

1 Why Is It Gaussian?

Let X be a normally distributed random variable with mean μ and variance σ^2 . Let $Y = aX + b$, where a and b are non-zero real numbers. Show explicitly that Y is normally distributed with mean $a\mu + b$ and variance $a^2\sigma^2$. The PDF for the Gaussian Distribution is $\frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(x-\mu)^2}{2\sigma^2}}$.

Solution:

Problem and solution taken from *A First Course in Probability* by Sheldon Ross, 8th edition.

Let $a > 0$.

We start with the cumulative distribution function (CDF) of Y , F_Y .

$$\begin{aligned}
 F_Y(x) &= \mathbb{P}[Y \leq x] && \text{By definition of CDF} \\
 &= \mathbb{P}[aX + b \leq x] && \text{Plug in } Y = aX + b \\
 &= \mathbb{P}\left[X \leq \frac{x-b}{a}\right] && \text{Because } a > 0 \\
 &= F_X\left(\frac{x-b}{a}\right) && \text{By definition of CDF. } F_X \text{ denotes the CDF of } X.
 \end{aligned} \tag{1}$$

Let f_Y denote the probability density function (PDF) of Y .

$$\begin{aligned}
 f_Y(x) &= \frac{d}{dx}F_Y(x) && \text{The PDF is the derivative of the CDF.} \\
 &= \frac{d}{dx}F_X\left(\frac{x-b}{a}\right) && \text{Plug in the result from (??)} \\
 &= \frac{1}{a} \cdot f_X\left(\frac{x-b}{a}\right) && \text{PDF is the derivative of CDF.} \\
 & && \text{Apply chain rule, } \frac{d}{dx}\left(\frac{x-b}{a}\right) = \frac{1}{a}. \\
 &= \frac{1}{a} \cdot \frac{1}{\sigma\sqrt{2\pi}} \cdot e^{-((x-b)/a-\mu)^2/(2\sigma^2)} && X \sim \mathcal{N}(\mu, \sigma^2). \\
 &= \frac{1}{a\sigma\sqrt{2\pi}} \cdot e^{-(x-b-a\mu)^2/(2\sigma^2a^2)} && \frac{x-b}{a} - \mu = \frac{1}{a}(x-b-a\mu)
 \end{aligned} \tag{2}$$

We have shown that f_Y equals the probability density function of a normal random variable with mean $b + a\mu$ and variance σ^2a^2 . So, Y is normally distributed with mean $b + a\mu$ and variance σ^2a^2 . The proof is done for $a > 0$. The proof for $a < 0$ is similar.

2 Sum of Independent Gaussians

In this question, we will introduce an important property of the Gaussian distribution: the sum of independent Gaussians is also a Gaussian.

Let X and Y be independent standard Gaussian random variables. Recall that the density of the standard Gaussian is

$$f(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right).$$

- (a) What is the joint density of X and Y ?
- (b) Observe that the joint density of X and Y , $f_{X,Y}(x,y)$, only depends on the quantity $x^2 + y^2$, which is the distance from the origin. In other words, the Gaussian is *rotationally symmetric*. Next, we will try to find the density of $X + Y$. To do this, draw a picture of the Cartesian plane and draw the region $x + y \leq c$, where c is a real number of your choice.
- (c) Now, rotate your picture clockwise by $\pi/4$ so that the line $X + Y = c$ is now vertical. Redraw your figure. Let X' and Y' denote the random variables which correspond to the $\pi/4$ clockwise rotation of (X, Y) and express the new shaded region in terms of X' and Y' .
- (d) By rotational symmetry of the Gaussian, (X', Y') has the same distribution as (X, Y) . Argue that $X + Y$ has the same distribution as $\sqrt{2}Z$, where Z is a standard Gaussian. This proves the following important fact: *the sum of independent Gaussians is also a Gaussian*. Notice that $X \sim \mathcal{N}(0, 1)$, $Y \sim \mathcal{N}(0, 1)$ and $Z \sim \mathcal{N}(0, 2)$. In general, if X and Y are independent Gaussians, then $X + Y$ is a Gaussian with mean $\mu_X + \mu_Y$ and variance $\sigma_X^2 + \sigma_Y^2$.
- (e) Recall the CLT:

If $\{X_i\}_{i \in \mathbb{N}}$ is a sequence of i.i.d. random variables with mean $\mu \in \mathbb{R}$ and variance $\sigma^2 < \infty$, then:

$$\frac{X_1 + \cdots + X_n - n\mu}{\sigma\sqrt{n}} \xrightarrow{\text{in distribution}} \mathcal{N}(0, 1) \quad \text{as } n \rightarrow \infty.$$

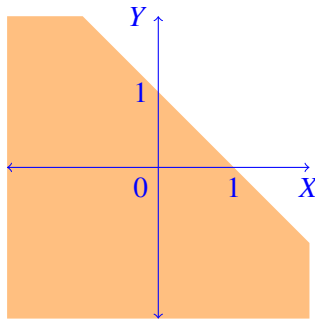
Prove that the CLT holds for the special case when the X_i are i.i.d. $\mathcal{N}(0, 1)$.

