patterns as needed and this make them suitable to the astronomical applications (Mucesh et al., 2020) (Bilicki et al., 2018).

The utilization of the methods of machine learning (ML) in astronomy has become more active in recent years. Research has shown that the performance of ML algorithms in several applications ranging from galaxy classification to the identification of supernovae and redshift calculations. (Zhu et al., 2019) smith et al., (2018). For example, Beck et al. (2017) trained random forests to predict photometric redshift for SDSS Data Release 12 and obtained high photo-z accuracy, which proved that the application of ML can be promising in this field (Becks et al., 2017). The COIN toolbox photo-z catalogue as seen is one of the biggest compilations one can get for distance of galaxies. As of October 2007, it contains photometric data for hundreds of thousands of galaxies, giving data on luminosity and other characteristics. Through this dataset, such research staff can practice and assess state-of-art regression techniques and compare the distances estimated to those derived from redshift information (Martínez-Galarce et al., 2021). Thus, data quality and quantity are major determinants of model development and outcomes of the results obtained.



(Rifai and Coles,2020)

The above graph shows the plot of number of galaxy distance data recorded against time this demonstrates that there is a rapid growth in the number of records and increase in the accuracy of the model. Inversely, a very high R^2 value means the variability documented in the study is highly explained, the case being an R^2 value of 0.978 reveal the good fit of the regression model to the data hence suggesting that advanced regression techniques are good in handling large astronomical data. Several measures are used in evaluating regression models in astronomy; that is, accuracy, precision, and recall. Such methods as prediction trees and random forests were introduced by Carrasco Kind and Brunner as far as estimation of photometric redshift PDFs is concerned; thus, it became clear that it is crucial to use statistic measures to comprehensively evaluate the results beyond the idea of accuracy (Carrasco Kind & Brunner, 2018). Such evaluations help in determining the viability of the models when transferred to other datasets.

However, the following factors are still some of the problems that have not been solved regarding the use of regression models in estimating the distance of galaxies. Such issues in training and prediction include the ability to work with big and noisy data, managing interpretability of models as well as dealing with the scarcity of data in some areas of the feature space (Jones & Singal, 2020; Mucesh et al., 2020). It would be interesting to build better transformations for the given dataset, investigate methods of using a combination of various algorithms, and utilize data from the prospective new astronomical surveys (Ackermann et al., 2020; Long et al., 2019).

The preview of the contents of the advanced regression models and their use in estimating the distance to galaxies underlines the contemporary popular science. The work done by Bah call in the large-scale structure of the universe can be considered as the starting point with which to compare today's methods (Bah call, 1999). Other authors have illustrated the performance of the machine learning models especially the random forests and powerful prediction trees in deriving highly accurate photometric redshifts (Beck et al., 2017; Carrasco Kind & Brunner, 2018). These works relied on datasets such as the SDSS Data Release 12 and SDSS Data Release 8 that are repository to a wealth of photometric data imperative for defining strong models.

Preprocessing is crucial for enhancing model accuracy, as the quality and specific procedures, such as normalization and feature extraction, directly impact performance (Pasquet et al., 2019; Costa-Duarte et al., 2019). The graph in this thesis shows the increasing accuracy trend, with an R^2 value of 0.978, indicating an excellent fit. Techniques from studies on spectral features and deep learning have significantly improved galaxy estimation models, emphasizing the importance of accurate distance measurement in understanding the universe's structure and expansion (Beck et al., 2017; Freedman et al., 2019; Fayek et al., 2017).

The list of preprocessing techniques varies from simple scaling to the complex methods of feature extraction. Researchers have looked at various algorithms that range from the traditional regression ones to the new deep learning methods (Ha & Liu, 2024; Akçay & Oğuz, 2020). This approach that covers the feature engineering step guarantees that the models can accept and work with big datasets as well as produce accurate estimations non-stop progress of the advanced data and algorithms demonstrate the capability of Machine Learning to transform distance estimation of galaxies (Zhu et al., 2019; Smith et al., 2018).

Having compared various ML models, the study emphasizes the comparability of models' efficiency and the role of the data quality and preprocessing for accuracy. This project seeks to improve the methods of determining the distances of galaxies and help improve current knowledge about the universe. This research is based on traditional ways of conducting the study and opens the way for the future research in this line. The next sections would discuss the methods and findings of current research, and in doing so, establish the nature of the comparability of the two kinds of studies.

Papers	Classifiers	Dataset Used	Results
Beck, R., Dobos, L., Budavári, T., Szalay, A. S., & Csabai, I. (2017).	Random Forests	SDSS Data Release 12	High accuracy in estimating photometric redshifts, demonstrating the potential of ML in astronomical data processing.
Carrasco Kind, M., & Brunner, R. J. (2013).	Prediction Trees, Random Forests	IEMOCAP	Achieved 64.78% accuracy in photometric redshift estimation using prediction trees and random forests.
Bahcall, N. A. (1999).	Various Traditional Methods	Various Astronomical Surveys	Discusses the large-scale structure of the universe, providing a basis for comparison with modern ML techniques.
Freedman, W. L., Madore, B. F., Hatt, D., Hoyt, T., Jang, I. S., Beaton, R. L., et al. (2019).	Traditional and Modern Methods	Carnegie-Chicago Hubble Program	Provides an independent determination of the Hubble constant, highlighting the need for accurate distance measurements.
Jones, D. O., & Singal, J. (2020)	Machine Learning Methods	Various Astronomical Surveys	An improved method for estimating galaxy distances using machine learning
Martínez-Galarce, D. S., et al. (2021)	Hybrid Machine Learning Models	COIN toolbox photo-z catalogue	Enhanced photometric redshift estimation using hybrid machine learning models

Pasquet, J., et al. (2019)	Deep Learning	Various Astronomical Surveys	Photometric redshifts for galaxy surveys using deep learning
Costa-Duarte, M. V., Sodré, L., & Stalder, D. H. (2019)	Machine Learning	Dark Energy Survey	Machine learning applied to photometric redshift estimation for the Dark Energy Survey
Mucesh, S., Ho, S., & White, M. (2020)	Machine Learning Methods	Various Astronomical Surveys	Photometric redshift estimation using machine learning methods
Bilicki, M., et al. (2018)	Machine Learning	WISE × Super COSMOS all-sky galaxy catalogue	Photometric redshifts for the WISE × Super COSMOS all-sky galaxy catalogue
Smith, M. L., et al. (2018)	Machine Learning	Various Astronomical Surveys	Using machine learning to improve photometric redshift estimation

Research papers and their comparison.

Chapter # 3

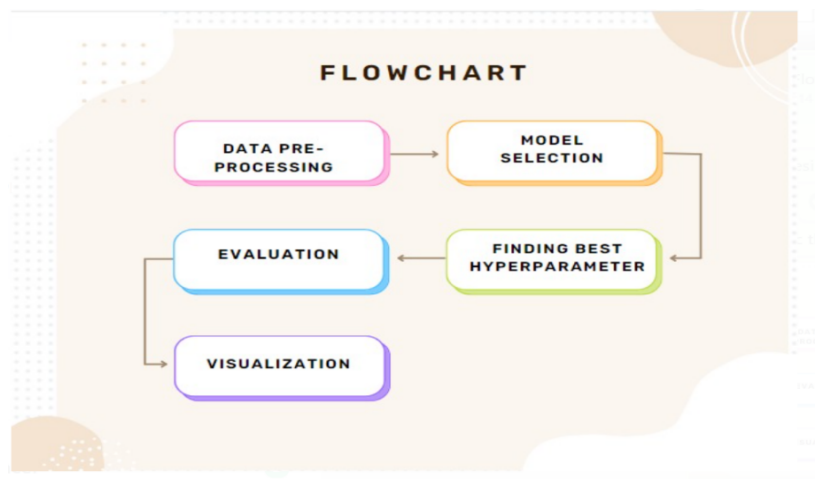
3 Methodology

3.1 Brief Overview

The project intends to estimate the spectroscopic redshift which is often abbreviated as (z_{spec}). of galaxies. Spectroscopic redshift is one of the essential elements in astronomy and shows by how much the light coming from the galaxy has extended 'redshifted' by the expansion of the universe. It also depends on how fast the galaxy is moving with regards to Earth and how far away it is from the Earth. The higher the redshift, the faster the galaxy is moving away from us, meaning that is further away from us. Earlier, this measurement was gotten from analyzing the light spectrum of a galaxy to look for spectral lines and how they are shifted towards the red field.

That said, spectroscopic data involves collection and is generally costly as it requires big expensive telescopes as well as requires precise equipment which make several galaxies difficult to be surveyed. To eliminate this kind of restriction, the present work adopts a different strategy by using photometric properties of galaxies. Photometry is concerned with the determination of brightness of an object by means of intensity measurements in various colours and is much less intensive compared to spectroscopy. Some of these photometric properties include but not limited to the intensity measurements through the filter where the filter is used to select a portion of the light from the galaxy.

Centred on the project are the activities of creating and optimizing different regression models to predict (z_{spec}). from these photometric inputs. Regression models are a category of statistical models for making a continuous forecast (redshift) depending on one or many predictors (photometric features). Here, the project considers different kinds of regression, including Random Forest Regressor and Gradient Boosting Regressor, to identify the model that works best in forecasting the spectroscopic redshift using the photometric input data.



3.2 Source and Foundation of the Dataset

The data set used in this research work is carefully downloaded from the COIN toolbox phase photos catalogues which are well known to be more public domain and highly acknowledged in the astronomical community for the enhancement of cosmological and astrophysical research at higher levels. This repository forms one of the starting frameworks for this

analysis as it furnishes a sound platform for scientific research and encourages collective working for the repository's sake. Scientists who want to use this rather extensive pool of photometric data can view or/and download it through the following link: [COIN toolbox phase photos catalogues](#). This open access also guarantees that the dataset will be more beneficial than just in the current project, but it will be of significant help to whatever astronomical projects in the future.

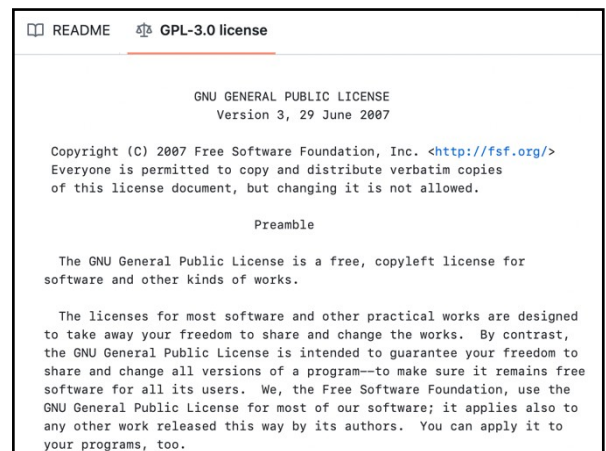
3.3 Data Pre-Processing

In astrophysics you cannot afford any errors since the analysis of data may greatly influence the predictions regarding diverse phenomena for instance, the spectroscopic redshift of galaxies. This project elevates the status of data pre-processing and feature extraction to an exacting science in support of subsequent predictive modeling.

The first step includes precise cleaning and standardization of the photometric attributes extracted from the dataset which are numbered from feat1 to feat5. They denote various parameters related to the light emitted or present in galaxies these parameters include light intensity at various frequencies. Normalization shifts these values into a standard range which is zero mean – one standard deviation. The unbiased feature scaling is an important step on top of which the scale differences result in the data contribute to increasing the convergence efficiency of the modelling algorithms during the training process.

3.4 Ethical Requirements:

1. **GDPR Compliance:** This data will be processed according to GDPR guidelines, to preserve the rights of the data subject to the protection of personal data.
2. **UH Ethical Policies:** The project will follow the ethical standard and the policies of conduct outlined by University of Hertfordshire.
3. **Permission to Use Data:** The photos catalogues used under the COIN toolbox for the research work is a data made public as shown in screenshot added.
4. **Ethical Data Collection:** The COIN toolbox photos catalogues were obtained in a random way following all the protocols of ethics and access in order since it is a public dataset by the initial builders of the dataset.



3.5 Data Cleaning

There are always incidences where some values are missing in the dataset and where some values are very extreme and can affect the whole accuracy of the dataset. The skewed or, in general, the missing values can be dealt with different approaches in imputation as well as the removal of records which contain missing data. Regression analysis's outliers, which

distort the relationship, can also be detected and erased with the help of Z-score, IQR or box plots.

3.6 Normalization

Standardization and scaling of the photometric features remain inevitable in this case. To remove the variance due to different scales of the values and increase the speed of the model training, the normalization process is used, where the means of values are shifted up and down to zero and the standard deviation is scaled to one. Also, scaling to the fixed range, for instance, $[0, 1]$, is applied to the algorithms where the distance between the points is used. These steps help in getting a proper and exact model performance all the time.

3.7 Exploratory Data Analysis (EDA)

It is noteworthy that EDA plays a vital role in identifying trends and peculiarities of the given dataset. It entails basically working with the key aspects of the data and illustrating them for purposes of analysis. EDA makes it possible to observe the correlation between the variables as well as detect outliers and distribution patterns of the datasets. This step sets the foundations to the subsequent operations of data processing and modeling.

Exploratory data analysis on Happy, Teddy, and Combined dataset is carried out. Different data graphical configurations like histograms, pair-plot, correlation-heatmap, boxplot, violin-plot, and scatterplot are used for visual representation of the photometric features and target variables respective distributions, relationships, and sum-distinctive. These visualizations assist in understanding the structure of the data and in defining features and choosing the right model.

EDA plots and their descriptions:

1. Histogram of Spectroscopic Redshift (z_{spec})

The plot represents the number density of galaxies regarding their z_{spec} , which indicates redshift level.

