Probing the Matter Density at High Redshift

Meghendra Singh1*, Shashikant Gupta2, Ashwini Pandey3 and Satendra Sharma4
1Dr.A.P.J.Abdul Kalam Technical University, Lucknow – 226021, Uttar Pradesh, India; meghendrasingh_db@yahoo.co.in
2GD Goenka University Gurgaon – 122103, Haryana, India; shashikantgupta.astro@gmail.com
3Amity University Haryana, Gurgaon – 122413, Haryana, India
4Yobe State University, Gujba Road, PMB 1144, Damaturu, Yobe State, Nigeria

Abstract

Objectives: We investigate the constraints on cosmological parameters from the observed set of 79 calibrated Gamma Ray Bursts (GRBs). Methods/Statistical Analysis: To measure cosmological parameters (ΩM, H0) for ΛCDM cosmology, we use Maximum-likelihood method. We marginalize over H0 using Bayesian approach as well. Finding: Our results gives the value of matter density is (ΩM = 0.18) and expansion rate (H0 = 82.5) for the set of GRBs. Application/Improvements: Method used in this paper helps us to estimate the cosmological parameter. Using this method we have obtain sensible answers in a straightforward manner.

Keywords: Bayesian, Bursts—Cosmology, Gamma Rays, Maximum-Likelihood, Observations—Cosmology

1. Introduction

The global mass-energy budget of the Universe is dynamic and is dominated by dark matter and dark energy1. The percentage of the baryonic matter and radiation is very little. Dark matter is treated as a pressure less fluid and does interact with electromagnetic radiation. Dark energy can be treated as a fluid with negative pressure and is responsible for acceleration of the expansion rate of the Universe. The equation of state of dark energy can be expressed in terms of pressure (P) and density (ρ) as P = wρ; where ρ is allowed to be negative. The value of equation of state parameter, w, decides the nature of dark energy; and is different for different cosmological models. For instance the value w=-1 is explained by adding a constant in the Einstein equation and is known as cosmological constant. The above model of the Universe is called the Lambda Cold Dark Matter (ΛCDM) cosmology.

Many such Cosmological models exist which provide different values for w. The detailed nature of dark energy and its evolution with time is among most important issues in cosmology. Measuring distances to very far away galaxies can constrain cosmological models. To measure great distances extremely bright astronomical objects with known luminosity are required. Gamma Ray Bursts (GRB) are the most intense explosions observed so far. They are believed to be detectable up to a very high redshift2–4. High energy photons from GRBs are almost immune to dust extinction. These advantages would draw GRBs an impressive cosmic probe for distance measurement and hence for constraining the cosmological models.

In section 2, we illustrate the data set and methodology used for our analysis. In section 3, we continue and put forward our results and conclusions.
2. Data and Methodology

Gamma-ray bursts (GRBs), which have isotropic energy up to 10$^{52}$ erg, would be the ideal tool to study the properties of early universe: including dark energy, star formation rate, and the metal enrichment history of the Universe. In this paper, investigation is carried out to constraint the cosmological parameters using the observed set of 79 calibrated GRBs for $\chi^2$ statistic introduced in 7,8. Marginalization over the Hubble Constant ($H_0$) is made for the observed sample for $\Lambda$CDM cosmology, and then the best-fit relations are applied to the observed sample to obtain a $\chi^2$ or a probability $P \propto \exp \left( -\frac{\chi^2}{2} \right)$ for this cosmology.

2.1 Bayesian Inference

The $\Lambda$CDM cosmology can be described in terms of the dimension less density parameter, $\Omega_M$, (being a measure of the density of both dark and baryonic matter), and the Hubble constant, $H_0$ (measure of expansion rate of the universe). Assuming that the $\Lambda$CDM cosmology is true, one can estimate these parameters from the cosmological data by maximizing the likelihood $p(x_1,...,x_n|a_j)$. Where $a_j$ denotes the parameters ($\Omega_M, H_0$).

The likelihood function $p(x_1,...,x_n|a_j)$ expresses the probability of obtaining the data ($x_1,...,x_n$) given the parameters($a_j$). This approach is known as frequentist approach of data analysis. However, the alternative approach, Bayesian Inference, is an intuitive combination of Bayes theorem and probability theory, allows one to define the probability for the parameters ($a_j$).

For the given data, the posterior probability $p(a_j|x_1,...,x_n)$ is proportional to the product of the prior information $p(a_j | I)$ and the likelihood function $p(|x_1,...,x_n|a_j)$.

$$p(a_j|x_1,...,x_n) \propto p(x_1,...,x_n|a_j)p(a_j)$$  \hspace{1cm} (1)

2.2 Marginalization

Many times only few parameters are essential in the given problem; other parameters being irrelevant are treated as nuisance parameters. An important aspect of Bayesian Decision Theory is that one can marginalize the posterior probability over such nuisance parameters. In the present context marginalization over $H_0$ is made treating it as a nuisance parameter. The equation takes the form:

$$p(\Omega_M) = \int_{-\infty}^{+\infty} p(\Omega_M, H_0) dH_0$$  \hspace{1cm} (2)

3. Results and Conclusion

First the dimensionless density parameter ($\Omega_M$) and the Hubble parameter ($H_0$) are calculated. These values are calculated by minimizing $\chi^2$ and are presented in Table 1. One can compare these values with the latest Supernovae type Ia results ($\Omega_M=0.27, H_0=70$).9 It is clear from the Table 1 that calibrated data sets of 79 GRBs favor smaller matter density ($\Omega_M$) and consequently higher expansion rate ($H_0$). The density parameter ($\Omega_M$) is of great importance and thus the Hubble parameter can be treated as a nuisance parameter. Marginalization over $H_0$ is carried out and the posterior probability is plotted in Figure 1. The probability is maximum for ($\Omega_M$)=0.19, which is also presented in Table 2.

It is clear that the value of matter density ($\Omega_M$) for the Maximum likelihood approach and Bayesian method is similar.

Table 1. Bestfit values of Cosmological parameters from GRB data

| Model | Data | No. of data points | $\Omega_M$ | $H_0$ |
|-------|------|--------------------|-----------|-------|
| $\Lambda$CDM | GRB | 79 | 0.18 | 82.50 |

Table 2. Bestfit value of $\Omega_M$ after marginalization over $H_0$

| Model | Data | No. of data points | $\Omega_M$ |
|-------|------|--------------------|----------|
| $\Lambda$CDM | GRB | 79 | 0.19 |

Figure 1. The probability distributions of $\Omega_M$ obtained from GRBs by marginalized over $H_0$. 
4. Acknowledgment

Meghendra Singh thanks DMRC for Support; Shashikant Gupta thanks Tarun Deep Saini for discourse; and colleagues of GD Goenka University for expert assistance.

5. References

1. Riess AG, Strolger LG, Tonry J, Challis P, Filippenko AV. Type Ia Supernova Discoveries at z 1 From the Hubble Space Telescope Evidence for Past Deceleration and Constraints on Dark Energy Evolution. The Astrophysical Journal. 2004; 607(2):665. Crossref

2. Lamb DQ, Reichart DE. Gamma-Ray Bursts as a Probe of the Very High Redshift Universe. The Astrophysical Journal. 2000 Jun; 536(1-8):1–18.

3. Ciardi B, Loeb A. Expected Number and Flux Distribution of Gamma-Ray Burst Afterglows with High Redshifts. The Astrophysical Journal. 2000; 540(2):687. Crossref

4. Bromm V, Loeb A. The Expected Redshift Distribution of Gamma-Ray Burst. The Astrophysical Journal. 2002 Jan; 575(1):111. Crossref

5. Gehrels N, Singh M. Gamma Ray Bursts. Science. 2012 Aug; 337(6097):932–6. Crossref, PMID:22923573

6. Liu J, Wei H. Cosmological Models and Gamma-Ray Bursts Calibrated by Using Pade Method. General Relativity and Gravitation. 2015; 47:141. Crossref

7. Gupta S, Saini T, Plaskar T. Direction Dependent Non-Gaussianity in High-z Supernova Data. 2008; 388(1):242–6.

8. Gupta S, Saini TP. Non-Gaussianity and direction dependent systematics in HST key project data. 2011; 415 (3):2594–9.

9. Gupta S, Singh M. High-z Supernova Type Ia Data: non-Gaussianity and Direction Dependence. 2014; 440(4):3257–61.