Solution:

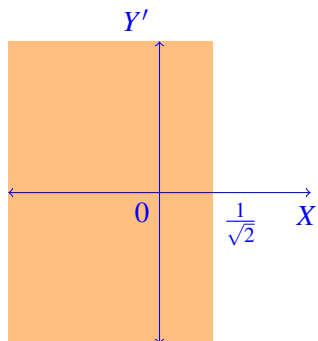
- (a) By independence, we have

$$f_{X,Y}(x,y) = f_X(x)f_Y(y) = \frac{1}{2\pi} \exp\left(-\frac{x^2 + y^2}{2}\right).$$

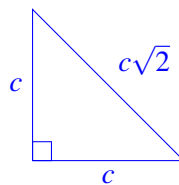
- (b) We draw the line for $c = 1$.



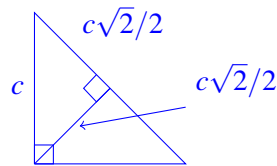
(c) Here is the new figure after the rotation (for $c = 1$).



For general $c \in \mathbb{R}$, the new region is $\{X' \leq c/\sqrt{2}\}$. To see why, draw the triangle: We want



to find the distance between the origin and the long side of the triangle, and we can do so by adding a diagonal:



(d) We observe that $\mathbb{P}(X + Y \leq c) = \mathbb{P}(X' \leq c/\sqrt{2}) = \mathbb{P}(\sqrt{2}X' \leq c)$, where X' is a standard Gaussian by rotational symmetry, so this proves the claim.

(e) Here, $\mu = 0$ and $\sigma = 1$. So, by the previous part,

$$\frac{X_1 + \cdots + X_n}{\sqrt{n}} \sim \frac{1}{\sqrt{n}} \mathcal{N}(0, n) \sim \mathcal{N}(0, 1).$$

3 Hypothesis testing

We would like to test the hypothesis claiming that a coin is fair, i.e. $P(H) = P(T) = 0.5$. To do this, we flip the coin $n = 100$ times. Let Y be the number of heads in $n = 100$ flips of the coin. We decide to reject the hypothesis if we observe that the number of heads is less than $50 - c$ or larger than $50 + c$. However, we would like to avoid rejecting the hypothesis if it is true; we want to keep the probability of doing so less than 0.05. Please determine c . (*Hints: use the central limit theorem to estimate the probability of rejecting the hypothesis given it is actually true.*)

You might need to use the table in the Appendix. Source: <http://cosstatistics.pbworks.com/w/page/27425647/Lesson>

Solution:

Let X_i be the random variable denoting the result of the i -th flip:

$$X_i = \begin{cases} 1 & \text{if the } i\text{-th flip is head,} \\ 0 & \text{if the } i\text{-th flip is tail.} \end{cases}$$

Then we have $Y = \sum_{i=1}^n X_i$. If the hypothesis is true, then $\mu = \mathbb{E}[X_i] = \frac{1}{2}$ and $\sigma^2 = \text{var}(X_i) = \frac{1}{2} \cdot \frac{1}{2} = \frac{1}{4}$. By central limit theorem, we know that

$$\begin{aligned} P\left(\frac{Y - n\mu}{\sqrt{n\sigma^2}} \leq z\right) &\approx \Phi(z) \\ P\left(\frac{Y - 100 \cdot \frac{1}{2}}{\sqrt{100 \cdot \frac{1}{4}}} \leq z\right) &\approx \Phi(z) \\ P\left(\frac{Y - 50}{5} \leq z\right) &\approx \Phi(z) \end{aligned}$$

where

$$\Phi(z) = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx.$$

We will reject the hypothesis when $|Y - 50| > c$. We also want $P(|Y - 50| > c) < 0.05$, or equivalently $P(|Y - 50| \leq c) > 0.95$. We have

$$P(|Y - 50| \leq c) = P\left(\frac{|Y - 50|}{5} \leq \frac{c}{5}\right) \approx 2\Phi\left(\frac{c}{5}\right) - 1.$$

The reason this is $\approx 2\Phi(\frac{c}{5}) - 1$ is because the probability we are looking for is the probability that Y is within $\frac{c}{5}$ standard deviations of the mean. By an area argument, we can see that this is $\Phi(\frac{c}{5}) - (1 - \Phi(\frac{c}{5})) = 2\Phi(\frac{c}{5}) - 1$. Let $2\Phi(\frac{c}{5}) - 1 = 0.95$, so $\Phi(\frac{c}{5}) = 0.975$ or $\frac{c}{5} = 1.96$. That is $c = 9.8$ flips. So we see that if we observe more than $50 + 10 = 60$ or less than $50 - 10 = 40$ heads, we can reject the hypothesis.