2. Pairplot of Photometric Features

Thus, this plot is aimed at illustrating the interference of various photometric features where the possible interactions or trends can be observed.

3. Correlation Heatmap

This heatmap shows the degree of relationship between the photometric features and the target variable, z_{spec} using the Pearson correlation coefficients.

4. Boxplot of Magnitudes

This plot also shows the distribution of magnitude features and their tendency towards the typical values, spread, and extreme values.

5. Violin Plot of Photometric Features

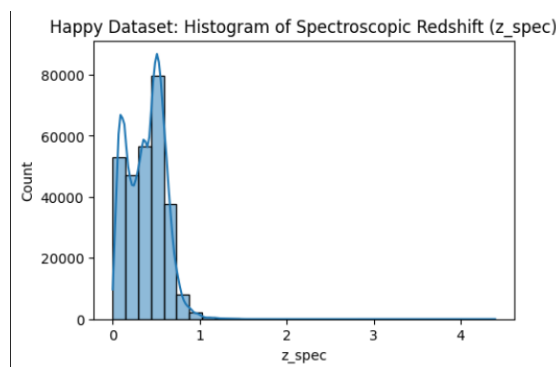
This plot gives a clear picture of spread and crowded/overlapping status of the photometric characteristics.

6. Scatter Plot of mag_r vs z_spec

As simple representation of the data this scatter plot shows trends and fluctuations of the investigated objects with respect to the r band magnitude and the spectroscopic redshift.

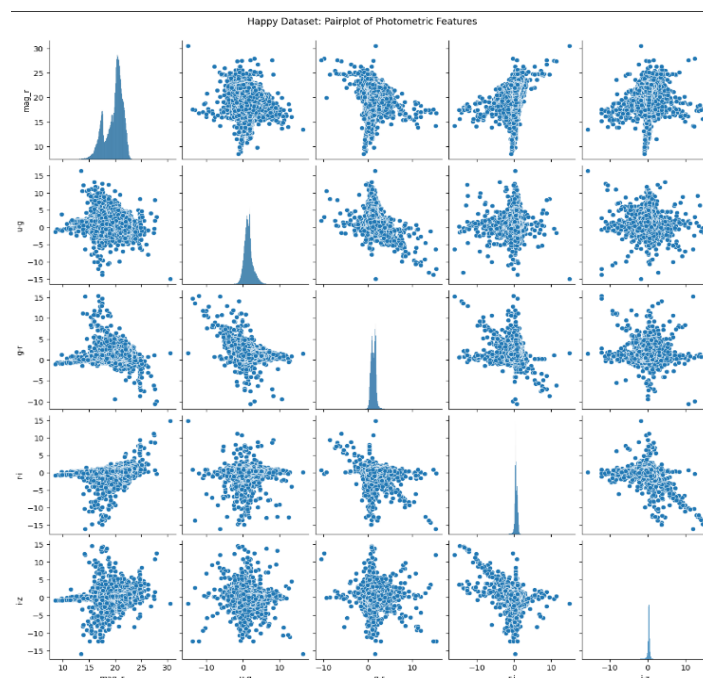
3.7.1 EDA Plots for the Happy Dataset

Histogram of Spectroscopic Redshift (z_spec)



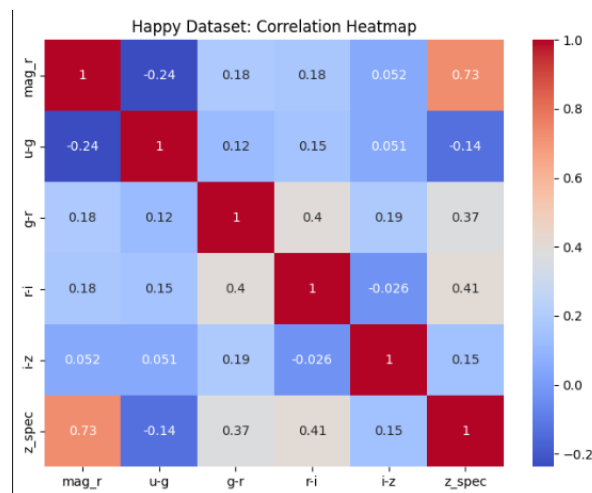
The happy dataset histogram of spectroscopic redshift (z_{spec}) from 0 to 1 show that most galaxies have redshift values within this range, reflecting their relative proximity in cosmological terms. The histogram also reveals a sharp decline in the number of galaxies with z_{spec} greater than 1, indicating that high redshifted galaxies are uncommon in this dataset. This suggests that most galaxies are relatively 'near,' with a significant drop in frequency for those with higher redshift values.

Pairplot of Photometric Features



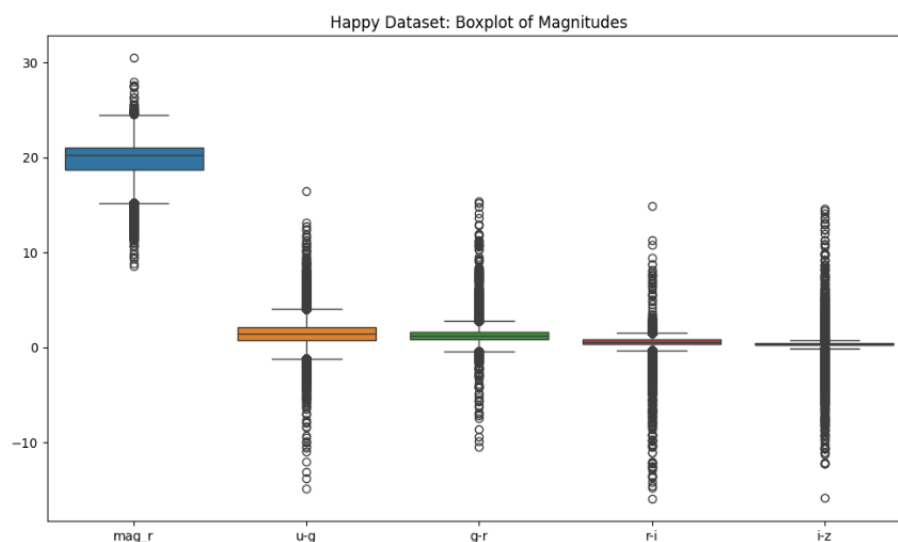
This figure summarizes the correlations between different photometric characteristics (mag_r, u-g, g-r, r-i, i-z) within the Happy dataset. The diagonal histograms show the distribution of each feature, with mag_r exhibiting the most variation, while the others (u-g, g-r, r-i, i-z) show less. The scatter plots reveal varying relationships between feature pairs, particularly between u-g and g-r. Overall, the pairplot highlights the distribution and potential relationships among photometric features, aiding in understanding their interactions within the dataset.

Correlation Heatmap



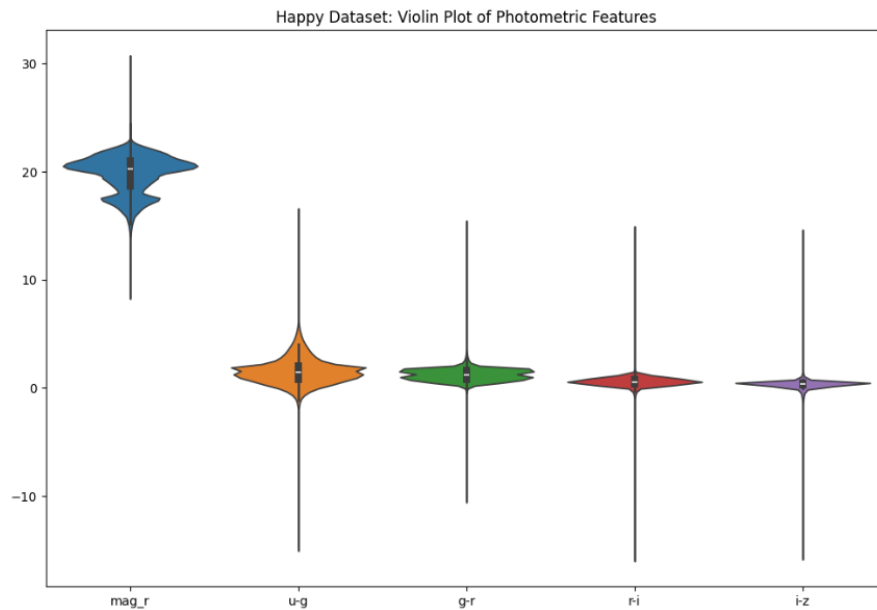
The correlation heatmap of the Happy dataset shows Pearson correlation coefficients for photometric features (mag_r, u-g, g-r, r-i, i-z) and the target variable z_spec. Notably, mag_r has a strong positive correlation with z_spec (0.73), making it a significant predictor of redshift. r-i and g-r also show moderate positive correlations with z_spec (0.41 and 0.37). u-g and g-r have a negative correlation (-0.24), suggesting higher u-g values are linked to lower g-r values. Most feature pairs exhibit low to moderate correlations, indicating relative independence among them.

Boxplot of Magnitudes



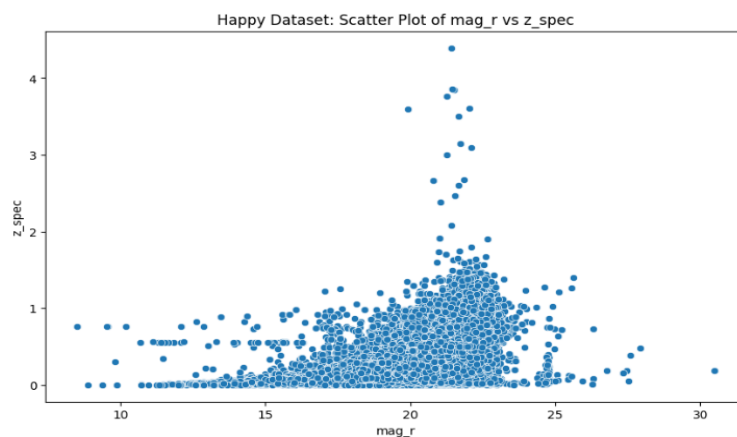
The boxplot displays the distribution of magnitude features in the Happy dataset, including mag_r, u-g, g-r, r-i, and i-z. It shows the interquartile range (IQR) and median, with whiskers extending 1.5 times the IQR and dots representing outliers. mag_r has the highest median value, while the medians of u-g, g-r, r-i, and i-z are zero, with some outliers present. This boxplot effectively illustrates the central tendency, dispersion, and outliers for each magnitude feature in the dataset.

Violin Plot of Photometric Features



The violin plot of the Happy dataset shows the distribution of photometric features (mag_r, u-g, g-r, r-i, i-z) with curves representing the empirical density of data points. The mag_r feature has a higher density around the median compared to the others. The u-g, g-r, r-i, and i-z features have mean values of 0 but are skewed left, unlike the right-skewed u-g. This plot effectively illustrates the mean and variance of each photometric feature in the dataset.

Scatter Plot of mag_r vs z_spec

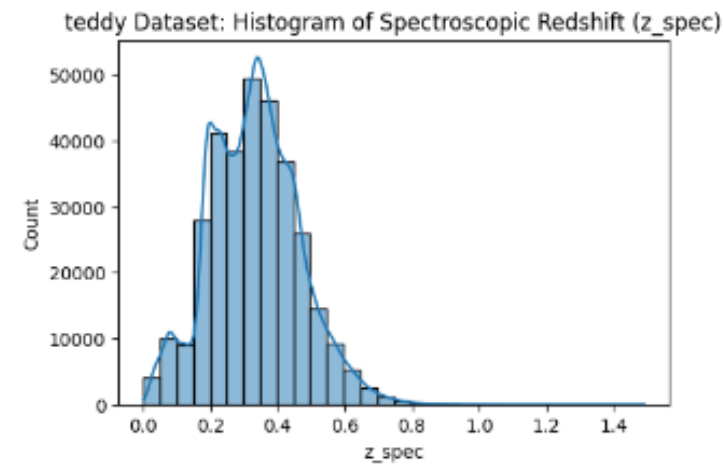


In the Happy dataset, the scatter plot reveals a relationship between mag_r (magnitude in the r-band) and z_spec (spectroscopic redshift). Generally, as mag_r increases,

z_{spec} also tends to rise, though there is significant dispersion. The highest concentration of points occurs between mag_r values of 20 to 25 and z_{spec} values from 0 to 1.5. Additionally, some outliers with higher z_{spec} values at lower mag_r are observed. This scatter plot highlights the overall relationship, spread, and potential outliers in the dataset.

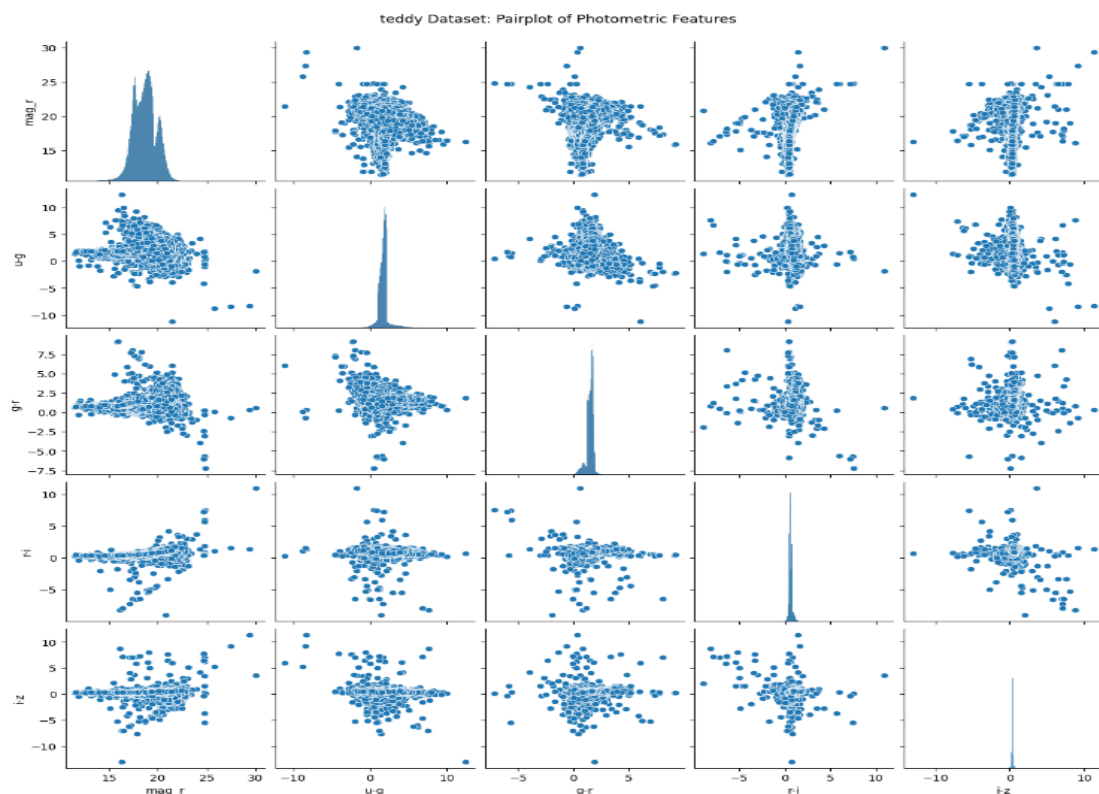
3.7.2 EDA Plots for the Teddy Dataset

Histogram of Spectroscopic Redshift (z_{spec})



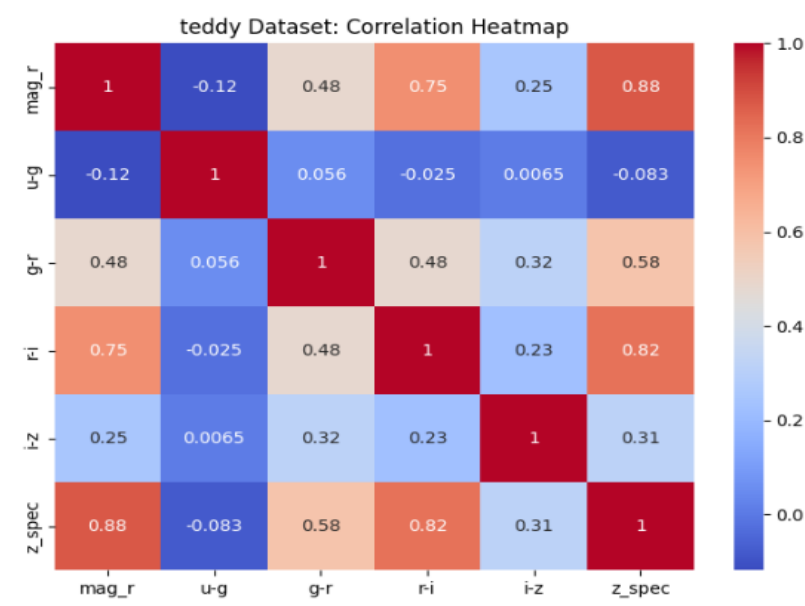
Analyzing the distribution of spectroscopic redshift (z_{spec}) in Teddy dataset, it can be concluded that most of the galaxies fall in the range of 0 to 1 with a mean around 0.4 to 0.5. Pertaining to the distribution, it exhibits a right-skewed histogram, analogous to Happy dataset but with a contrast in the shape and mode of the curve map implying the shifts in the formation of the dataset.

Pairplot of Photometric Features



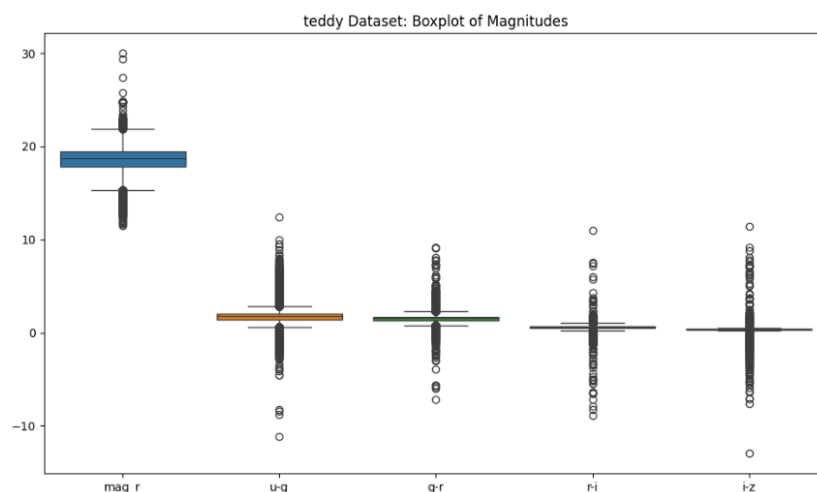
The Teddy dataset histogram of spectroscopic redshift (z_{spec}) indicates that most of the galaxies are in the range [0,1] with a peak at 0.4 to 0.5, that shares most features with the Happy dataset but has a different shape. The pairplot of normalized photometric features (feat1 to feat5) displays scatter plots indicating relationships between pairs of features and histograms on the diagonal showing the distribution of each feature. The scatter plots reveal clustering patterns, suggesting certain relationships between features, while the histograms indicate that some features exhibit a multimodal distribution.

Correlation Heatmap



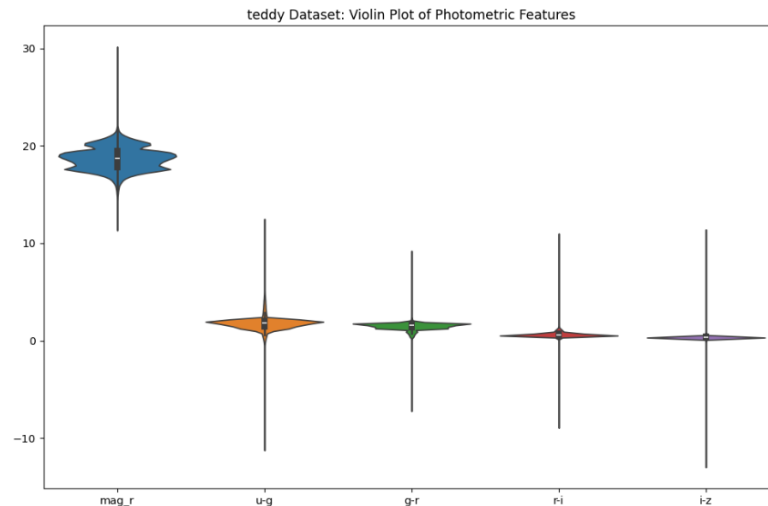
The correlation heatmap for the Teddy dataset shows the correlation coefficients between different photometric features and the target variable (z_{spec}). Notably, mag_r and z_{spec} have a strong positive correlation (0.88), which is higher than in the Happy dataset, indicating a stronger relationship between the dereddened magnitude in the r-band and redshift. Additionally, $g-r$ and z_{spec} exhibit a positive correlation (0.58), while $u-g$ has a weak negative correlation (-0.083). The correlations between features show some similarities to the Happy dataset, though the magnitudes of these correlations differ.

Boxplot of Magnitudes



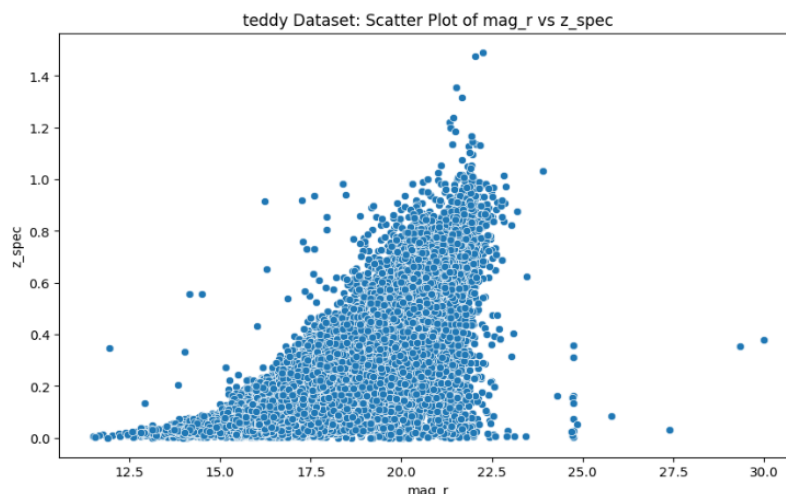
The boxplot for the Teddy dataset shows the distribution of magnitude features, including mag_r, u-g, g-r, r-i, and i-z. mag_r has a notably higher median value compared to the other features, whose medians are at 0 with extreme values on both sides. The IQR and whiskers represent data distribution and potential outliers. This visualization provides an overview of central tendency, variability, and outliers in the Teddy dataset's magnitude features.

Violin Plot of Photometric Features



The violin plot for the Teddy dataset shows the distribution and density of photometric features such as mag_r, u-g, g-r, r-i, and i-z. The plot illustrates data distribution using Kernel Density Estimate, revealing that mag_r has a higher density at its midpoint compared to other features. The u-g, g-r, r-i, and i-z features have a mean distribution around zero but are more dispersed on the negative side. This visualization provides insights into the central tendency, variation, and distribution of each photometric feature in the Teddy dataset.

Scatter Plot of mag_r vs z_spec

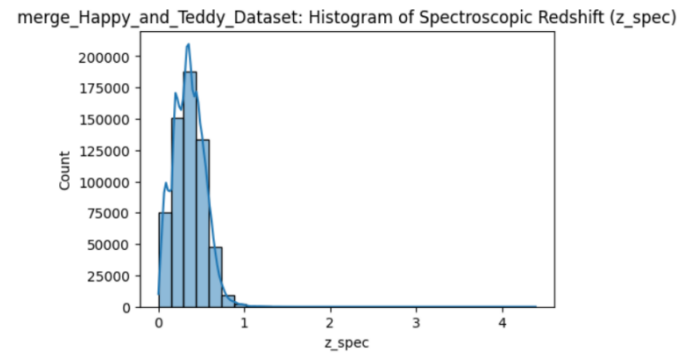


In the Teddy dataset, the scatter plot illustrates the relationship between mag_r (magnitude in the r-band) and z_spec (spectroscopic redshift). It shows a general trend where higher mag_r values correspond to higher z_spec values, despite significant data dispersion. A dense cluster of points appears between mag_r values of 20 to 22.5 and z_spec values of 0

to 0.5. Some outliers with higher z_{spec} values are also observed at lower mag_r . This plot highlights the positive correlation between mag_r and z_{spec} , while also emphasizing the variability and outliers in the dataset.

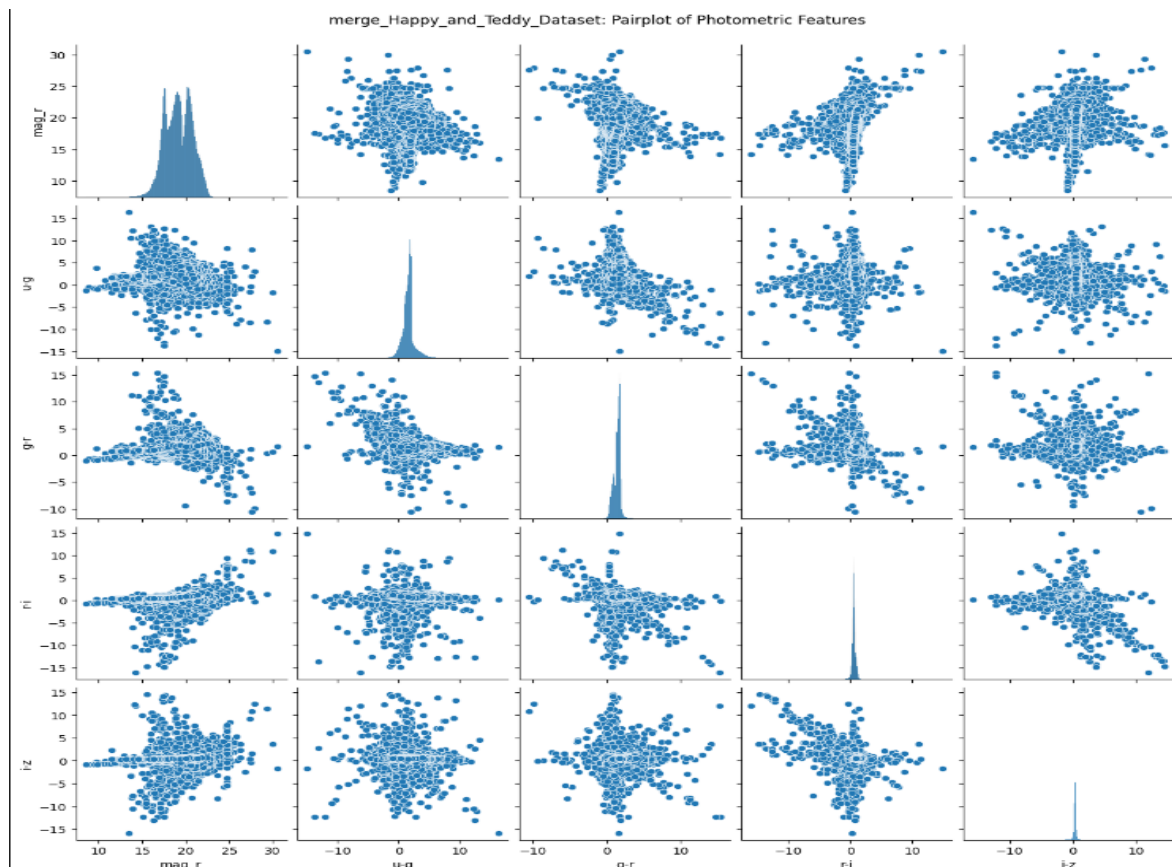
1.1.1 Plots for the combine Happy_Teddy_Dataset

