Composite Spectral Energy Distribution and Clustering Methods

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Keywords

galaxies: evolution, methods: data analysis, methods: Bayesian non-parametric

Abstract

Composite SEDs and Bayesian non-parametric clustering. Photometry and medium bands: surveys Spectral Energy Distributions: fitting template, FAST, EAZY Composite SEDs: evolution from grouping methods Bayesian non-parametric on functional data: 1. Dirichlet Processes for clustering 2. Gaussian Processes on Spectral data 3. Clustering on functional data

Contents

1. INTRODUCTION

improvement of Photometry data on redshift rage 3-4.

2. GALAXY EVOLUTION IN TERMS OF COMPOSITE SPECTRAL ENERGY DISTRIBUTIONS (SEDs)

2.1. Medium-Band Photometry

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2.2. Fitting Template of Spectral Energy Distributions (SEDs)

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2.3. Composite Spectral Energy Distributions (SEDs)

3. BAYESIAN MACHINE LEARNING FOR MODELING SPECTRAL DATA

Bayesian machine learning is a branch of machine learning which aims to solve machine learning problems in a Bayesian perspective. Instead of optimizing the parameters of interest from data using an empirical loss function (e.g., a least-squared function), Bayesian methods build generative models to randomly sample data from parameters and try to maximize the likelihood between observed data and hidden parameters (Barber 2012).

The difference between Bayesian statistics and Bayesian "machine learning" is that Bayesian "machine learning" is trying to approximate *non-linear* functions (Bishop & Tipping 2003). After the publish of Rasmussen & Williams (2005), learning unknown complicated functions from observed data using *Gaussian processes* (GP) became popular.

A *Gaussian process* is a bunch of random variables, and any finite subset of these random variables is a joint Gaussian distribution (Rasmussen & Williams 2005). GP could be a powerful tool to model any kind of functional data (continuous data) in a non-parametric way. By non-parametric, it actually means we use infinite many parameters to describe our function (Gelman et al. 2014). GP could be treated as a random function (or a stochastic process) which draws samples from the n-dimensional distribution,

$$\mu(x_1), ..., \mu(x_n) \sim Normal((m(x_1), ..., m(x_n)), K(x_1, ..., x_n)) \quad 1.$$

(Garnett et al. 2017)

3.1. Gaussian Processes for Modeling Spectra

3.2. Bayesian Model Selection with Different Types of Galaxies

3.3. Dirichlet Processes for Clustering

3.4. Possibility: Dirichlet Processes combined with Gaussian Process for Modeling Composite SEDs

SUMMARY POINTS

1. Summary point 1. These should be full sentences.

FUTURE ISSUES

1. Future issue 1. These should be full sentences.

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