4 Appendix



Probability Content from $-\infty$ to Z

z	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09
0.0	0.5000	0.5040	0.5080	0.5120	0.5160	0.5199	0.5239	0.5279	0.5319	0.5359
0.1	0.5398	0.5438	0.5478	0.5517	0.5557	0.5596	0.5636	0.5675	0.5714	0.5753
0.2	0.5793	0.5832	0.5871	0.5910	0.5948	0.5987	0.6026	0.6064	0.6103	0.6141
0.3	0.6179	0.6217	0.6255	0.6293	0.6331	0.6368	0.6406	0.6443	0.6480	0.6517
0.4	0.6554	0.6591	0.6628	0.6664	0.6700	0.6736	0.6772	0.6808	0.6844	0.6879
0.5	0.6915	0.6950	0.6985	0.7019	0.7054	0.7088	0.7123	0.7157	0.7190	0.7224
0.6	0.7257	0.7291	0.7324	0.7357	0.7389	0.7422	0.7454	0.7486	0.7517	0.7549
0.7	0.7580	0.7611	0.7642	0.7673	0.7704	0.7734	0.7764	0.7794	0.7823	0.7852
0.8	0.7881	0.7910	0.7939	0.7967	0.7995	0.8023	0.8051	0.8078	0.8106	0.8133
0.9	0.8159	0.8186	0.8212	0.8238	0.8264	0.8289	0.8315	0.8340	0.8365	0.8389
1.0	0.8413	0.8438	0.8461	0.8485	0.8508	0.8531	0.8554	0.8577	0.8599	0.8621
1.1	0.8643	0.8665	0.8686	0.8708	0.8729	0.8749	0.8770	0.8790	0.8810	0.8830
1.2	0.8849	0.8869	0.8888	0.8907	0.8925	0.8944	0.8962	0.8980	0.8997	0.9015
1.3	0.9032	0.9049	0.9066	0.9082	0.9099	0.9115	0.9131	0.9147	0.9162	0.9177
1.4	0.9192	0.9207	0.9222	0.9236	0.9251	0.9265	0.9279	0.9292	0.9306	0.9319
1.5	0.9332	0.9345	0.9357	0.9370	0.9382	0.9394	0.9406	0.9418	0.9429	0.9441
1.6	0.9452	0.9463	0.9474	0.9484	0.9495	0.9505	0.9515	0.9525	0.9535	0.9545
1.7	0.9554	0.9564	0.9573	0.9582	0.9591	0.9599	0.9608	0.9616	0.9625	0.9633
1.8	0.9641	0.9649	0.9656	0.9664	0.9671	0.9678	0.9686	0.9693	0.9699	0.9706
1.9	0.9713	0.9719	0.9726	0.9732	0.9738	0.9744	0.9750	0.9756	0.9761	0.9767
2.0	0.9772	0.9778	0.9783	0.9788	0.9793	0.9798	0.9803	0.9808	0.9812	0.9817
2.1	0.9821	0.9826	0.9830	0.9834	0.9838	0.9842	0.9846	0.9850	0.9854	0.9857
2.2	0.9861	0.9864	0.9868	0.9871	0.9875	0.9878	0.9881	0.9884	0.9887	0.9890
2.3	0.9893	0.9896	0.9898	0.9901	0.9904	0.9906	0.9909	0.9911	0.9913	0.9916
2.4	0.9918	0.9920	0.9922	0.9925	0.9927	0.9929	0.9931	0.9932	0.9934	0.9936
2.5	0.9938	0.9940	0.9941	0.9943	0.9945	0.9946	0.9948	0.9949	0.9951	0.9952
2.6	0.9953	0.9955	0.9956	0.9957	0.9959	0.9960	0.9961	0.9962	0.9963	0.9964
2.7	0.9965	0.9966	0.9967	0.9968	0.9969	0.9970	0.9971	0.9972	0.9973	0.9974
2.8	0.9974	0.9975	0.9976	0.9977	0.9977	0.9978	0.9979	0.9979	0.9980	0.9981
2.9	0.9981	0.9982	0.9982	0.9983	0.9984	0.9984	0.9985	0.9985	0.9986	0.9986
3.0	0.9987	0.9987	0.9987	0.9988	0.9988	0.9989	0.9989	0.9989	0.9990	0.9990

Table 1: Table of the Normal Distribution