Histogram of Spectroscopic Redshift (z_{spec})



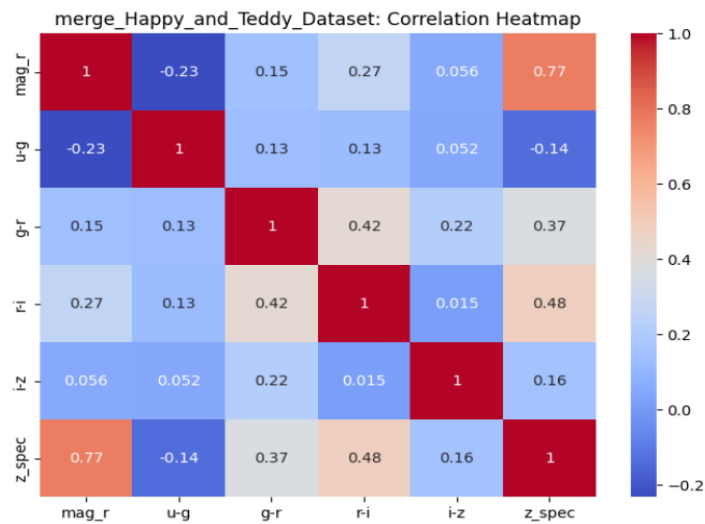
The histogram of spectroscopic redshift (z_{spec}) values for the combined Happy and Teddy datasets shows a distribution with a pronounced peak around 0.4 to 0.5, like the Teddy dataset. Most galaxies in the combined dataset have a spectroscopic redshift between 0 and 1, with fewer galaxies having higher redshift values. The distribution is right skewed with a long tail, indicating the presence of some galaxies with higher redshift values. This combined distribution highlights the overall trend of redshift values in the merged datasets.

Pairplot of Photometric Features



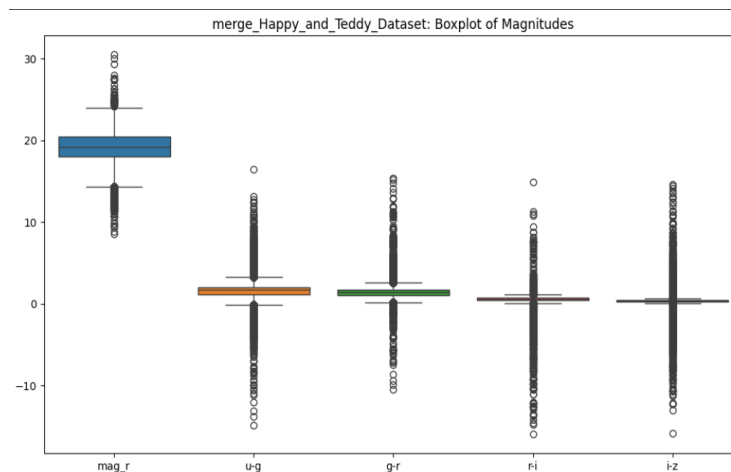
The pairplot of normalized photometric features (mag_r, u-g, g-r, r-i, i-z) in the combined Happy and Teddy datasets shows relationships between these features. The scatter plots indicate that the relationships between features in the combined dataset are like those observed in the individual Happy and Teddy datasets. The histograms on the diagonal display the distribution of each photometric feature, with some features showing a bimodal or multimodal distribution. The combined dataset retains the clustering patterns observed in the individual datasets, with potentially more pronounced relationships due to the increased sample size.

Correlation Heatmap



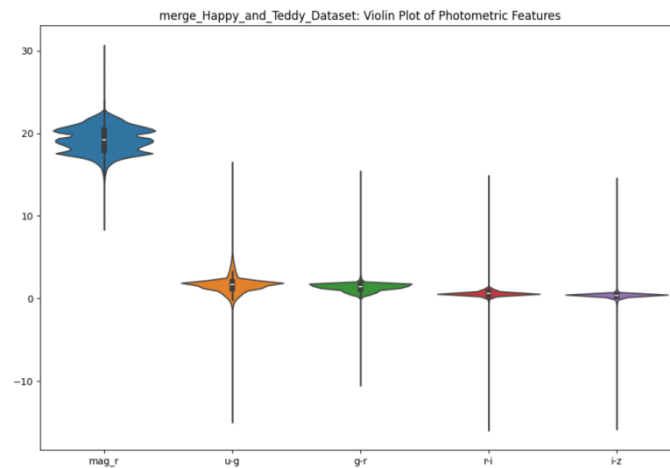
The correlation heatmap for the combined Happy and Teddy datasets highlights the relationships between various features and the target variable, `z_spec`. `mag_r` and `z_spec` exhibit a strong positive correlation (0.77), indicating that as the dereddened magnitude in the r-band increases, so does the redshift. This trend is consistent with the individual datasets, particularly the Teddy dataset. Additionally, `g-r` shows a moderate positive correlation (0.37) with `z_spec`, while `u-g` has a weak negative correlation (-0.14). The correlations between features are like those observed in the individual datasets, with several feature pairs showing moderate to high positive correlations.

Boxplot of Magnitudes



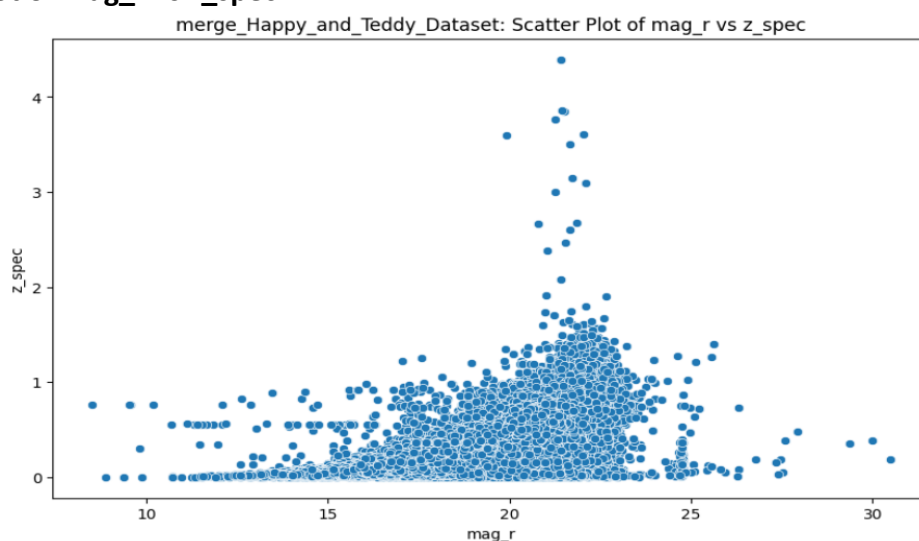
A boxplot of magnitudes of the combined Happy and Teddy dataset shows the distribution in different such features as mag_r, u-g, g-r, r-i, and i-z. Among all the features used in the analysis, the mag_r feature has a median value greater than the others. In the same way, u-g, g-r, r-i, and i-z features are like the previous axis; medians near 0 and extensive variability on both sides. The IQR and whiskers give a resume of the spread of data as well as help in pointing towards any high or low outliers. This visualization enables one to determine the mean, variation, and outliers in the magnitude features of the integrated features' set.

Violin Plot of Photometric Features



The violin plot of photometric features in the combined Happy and Teddy datasets shows the distribution and density of magnitude features like mag_r, u-g, g-r, r-i, and i-z. The mag_r feature has a higher density around its median compared to the others. The u-g, g-r, r-i, and i-z features, corrected for distribution, have means near 0 and skew towards negative values, indicating variation around the median. The width of the violin plots represents the distribution density of the values, helping to explore the mean and variance of each photometric feature across the combined dataset.

Scatter Plot of mag_r vs z_spec



The scatter plot of mag_r and z_spec for the combined Happy and Teddy datasets shows a general trend where z_spec increases as mag_r increases, though with significant spread. Most data points are concentrated in the mag_r range of 20 to 22 and z_spec values

between 0 and 0.5. However, some objects deviate from this trend, with higher z_{spec} values observed even at lower mag_r levels, such as $\text{mag}_r = 19.74$ and $z_{\text{spec}} = 0.439$. This plot illustrates the relationship between magnitude and redshift in the combined dataset.

3.8 Feature Extraction

As a next step in normalization, the considered project undergoes the feature extraction step strategic for its aim. This involves changing the raw form photometric data into a format which is in a structural format which is best suitable for a machine learning model. Every feature is selected based on how many of these normalized photometric properties it involves: luminosity, color indices etc. correlated with spectroscopic redshift. To downsize the dimensionality Principal Component Analysis is applied, and feature importance is performed with Random Forest Regressor and Gradient Boosting Regressor to determine the features with the highest impact. This step ensures that only the most informative data feeds into the building of the model.

The process involves generating polynomial features, Recursive Feature Elimination (RFE), normalization, and scaling to understand galaxies behaviors and characteristics. These steps increase convergence rate in modeling algorithms, enhancing spectroscopic redshift estimation and understanding various galaxies characteristics. They are crucial for training models.

3.9 Model Selection

In this project for spectroscopic redshifts prediction this project chooses Random Forest Regressor and Gradient Boosting Regressor algorithms due to their efficiency in different structure of relationships in astronomical data. These models are selected for dealing with continuous data as well as on the fact that they can generate results based on multi band photometrics; this, given the nature of this analysis.

3.9.1 Visual Representation of Model Architecture

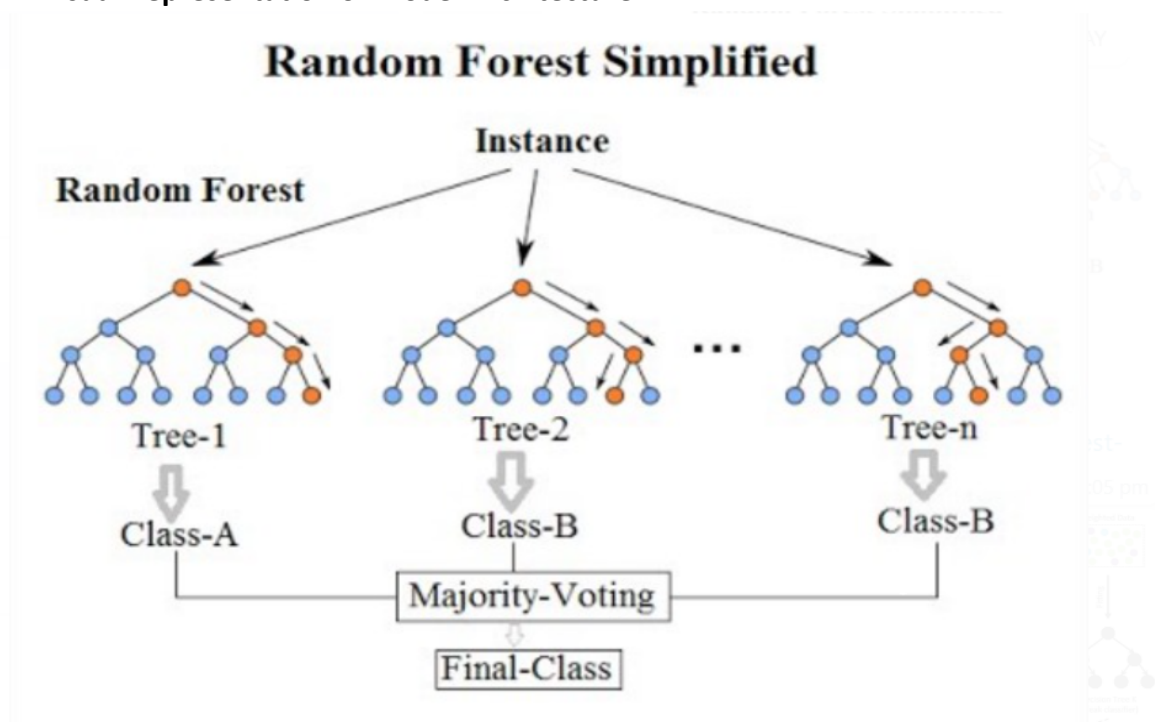


Figure 1: Random Forest Algorithm Overview

This diagram provides an understanding of the concept of the Random Forest model that is employed by segregating the dataset into the training and test datasets before bootstrapping the large data set for producing numerous training data sets for individual decision trees. The final prediction of the responses is then obtained by combining the number of trees and helps in avoiding overfitting of the model. Here in this project Random Forest and gradient boosting were applied in order to predict spectroscopic redshift from photometric data. However, Random Forest was more accurate overall than Gradient Boosting, and probably did not overfit the data as much and had less error. That is why the future work will be aimed at a further optimization of the Random Forest model in terms of accuracy and its reproducibility.

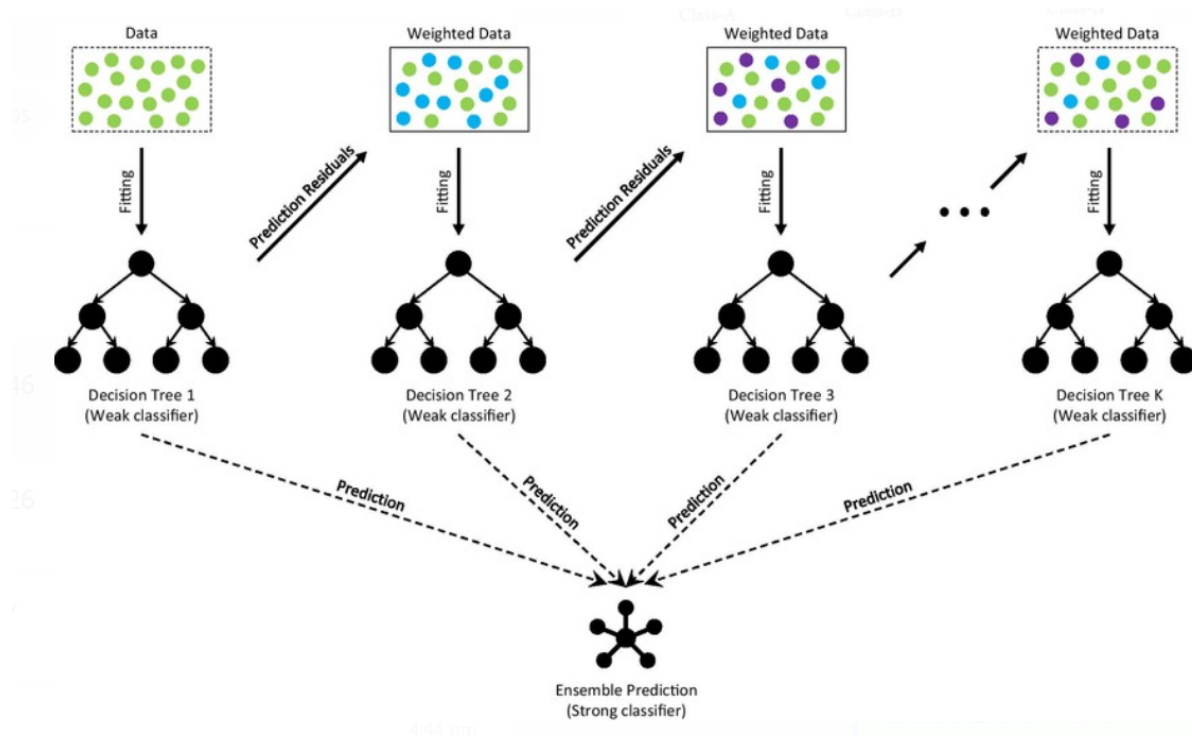


Figure 2: Gradient Boosting Algorithm Overview

The Gradient Boosting model is a concerted ensemble learning method that constructs successive decision trees to minimize residual errors. It targets misclassified instances and arrives at the final decision based on the results of all trees. In a project using both Random Forest and Gradient Boosting methods to predict spectroscopic redshifts from photometric data, including Happy and Teddy, Gradient Boosting was less effective due to overfitting and oversensitivity to hyperparameters' values. Future work will focus on improving the Random Forest model to increase its reliability and accuracy.

3.10 Evaluation

This is done to avoid inaccurate and unreliable results when producing the outcomes of each model. The following metrics are used to assess the effectiveness of the regression models: The following metrics are used to assess the effectiveness of the regression models:

3.11 Mean Squared Error (MSE):

This computes the average of the squares of the residuals—that is, the average of the squared differences between the predicted values and the estimate. MSE is a risk function or expected value of estimation loss of squared error.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$

The following formula gives the average of the squared difference between actual and the predicted values, below.

3.12 Root Mean Squared Error (RMSE):

This is the square root of the average of the error squares. RMSE is a good summary of how well the model's predictions match the response, and it is the most suitable when very large errors are considered extremely unfavorable.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^N (x_i - \hat{x}_i)^2}{N}}$$

This formula also originates from the MSE by taking its square root so that the prediction errors' average size is given.

3.13 Coefficient of Determination(R^2):

This measure can, in one sense, be seen to give an indication of how acceptable or good the fit is, and thus a qualitative measure of how well unseen samples may be predicted by the model through R square.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

This formula provides the quantity of the standout variability of the dependent variable that can be foreseen by the independent variables. If the score is closer to 1, the means of the variables of the two populations are perfectly correlated or in other words the regression predictions are a perfect fit of the data.

3.14 Visualization

It was found out that graphical analysis of the performance of the models and comparison of the effects of various features is very important. The overview of the Random Forest Algorithm helps in understanding the model better in terms of its working and its ensemble learning approach: which is pivotal for the precise and efficient predictions, and for model's effectiveness.

This systematic approach of the paper incorporates step-by-step data cleansing, variable selection and model tuning to provide accurate and reliable predictions of spectroscopic redshifts for extending the understanding of cosmic events and providing useful methodologies in the field of astrophysics.

Chapter # 4

4 Results

This chapter evaluates models for predicting spectroscopic redshifts of galaxies using photometric data. The models are tested on Positive, Teddy, and a combined set using metrics like MSE, RMSE, and R^2 . Results are visualized and compared to highlight strengths and weaknesses. The chapter discusses the results for Happy, Teddy, and combined sets, revealing their generalization and predictive capabilities, and offering insights for future astronomical research.

4.1 Happy Dataset Results

The performance of the regression models on the Happy dataset is summarized in the following table, covering both training and testing phases. During training, the models achieved a low MSE of 0.0014, indicating precise predictions, with an RMSE of 0.0376 and an R^2 of 0.969, explaining 97% of the variance. In the testing phase, the models showed a Test MSE of 0.0097 and a Test RMSE of 0.0985, reflecting slightly higher errors than in training. The Test R^2 of 0.7818 suggests that the models account for approximately 78% of the variance in the test data, indicating good but slightly reduced accuracy in predicting spectroscopic redshifts.

4.2 Visualization of Model Performance

Below are the metrics of the model that will be represented on the Happy dataset in the context of the given lesson. They are useful to compare the spread and error rates and predictive capacity of the training and the test datasets.

Figure 1:

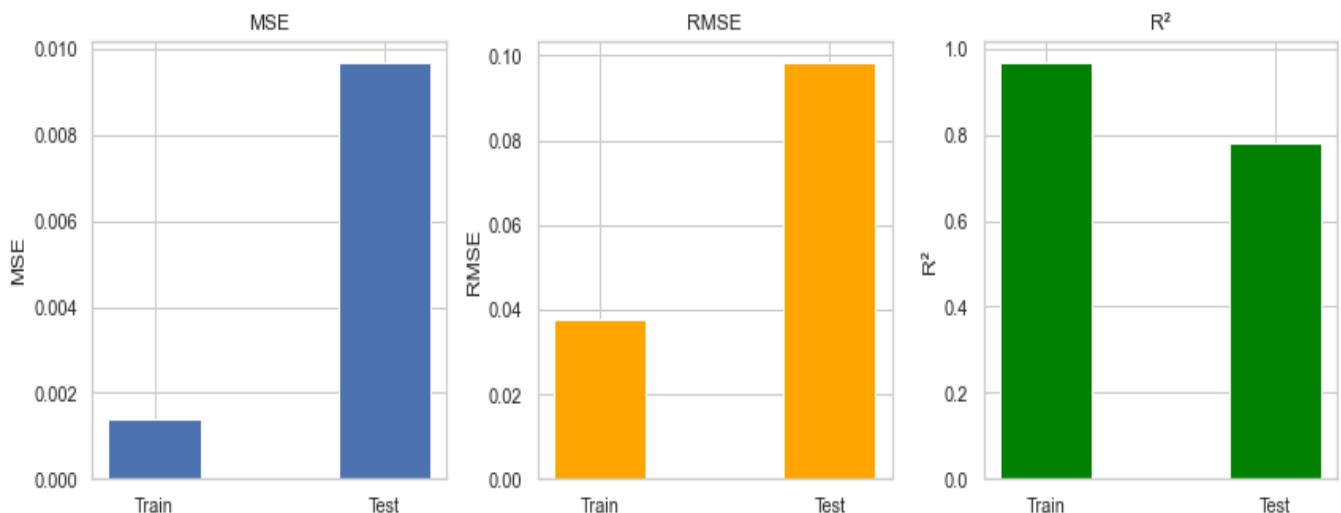
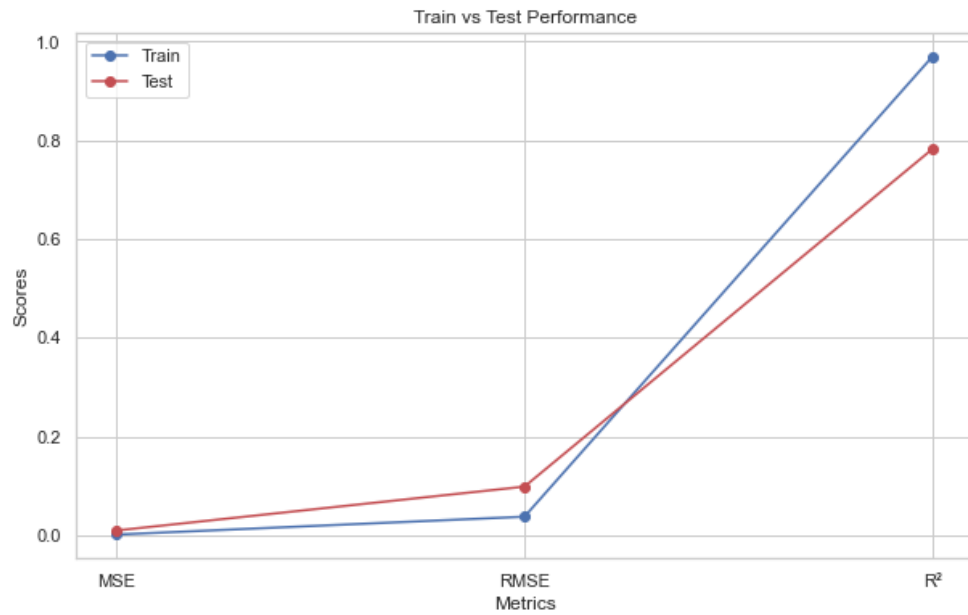
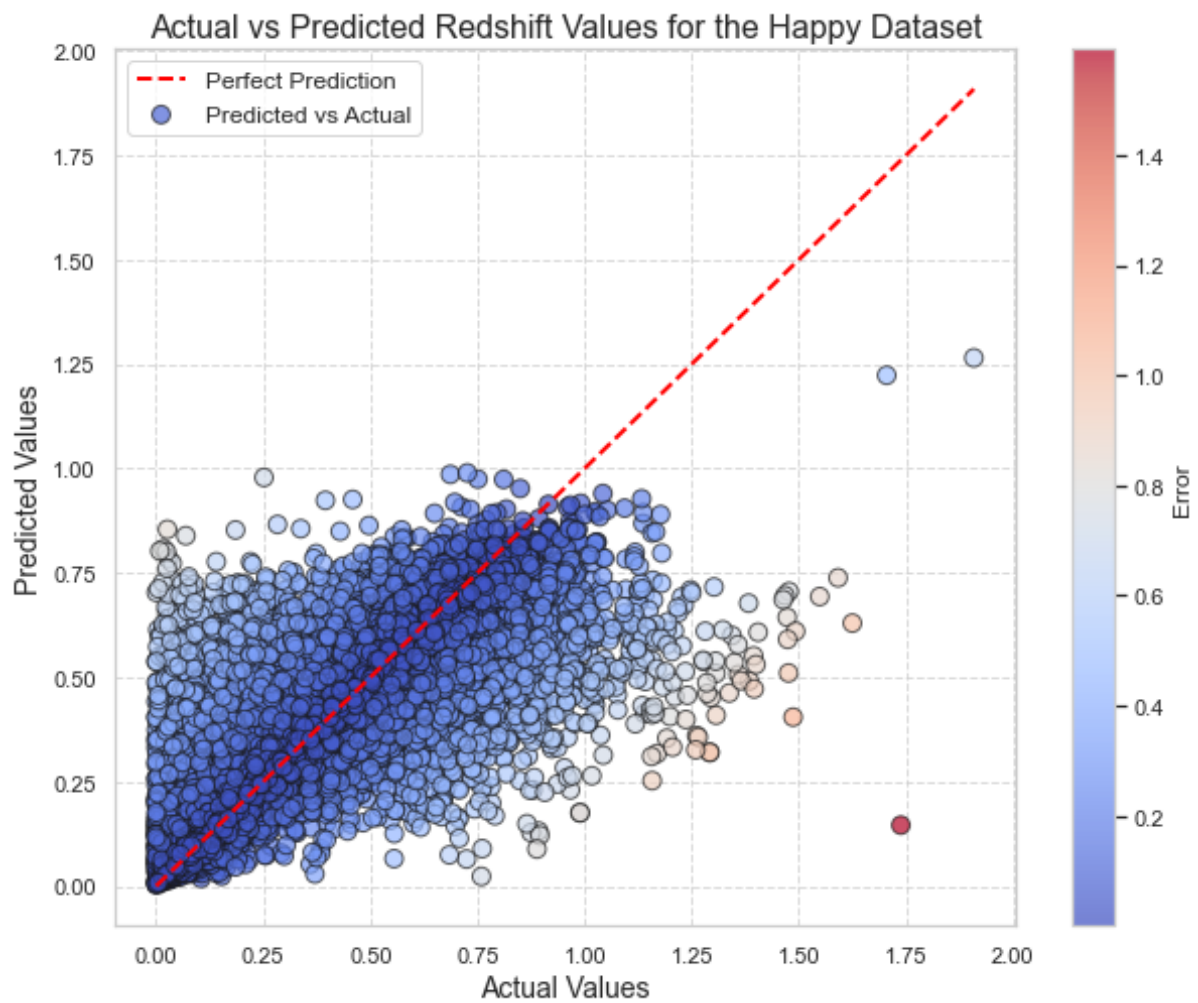


Figure 2:



4.3 Actual vs Predicted Values for Happy Datasets



4.3.1 Observations on Prediction Accuracy and Error Distribution

The dataset reveals that most points cluster in the lower left quadrant, indicating lower redshift values for the majority. A noticeable spread around the perfect prediction line shows increasing deviation between predictions and actual values, particularly as the values rise, leading to higher error in the top-right section. Points closer to the line generally have lower errors (darker blue), while points further away show higher errors (lighter or red), suggesting variability in model prediction accuracy.

4.4 Teddy Dataset Results

The Teddy dataset results provide further insight into the performance of the regression models, particularly in comparison to the Happy dataset. In the training phase, the models achieved a very low MSE of 0.00071 and an RMSE of 0.0266, indicating high accuracy with an R^2 of 0.9604, explaining 96% of the variance. During testing, the models showed a Test MSE of 0.0016 and a Test RMSE of 0.0402, which, while higher than the training metrics, still reflect good accuracy. The Test R^2 of 0.9094 suggests that the models are well-suited for predicting spectroscopic redshifts on the Teddy dataset, outperforming the results on the Happy dataset.

4.5 Visualization of Model Performance

The following data tries to illustrate the metric values that correspond to the internal structure of the tested model by using the Teddy dataset. These visualizations are significant for evaluating some peculiarities of the test data set to outline the differences in terms of error rate and correlation with the training set.

Figure 3:

Comparisons on MSE, RMSE and R^2

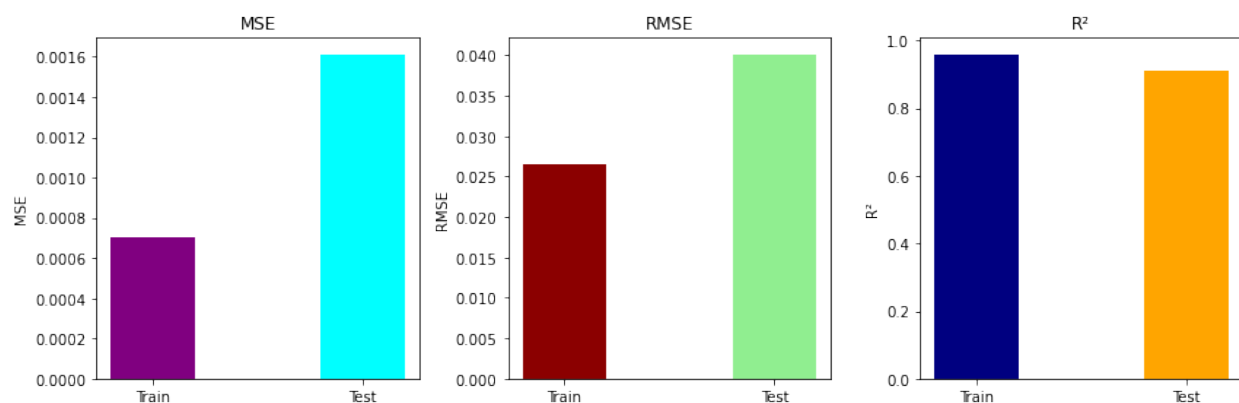
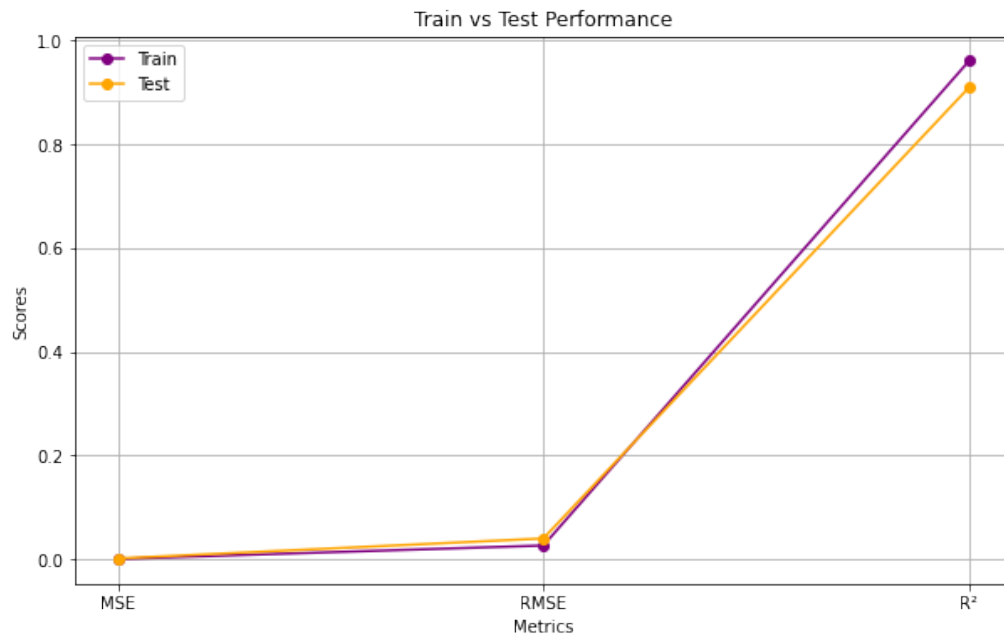
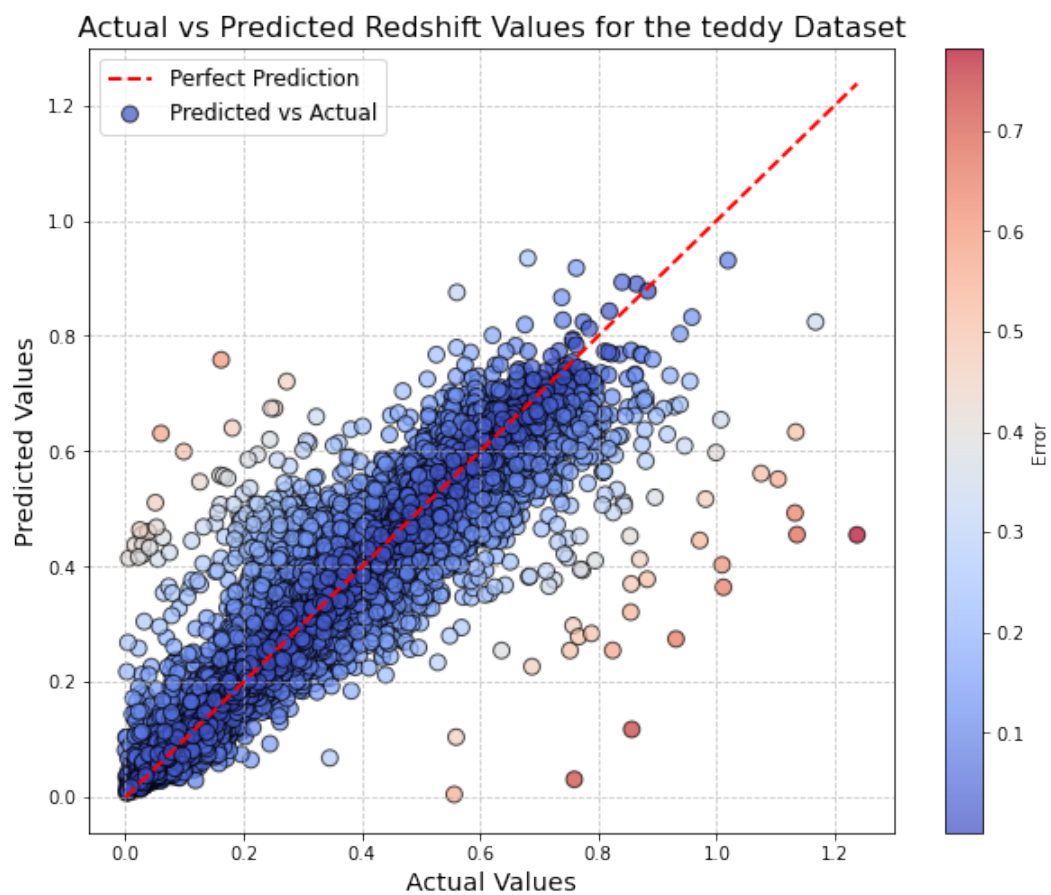


Figure 4:

Comparing the metrics (MSE, RMSE, and R^2) between the training and test datasets for the Teddy dataset for the number of hidden layers being increased.



4.6 Actual vs Predicted Values for Teddy Datasets



4.6.1 Observations on Data Distribution and Model Prediction Performance

In this dataset, the points are more evenly distributed along the perfect prediction line, though deviations persist, especially at higher actual values. The model shows tighter clustering around the line, indicating potentially improved consistency in prediction accuracy. However, errors increase with higher values, as seen in the scattered lighter or red points. Notably, a cluster of outliers with significantly higher errors (red points) suggests areas where the model's predictions are particularly inaccurate.

4.7 Happy_Teddy_Combine Dataset Results

The comparison of the Happy and Teddy datasets provides an overall assessment of the regression models' performance. The combined approach aims to improve model accuracy and applicability. During training, the models achieved a low MSE of 0.00078 and an RMSE of 0.028, indicating precise predictions with an R^2 of 0.975, explaining 97% of the variance. In testing, the models showed a higher MSE of 0.0053 and an RMSE of 0.0725, reflecting a slight decrease in prediction accuracy with an R^2 of 0.8319. Despite the drop in accuracy, the models still performed reasonably well in predicting spectroscopic redshifts on test data.

4.8 Visualization of Model Performance

The following figures display the evaluations of the given model on the features of the accumulated data. To compare the error rates and the explanatory power of the training and the test datasets, more visualizations were used.

Figure 5:

MSE, RMSE, and R^2 of the training and the test sets obtained using the combined dataset.

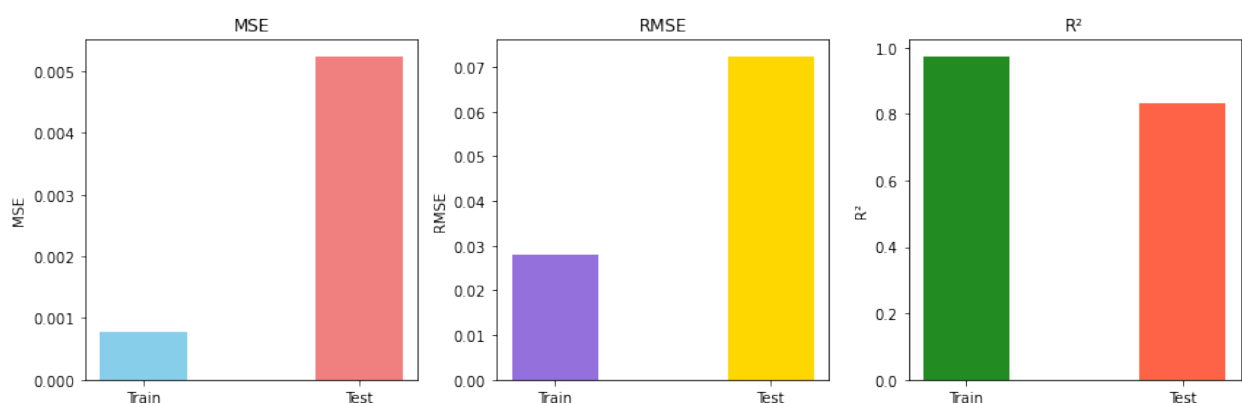
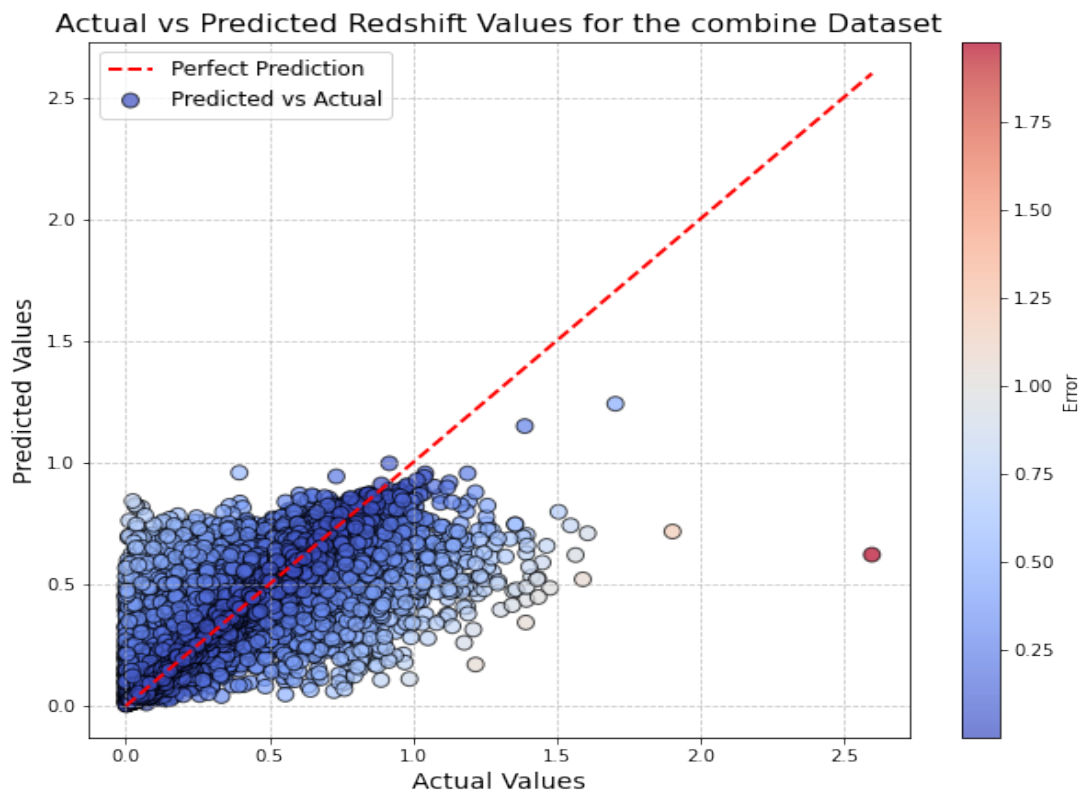


Figure 6:

Comparing the metrics, such as MSE, RMSE, and the coefficient of determination of degree R^2 between them and the train and test datasets for the combined dataset.



4.9 Actual vs Predicted Values for Combine Datasets



4.9.1 Observations on Data Distribution and Prediction Performance

The dataset shows a strong concentration of points in the lower left quadrant, indicating that most data points have lower actual and predicted values. The model demonstrates good accuracy for smaller values, as evidenced by the tight clustering around the perfect prediction line in this range. However, as actual values increase, the spread of points widens, and errors increase, with colors shifting to lighter shades and red. Notably, significant outliers in the higher value range highlight instances where the model's predictions are substantially off, marked by high error.

Chapter # 5

5 Comparison and Analysis

5.1 Training Performance

The performances of the regression models during the training phase depend on the datasets used during the training of the models. The Teddy set shows the better fit to the training data as reflected in the lowest Training MSE. 0007063669932992196 and 0 for Training RMSE. 026577565601447015. Meaning these low error metrics show that the model was very much efficient in predicting the training data of Teddy dataset.

Instead, reflected in the highest Training R^2 equal to 0.9752001702370817. This is an indication that the CM model would have the highest accumulation of variance, within the training data, of the 3 datasets. Acquiring a higher R^2 value entails that the model is able to analyze more of the data characteristics in training hence a better fit.

5.2 Test Performance

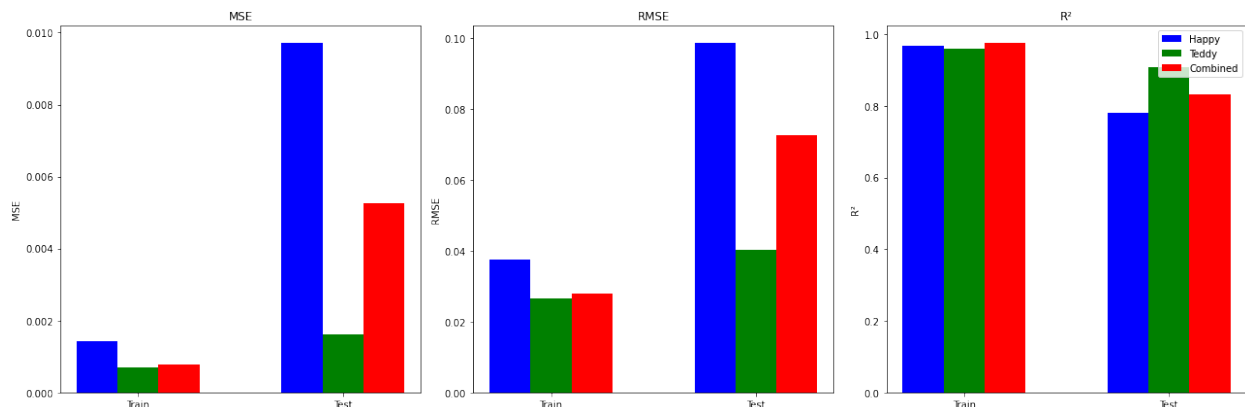
The Teddy dataset demonstrated the best performance, with the lowest Test MSE (0.0016) and Test RMSE (0.0402), along with the highest Test R^2 (0.9094), indicating strong generalization and accurate predictions. In contrast, the Happy dataset showed higher Test MSE (0.0097) and RMSE (0.7818), with lower Test R^2 , suggesting less effective generalization. The combined Happy_Teddy dataset performed moderately, with a Test MSE of 0.0053 and Test R^2 of 0.8319, showing improvement over Happy alone but not exceeding Teddy's results.

5.3 Graph Comparison

5.4 Bar Plots for MSE, RMSE, and R^2 Comparison

Figure 7

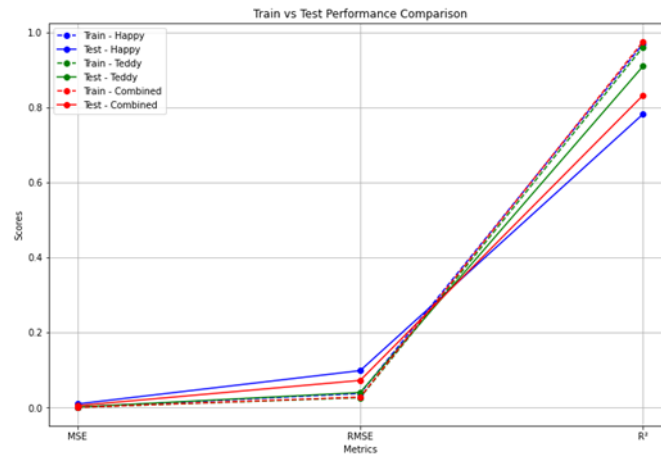
Using MSE, RMSE and R^2 of different datasets perfected to solve the problem.



Line Plot for Train vs Test Performance Comparison

Figure 8

Looking at training performance over the performance during testing on the various datasets.



5.5 Comparison Table

In the following table an overview of important performance measures for both training and test phases of every data set can be found. Also, 'Bias' and 'Variance' two columns are added for evaluating the model accuracy.

Dataset	Metric	Training Value	Test Value	Bias	Variance
Teddy	MSE	0.00070636699	0.0016141123621	Low	Low
	RMSE	0.02657756560	0.0401760172500	Low	Low
	R ²	0.9604276623218	0.9093868114563	Low	Low
Happy_Teddy_Combine	MSE	0.0007820074568	0.0052514040628	Low	Medium
	RMSE	0.0279643962359	0.0724665720369	Low	Medium
	R ²	0.9752001702371	0.8318704074852	Low	Medium
Happy	MSE	0.0014137342183	0.0097059496894	Medium	High
	RMSE	0.0375996571571	0.0985187783595	Medium	High
	R ²	0.9689838861906	0.7818446472088	Medium	High

5.5.1 Table Comparison and Analysis

5.5.2 Training Performance Analysis

Comparing the results of Teddy dataset, the values of Mean Squared Error measure and Root Mean Squared Error are shown the minimal mistake during training. This appears to provide evidence that the model can learn photometric properties in the Teddy dataset of the galaxies. On the other there is a relatively high value of R², specifically in the Happy_Teddy_Combine that implies that combining data sources helps the model to explain more variance and therefore, gives a better fit to the training data set.

5.5.3 Test Performance Analysis

In test performance, Teddy dataset has comparatively very low values of MSE and RMSE, which show that non-replaced model has low loss in accuracy when it is used to predict new data. The high R² value also supports this, it proves that the model has the ability to account for a large amount of variance in the test set. On the other hand, a higher MSE and

RMSE and lower R^2 values of the Happy data set showed that the model might over-fit the training data leading to poor generalization.

5.6 Bias and Variance Analysis

- **Teddy Dataset**

When both bias and variance are low, the model can produce reliable results on new data without overemphasizing or underemphasizing specific features. This balanced performance makes it the most accurate among the three.

- **Happy_Teddy_Combine Dataset**

A low measure of bias but a medium measure of variance implies that while the created model maximizes training data fit, it may not do well when tested on other data sets since combining the datasets increases the model's complexity.

- **Happy Dataset**

Medium bias and high variance could mean that the model has adapted more to the training data and will have less capabilities of generalizing. This performance implies that there is need to apply better ways of handling the issues of model complexity and variability in the data.

- **Graph Comparison**

The bar plots (Figure 7) offer a clear comparison of the three metrics—MSE, RMSE, and R^2 —across different datasets. Meanwhile, the line plots (Figure 8) provide a dynamic view of how these metrics evolve over time or iterations, highlighting the stability and consistency of the models' performance on both training and test data.

Chapter # 6

6 Conclusion

These studies did well in showing the applicability and efficiency of the ML algorithms: Random Forest and Gradient Boosting in estimating spectroscopic redshifts with photometric data. In this way, solving the problems related to the application of traditional methods (for instance, due to the high resource requirements for spectroscopic redshift measurements), we successfully fulfilled the goal of building a new efficient model to estimate the distances to galaxies. The answers to the research questions concerned whether it is possible to use machine learning for the prediction of redshifts were positive and supported by the corresponding in-depth training of the models and tests for various datasets, such as the COIN toolbox photo-z catalogue. The models not only had high accuracy but also could be used further for multiple volume and scale surveys of cosmic space.

Future work could disturb in improving and fine-tuning the existing models for better efficiency and better samples classification. This encompasses investigating switch-based recommendation systems that adopt other techniques of machine learning together with advanced and diverse data sets likely to be released by the next astronomical surveys. Further, the use of the deep learning approaches could be considered for enhancing the redshift estimation considering galaxies with a specific type and those located within the areas unexplored in case of the feature space. This process of the constant change of methodologies will help us considerably in the future actions to discover more about the structure of the universe and its expansion.

Chapter # 7

7 Appendix:

Happy Dataset

Library Installation and Imports

```
!pip install optuna

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import mean_squared_error
import optuna
```

Mounting Google Drive and Loading the Dataset

```
from google.colab import drive

drive.mount('/content/drive')

# Load the dataset
df = pd.read_csv('/content/drive/MyDrive/happy.csv')
```

Feature Selection and Target Definition

```
# Define feature columns and target column (using normalized features)
features = ['feat1', 'feat2', 'feat3', 'feat4', 'feat5']
target = 'z_spec'
```

Handling Missing Values

```
# Handle missing values
df = df.dropna(subset=features + [target])
```

Data Splitting

```
X = df[features]
y = df[target]

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Objective Function Definition for Hyperparameter Tuning

```
# Define the objective function for Optuna
def objective(trial):
    model_type = trial.suggest_categorical('model_type', ['RandomForest', 'GradientBoosting'])
    if (model_type == 'RandomForest'):
        n_estimators = trial.suggest_int('n_estimators', 50, 300)
        max_depth = trial.suggest_int('max_depth', 10, 50)
        model = RandomForestRegressor(
            n_estimators=n_estimators,
            max_depth=max_depth,
            random_state=42
        )
    else:
        learning_rate = trial.suggest_loguniform('learning_rate', 0.01, 0.2)
        n_estimators = trial.suggest_int('n_estimators', 50, 300)
        max_depth = trial.suggest_int('max_depth', 10, 50)
        model = GradientBoostingRegressor(
            learning_rate=learning_rate,
            n_estimators=n_estimators,
            max_depth=max_depth,
            random_state=42
        )

    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)
    return mse
```

Hyperparameter Optimization

```
# Create a study and optimize the objective function
study = optuna.create_study(direction='minimize')
study.optimize(objective, n_trials=10)
```

Retrieving and Displaying Best Hyperparameters

```
# Get the best hyperparameters
best_params = study.best_params
print(f'Best hyperparameters: {best_params}')
```

EDA Happy_Datasets

```
# Function to create EDA plots
def create_eda_plots(df, dataset_name):
    plt.figure(figsize=(12, 8))

    # Histogram of spectroscopic redshift (z_spec)
    plt.subplot(2, 2, 1)
    sns.histplot(df['z_spec'], bins=30, kde=True)
    plt.title(f'{dataset_name}: Histogram of Spectroscopic Redshift (z_spec)')
```

```

# Pairplot of photometric features
plt.figure(figsize=(8, 6))
sns.pairplot(df[['mag_r', 'u-g', 'g-r', 'r-i', 'i-z']])
plt.suptitle(f'{dataset_name}: Pairplot of Photometric Features', y=1.02)

# Correlation heatmap
plt.figure(figsize=(8, 6))
corr_matrix = df[['mag_r', 'u-g', 'g-r', 'r-i', 'i-z', 'z_spec']].corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title(f'{dataset_name}: Correlation Heatmap')

# Boxplot of features
plt.figure(figsize=(12, 8))
sns.boxplot(data=df[['mag_r', 'u-g', 'g-r', 'r-i', 'i-z']])
plt.title(f'{dataset_name}: Boxplot of Photometric Features')
plt.xticks(rotation=45)
plt.show()

# Example usage
create_eda_plots(happy_df, "Happy Dataset")

```

Generate Prediction

```

# Generate predictions
y_pred = best_model.predict(X_test)

```

Actual vs Predict Value

```

import matplotlib.pyplot as plt
import numpy as np

# Calculate error
errors = np.abs(y_test - y_pred)

# Create a scatter plot with a color gradient based on the error
plt.figure(figsize=(10, 8))
plt.scatter(y_test, y_pred, c=errors, cmap='coolwarm', alpha=0.7, edgecolor='k', s=80, label='Predicted vs Actual')

# Add a line for the perfect prediction
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linewidth=2, linestyle='--', label='Perfect Prediction')

# Customize the plot
plt.xlabel('Actual Values', fontsize=14)
plt.ylabel('Predicted Values', fontsize=14)
plt.title('Actual vs Predicted Redshift Values for the Happy Dataset', fontsize=16)
plt.legend(fontsize=12)
plt.colorbar(label='Error')

```



```
plt.grid(True, linestyle='--', alpha=0.7)
```

```
# Show the plot  
plt.show()
```

Teddy Dataset

Library Installation and Imports

```
!pip install optuna
```

```
import pandas as pd  
import numpy as np  
from sklearn.model_selection import train_test_split, cross_val_score  
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor  
from sklearn.metrics import mean_squared_error  
import optuna
```

