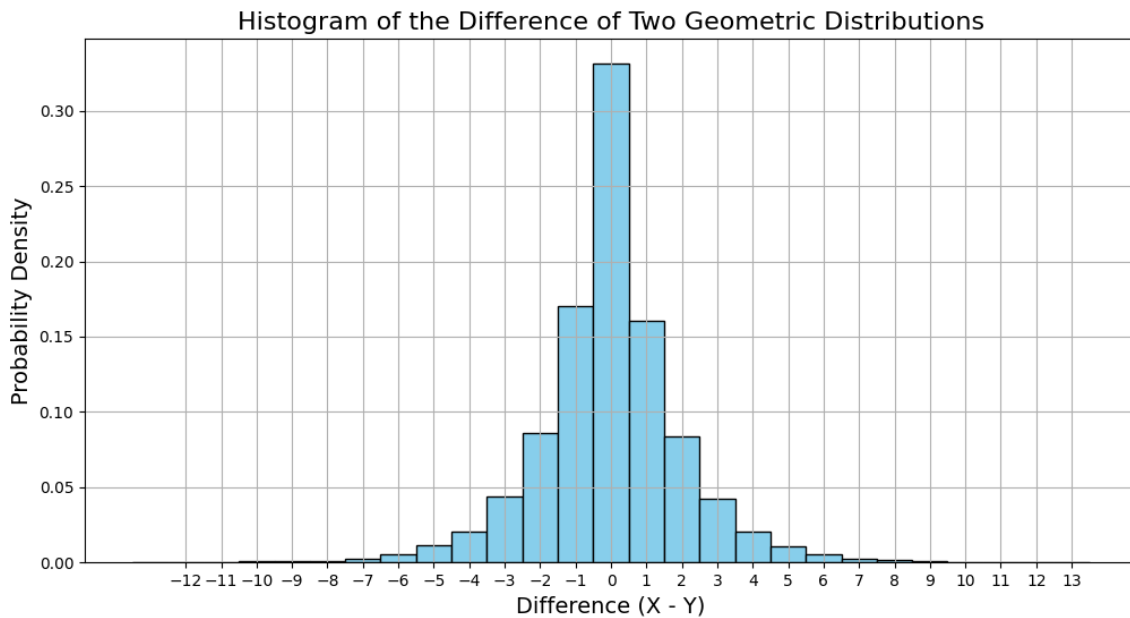


# 202410270542 Correlated Geometric vs Binomial Distribution

## Difference Between Two Geometric Distributions



## Introduction to the Geometric Distribution

The geometric distribution models the number of Bernoulli trials needed to achieve the first success. It is a discrete probability distribution with the following properties:

**Support:**

$$k = 1, 2, 3, \dots$$

**Probability Mass Function (PMF):**

$$P(X = k) = p(1 - p)^{k-1}$$

where:

- $p$  is the probability of success on each trial.
- $(1 - p)$  is the probability of failure on each trial.

**Mean:**

$$\mu = E[X] = \frac{1}{p}$$

**Variance:**

$$\sigma^2 = \text{Var}(X) = \frac{1-p}{p^2}$$

**Properties:**

- The geometric distribution is memoryless, meaning the probability of success on the next trial is independent of the number of failures that have already occurred.
- It is a discrete distribution over positive integers.
- The distribution is skewed to the right, especially for smaller values of  $p$ .

## Difference Between Two Geometric Distributions

Consider two independent geometric random variables  $X$  and  $Y$ , each representing the number of trials until the first success, with the same probability of success  $p$ . We are interested in the distribution of their difference:

**Difference:**

$$D = X - Y$$

**Properties of  $D$**

- **Support:**

$$D \in \{\dots, -2, -1, 0, 1, 2, \dots\}$$

- **Mean:**

Since  $X$  and  $Y$  are independent and identically distributed (i.i.d.), their expected values are the same:

$$E[D] = E[X - Y] = E[X] - E[Y] = \frac{1}{p} - \frac{1}{p} = 0$$

- **Variance:**

Because  $X$  and  $Y$  are independent:

$$\text{Var}(D) = \text{Var}(X - Y) = \text{Var}(X) + \text{Var}(Y) = 2 \times \frac{1-p}{p^2} = \frac{2(1-p)}{p^2}$$

- **Distribution of  $D$ :**

The distribution of  $D$  is symmetric around zero when  $X$  and  $Y$  are identically distributed.

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## Probability Mass Function of $D$

Computing the exact PMF of  $D$  involves convolution of the PMFs of  $X$  and  $Y$ . Since  $X$  and  $Y$  are independent, the PMF of  $D$  can be expressed as:

$$P(D = k) = \sum_{n=1}^{\infty} P(X = n + k)P(Y = n), \quad \text{for all integers } k$$

This calculation can be complex due to the infinite summation. However, for practical purposes, we can approximate the distribution of  $D$  via simulation.

## Correlated Geometric Differences Using Copula

### Generating Correlated Differences $X_1$ and $X_2$

To generate correlated differences  $X_1 = Z_{11} - Z_{12}$  and  $X_2 = Z_{21} - Z_{22}$  between pairs of geometric distributions, we apply a copula method. This allows us to introduce a specified correlation directly between  $X_1$  and  $X_2$  without altering the underlying distributions. Here's the step-by-step process:

### Steps

#### 1. Define the Independent Geometric Variables:

For each difference, we define two independent geometric distributions. The parameters are as follows:

- $p_1$ : Probability of success for the first pair  $(Z_{11}, Z_{12})$
- $p_2$ : Probability of success for the second pair  $(Z_{21}, Z_{22})$

#### 2. Compute Differences:

Define:

$$X_1 = Z_{11} - Z_{12}$$

$$X_2 = