

"Hunting for primordial non-Gaussianity in CMB"

~ Lecture on non-Gaussianity, given at IEPSC ~
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GRAND THEME

- Detection of any forms of PRIMORDIAL non-Gaussianity* is a breakthrough in cosmology.

* Non-Gaussianity = deviation from a Gaussian distribution.

Outline of the lecture

1. Basics of Gaussian and non-Gaussian statistics. (July 7)

2. Effects of non-Gaussianity on cosmological fluctuations. (July 8)

3. Measuring non-Gaussianity from the cosmological data. (July 9)

Reference

• E. Komatsu, *Classical and Quantum Gravity*, 27, 124010 (2010)
(arXiv: 1003.6097)

• E. Komatsu, astro-ph/0206039 (also see arXiv:0902.4959)

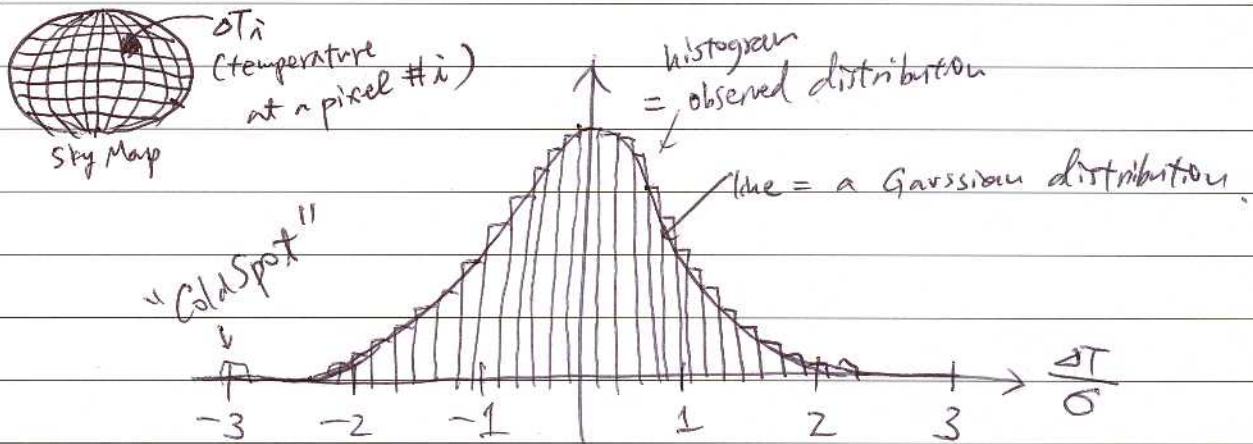
1. Basics of Gaussian and non-Gaussian statistics

1.1. Gaussian distribution.

one point

The observed distribution of temperature fluctuations of CMB on the sky is very close to a Gaussian distribution:

$$\text{1-point distribution} = \frac{1}{(2\pi)^{N_{\text{pix}}/2} \prod_i \sigma_i} \exp \left[-\frac{1}{2} \sum_i \frac{(\Delta T)_i^2}{\sigma_i^2} \right]$$



The basic properties of a one-point Gaussian distribution:

For $p(x) \equiv \frac{1}{\sqrt{2\pi}\sigma} e^{-x^2/2\sigma^2}$ where $x \equiv \Delta T$

- $\langle x \rangle \equiv \int_{-\infty}^{\infty} x p(x) dx = 0$ [zero mean]
- $\langle x^2 \rangle \equiv \int_{-\infty}^{\infty} x^2 p(x) dx = \sigma^2$ [variance]
- $\langle x^3 \rangle \equiv \int_{-\infty}^{\infty} x^3 p(x) dx = 0$ [zero skewness] $\equiv \langle x^3 \rangle$
- $\langle x^4 \rangle \equiv \int_{-\infty}^{\infty} x^4 p(x) dx = 3\sigma^4$ [zero kurtosis] $\equiv \langle x^4 \rangle - 3\langle x^2 \rangle^2$
- $\langle x^5 \rangle \equiv \int_{-\infty}^{\infty} x^5 p(x) dx = 0$, etc.

IMPORTANT
 σ determines everything about a Gaussian!!

But, the 1-point distribution cannot be a full description of CMB, as CMB temperatures at 2 points on the sky are not independent, but CORRELATED.

So, the exact distribution that describes the Gaussian CMB temperature anisotropy is given by the so-called "multi-variate" Gaussian distribution =

$$P(\delta T) = \frac{1}{(2\pi)^{M p_i x/2} |\xi|^{1/2}} \exp \left[-\frac{1}{2} \sum_{ij} \delta T_i (\xi^{-1})_{ij} \delta T_j \right]$$

where ξ_{ij} is the 2-point correlation, or the covariance matrix, defined by

$$\xi_{ij} \equiv \langle \delta T_i \delta T_j \rangle$$

Of course, it still preserves the basic property of a Gaussian distribution: ξ_{ij} determines everything, and

e.g., $\langle \delta T_i \delta T_j \delta T_k \rangle = 0$.

Wick's theorem:

$$\langle X^4 \rangle = 3 \langle X^2 \rangle^2$$

more generally,

$$\langle X_1 X_2 X_3 X_4 \rangle = \langle X_1 X_2 \rangle \langle X_3 X_4 \rangle + \langle X_1 X_3 \rangle \langle X_2 X_4 \rangle + \langle X_1 X_4 \rangle \langle X_2 X_3 \rangle$$

when $X_1 = X_2 = X_3 = X_4 \equiv X$, then, of course, we recover $\langle X^4 \rangle = 3 \langle X^2 \rangle^2$.

★ For Gaussian fluctuations, all even moments are given by products of 2-point functions, and all odd moments vanish.

We often work with the harmonic coefficient of the temperature anisotropy: $\delta T(\hat{n}_i) = \sum_{\ell m} a_{\ell m} Y_{\ell m}(\hat{n}_i)$, or

$$a_{\ell m} = \int d\hat{n} \delta T(\hat{n}) Y_{\ell m}^*(\hat{n})$$

In terms of $a_{\ell m}$, we have

$$p(a_{\ell m}) = \frac{1}{(2\pi)^{N_{\text{harm}}/2} |C|} \exp \left[-\frac{1}{2} \sum_{\substack{\ell m \\ \ell' m'}} a_{\ell m}^* (C^{-1})_{\ell m, \ell' m'} a_{\ell' m'} \right]$$

where

$$C_{\ell m, \ell' m'} \equiv \langle a_{\ell m}^* a_{\ell' m'} \rangle$$

This distribution provides the full description of a Gaussian CMB: it contains all information on it. Again, it is fully determined by the covariance matrix, $C_{\ell m, \ell' m'}$, and we have, e.g.,

$$\langle a_{\ell m} a_{\ell' m'} a_{\ell'' m''} \rangle = 0.$$

Under the special circumstance that CMB is statistically homogeneous & isotropic, or equivalently, CMB is invariant under translation & rotation on the sky, then

$$C_{\ell m, \ell' m'} = C_{\ell} \delta_{\ell \ell'} \delta_{m m'}$$

translation & rotation invariance.

Q: derive this from $\xi_{ij} = \langle \delta T_i \delta T_j \rangle = \xi(|\hat{n}_i - \hat{n}_j|)$, i.e., ξ depends only on the separation between i & j .

1.2. Non-Gaussian Distribution

Now, what about a non-Gaussian distribution?

In order to study it, we must know what its probability distribution is. However — once we deviate from a Gaussian distribution, we face infinite number of possibilities!!

Are we totally clueless?

Fortunately not --- because we know, from observations, that CMB is very close to a Gaussian distribution!!

In other words, it makes sense to "Taylor-expand" the probability distribution around a Gaussian distribution.

How do we do that in practice??

Taylor expansion of a function $f(x)$ around $x=0$:

$$f(x) = \sum_{n=0}^{\infty} \frac{x^n}{n!} \frac{d^n f}{dx^n}.$$

★ Can we do the same thing for a Gaussian distribution?

→ Yes, and it is called the "Gram-Charlier expansion."