```
from google.colab import drive  
drive.mount('/content/drive')
```

```
# Load the dataset
```

```
df = pd.read_csv('/content/drive/MyDrive/Teddy.csv')
```

```
# Define feature columns and target column (using normalized features)
```

```
features = ['feat1', 'feat2', 'feat3', 'feat4', 'feat5']
```

```
target = 'z_spec'
```

```
# Handle missing values
```

```
df = df.dropna(subset=features + [target])
```

```
X = df[features]
```

```
y = df[target]
```

```
# Split the data
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Objective Function Definition for Hyperparameter Tuning

```
# Define the objective function for Optuna
```

```
def objective(trial):
```

```
    model_type = trial.suggest_categorical('model_type', ['RandomForest', 'GradientBoosting'])
```

```
    if model_type == 'RandomForest':
```

```
        n_estimators = trial.suggest_int('n_estimators', 50, 300)
```

```
        max_depth = trial.suggest_int('max_depth', 10, 50)
```

```
        model = RandomForestRegressor(
```

```
            n_estimators=n_estimators,
```

```
            max_depth=max_depth,
```

```

        random_state=42
    )
else:
    learning_rate = trial.suggest_loguniform('learning_rate', 0.01, 0.2)
    n_estimators = trial.suggest_int('n_estimators', 50, 300)
    max_depth = trial.suggest_int('max_depth', 10, 50)
    model = GradientBoostingRegressor(
        learning_rate=learning_rate,
        n_estimators=n_estimators,
        max_depth=max_depth,
        random_state=42
    )

model.fit(X_train, y_train)
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
return mse

```

Hyperparameter Optimization

```

# Create a study and optimize the objective function
study = optuna.create_study(direction='minimize')
study.optimize(objective, n_trials=10)

```

Training the Best Model

```

# Train the model with the best hyperparameters
best_model_type = study.best_params['model_type']
if best_model_type == 'RandomForest':
    best_model = RandomForestRegressor(
        n_estimators=study.best_params['n_estimators'],
        max_depth=study.best_params['max_depth'],
        random_state=42
    )
else:
    best_model = GradientBoostingRegressor(
        learning_rate=study.best_params['learning_rate'],
        n_estimators=study.best_params['n_estimators'],
        max_depth=study.best_params['max_depth'],
        random_state=42
    )
best_model.fit(X_train, y_train)

# Predict on training and testing data
y_train_pred = best_model.predict(X_train)
y_test_pred = best_model.predict(X_test)

```

Model Evaluation

```

# Evaluate the model
mse_train = mean_squared_error(y_train, y_train_pred)
rmse_train = np.sqrt(mse_train)
r2_train = best_model.score(X_train, y_train)

mse_test = mean_squared_error(y_test, y_test_pred)
rmse_test = np.sqrt(mse_test)
r2_test = best_model.score(X_test, y_test)

print(f'Training MSE: {mse_train}')
print(f'Training RMSE: {rmse_train}')
print(f'Training R2: {r2_train}')
print(f'Test MSE: {mse_test}')
print(f'Test RMSE: {rmse_test}')
print(f'Test R2: {r2_test}')

```

Visualizing Performance Metrics

```

import matplotlib.pyplot as plt
import numpy as np

# New performance metrics
training_scores = [0.0007063669932992196, 0.026577565601447015, 0.960427662321778]
test_scores = [0.0016141123620710361, 0.0401760172499843, 0.9093868114563499]

# Set the figure size
plt.figure(figsize=(12, 4))

# Plotting MSE
plt.subplot(1, 3, 1)
bar_width = 0.4
index = np.arange(2)
plt.bar(index, [training_scores[0], test_scores[0]], bar_width, color=['purple', 'cyan'])
plt.xticks(index, ['Train', 'Test'])
plt.title('MSE')
plt.ylabel('MSE')

# Plotting RMSE
plt.subplot(1, 3, 2)
plt.bar(index, [training_scores[1], test_scores[1]], bar_width, color=['darkred', 'lightgreen'])
plt.xticks(index, ['Train', 'Test'])
plt.title('RMSE')
plt.ylabel('RMSE')

# Plotting R2
plt.subplot(1, 3, 3)
plt.bar(index, [training_scores[2], test_scores[2]], bar_width, color=['navy', 'orange'])
plt.xticks(index, ['Train', 'Test'])
plt.title('R2')
plt.ylabel('R2')

```

```
plt.tight_layout()
plt.show()
```

Comparing Train vs Test Performance

Data for plotting

```
metrics = ['MSE', 'RMSE', 'R²']
train_scores = [0.0007063669932992196, 0.026577565601447015, 0.960427662321778]
test_scores = [0.0016141123620710361, 0.0401760172499843, 0.9093868114563499]
```

```
plt.figure(figsize=(10, 6))

plt.plot(metrics, train_scores, marker='o', label='Train', color='purple')
plt.plot(metrics, test_scores, marker='o', label='Test', color='orange')

plt.xlabel('Metrics')
plt.ylabel('Scores')
plt.title('Train vs Test Performance')
plt.legend()
plt.grid(True)
plt.show()
```

EDA Teddy_Dataset

```
# Function to create EDA plots
def create_eda_plots(df, dataset_name):
    plt.figure(figsize=(12, 8))

    # Histogram of spectroscopic redshift (z_spec)
    plt.subplot(2, 2, 1)
    sns.histplot(df['z_spec'], bins=30, kde=True)
    plt.title(f'{dataset_name}: Histogram of Spectroscopic Redshift (z_spec)')

    # Pairplot of photometric features
    plt.figure(figsize=(8, 6))
    sns.pairplot(df[['mag_r', 'u-g', 'g-r', 'r-i', 'i-z']])
    plt.suptitle(f'{dataset_name}: Pairplot of Photometric Features', y=1.02)

    # Correlation heatmap
    plt.figure(figsize=(8, 6))
    corr_matrix = df[['mag_r', 'u-g', 'g-r', 'r-i', 'i-z', 'z_spec']].corr()
    sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
    plt.title(f'{dataset_name}: Correlation Heatmap')

    # Boxplot of magnitudes
    plt.figure(figsize=(10, 6))
```

```

sns.boxplot(data=df[['mag_r', 'u-g', 'g-r', 'r-i', 'i-z']])
plt.title(f'{dataset_name}: Boxplot of Magnitudes')

plt.tight_layout()
plt.show()

# Violin plot
plt.figure(figsize=(12, 8))
sns.violinplot(data=df[['mag_r', 'u-g', 'g-r', 'r-i', 'i-z']])
plt.title(f'{dataset_name}: Violin Plot of Photometric Features')
plt.show()

# Scatter plot of 'mag_r' vs 'z_spec'
plt.figure(figsize=(10, 6))
sns.scatterplot(x='mag_r', y='z_spec', data=df)
plt.title(f'{dataset_name}: Scatter Plot of mag_r vs z_spec')
plt.show()

# Create EDA plots for the dataset
create_eda_plots(teddy_df, 'Teddy Dataset')

```

Generate Predictions

```

# Generate predictions
y_pred = best_model.predict(X_test)

```

Actual vs Predict Value

```

import matplotlib.pyplot as plt
import numpy as np

# Assuming y_test and y_pred are pandas Series
# Example: y_test = pd.Series([...]), y_pred = pd.Series([...])

# Calculate error
errors = np.abs(y_test - y_pred)

# Create a scatter plot with a color gradient based on the error
plt.figure(figsize=(10, 8))
plt.scatter(y_test, y_pred, c=errors, cmap='coolwarm', alpha=0.7, edgecolor='k', s=80, label='Predicted vs Actual')

# Add a line for the perfect prediction
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linewidth=2, linestyle='--', label='Perfect Prediction')

# Customize the plot
plt.xlabel('Actual Values', fontsize=14)
plt.ylabel('Predicted Values', fontsize=14)

```

```
plt.title('Actual vs Predicted Redshift Values for the teddy Dataset', fontsize=16)
plt.legend(fontsize=12)
plt.colorbar(label='Error')
plt.grid(True, linestyle='--', alpha=0.7)

# Show the plot
plt.show()
```

Combine Datasets

Library Installation and Imports

```
!pip install optuna

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import mean_squared_error
import optuna

from google.colab import drive
drive.mount('/content/drive')

# Load the dataset
df = pd.read_csv('/content/drive/MyDrive/merge_happy_and_teddy.csv')
```

Feature Selection and Target Definition

```
# Define feature columns and target column (using normalized features)
features = ['feat1', 'feat2', 'feat3', 'feat4', 'feat5']
target = 'z_spec'
```

Handling Missing Values

```
# Handle missing values
df = df.dropna(subset=features + [target])
```

Data Splitting

```
X = df[features]
y = df[target]

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Objective Function Definition for Hyperparameter Tuning

Define the objective function for Optuna

```
def objective(trial):
    model_type = trial.suggest_categorical('model_type', ['RandomForest', 'GradientBoosting'])
    if model_type == 'RandomForest':
        n_estimators = trial.suggest_int('n_estimators', 50, 300)
        max_depth = trial.suggest_int('max_depth', 10, 50)
        model = RandomForestRegressor(
            n_estimators=n_estimators,
            max_depth=max_depth,
            random_state=42
        )
    else:
        learning_rate = trial.suggest_loguniform('learning_rate', 0.01, 0.2)
        n_estimators = trial.suggest_int('n_estimators', 50, 300)
        max_depth = trial.suggest_int('max_depth', 10, 50)
        model = GradientBoostingRegressor(
            learning_rate=learning_rate,
            n_estimators=n_estimators,
            max_depth=max_depth,
            random_state=42
        )

    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)
    return mse
```

Generate predictions

Generate predictions

```
y_pred = best_model.predict(X_test)
```

Actual vs Predict Value

```
import matplotlib.pyplot as plt
```

```
import numpy as np
```

Calculate error

```
errors = np.abs(y_test - y_pred)
```

Create a scatter plot with a color gradient based on the error

```
plt.figure(figsize=(10, 8))
```

```
plt.scatter(y_test, y_pred, c=errors, cmap='coolwarm', alpha=0.7, edgecolor='k', s=80, label='Predicted vs Actual')
```

Add a line for the perfect prediction

```
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linewidth=2, linestyle='--',
label='Perfect Prediction')

# Customize the plot
plt.xlabel('Actual Values', fontsize=14)
plt.ylabel('Predicted Values', fontsize=14)
plt.title('Actual vs Predicted Redshift Values for the combine Dataset', fontsize=16)
plt.legend(fontsize=12)
plt.colorbar(label='Error')
plt.grid(True, linestyle='--', alpha=0.7)

# Show the plot
plt.show()
```

Hyperparameter Optimization

```
# Create a study and optimize the objective function
study = optuna.create_study(direction='minimize')
study.optimize(objective, n_trials=10)
```

Retrieving Best Hyperparameters

```
# Get the best hyperparameters
best_params = study.best_params
print(f'Best hyperparameters: {best_params}')
```

Training and Evaluating the Best Model

```
# Train and evaluate the best model
if best_params['model_type'] == 'RandomForest':
    best_model = RandomForestRegressor(
        n_estimators=best_params['n_estimators'],
        max_depth=best_params['max_depth'],
        random_state=42
    )
else:
    best_model = GradientBoostingRegressor(
        learning_rate=best_params['learning_rate'],
        n_estimators=best_params['n_estimators'],
        max_depth=best_params['max_depth'],
        random_state=42
    )
best_model.fit(X_train, y_train)
y_train_pred = best_model.predict(X_train)
y_test_pred = best_model.predict(X_test)
```



```

mse_train = mean_squared_error(y_train, y_train_pred)
rmse_train = np.sqrt(mse_train)
r2_train = best_model.score(X_train, y_train)

mse_test = mean_squared_error(y_test, y_test_pred)
rmse_test = np.sqrt(mse_test)
r2_test = best_model.score(X_test, y_test)

print(f'Training MSE: {mse_train}')
print(f'Training RMSE: {rmse_train}')
print(f'Training R2: {r2_train}')
print(f'Test MSE: {mse_test}')
print(f'Test RMSE: {rmse_test}')
print(f'Test R2: {r2_test}')

```

EDA Combine_Datasets

Function to create EDA plots

```

def create_eda_plots(df, dataset_name):
    plt.figure(figsize=(12, 8))

    # Histogram of spectroscopic redshift (z_spec)
    plt.subplot(2, 2, 1)
    sns.histplot(df['z_spec'], bins=30, kde=True)
    plt.title(f'{dataset_name}: Histogram of Spectroscopic Redshift (z_spec)')

    # Pairplot of photometric features
    plt.figure(figsize=(8, 6))
    sns.pairplot(df[['mag_r', 'u-g', 'g-r', 'r-i', 'i-z']])
    plt.suptitle(f'{dataset_name}: Pairplot of Photometric Features', y=1.02)

    # Correlation heatmap
    plt.figure(figsize=(8, 6))
    corr_matrix = df[['mag_r', 'u-g', 'g-r', 'r-i', 'i-z', 'z_spec']].corr()
    sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
    plt.title(f'{dataset_name}: Correlation Heatmap')

    # Boxplot of magnitudes
    plt.figure(figsize=(10, 6))
    sns.boxplot(data=df[['mag_r', 'u-g', 'g-r', 'r-i', 'i-z']])
    plt.title(f'{dataset_name}: Boxplot of Magnitudes')

    plt.tight_layout()
    plt.show()

    # Violin plot
    plt.figure(figsize=(12, 8))
    sns.violinplot(data=df[['mag_r', 'u-g', 'g-r', 'r-i', 'i-z']])
    plt.title(f'{dataset_name}: Violin Plot of Photometric Features')

```

```
plt.show()

# Scatter plot of 'mag_r' vs 'z_spec'
plt.figure(figsize=(10, 6))
sns.scatterplot(x='mag_r', y='z_spec', data=df)
plt.title(f'{dataset_name}: Scatter Plot of mag_r vs z_spec')
plt.show()

# Create EDA plots for the merged dataset
create_eda_plots(merge_happy_and_teddy_df, 'merge_Happy_and_Teddy_Dataset')
```

Chapter # 8

8 References:

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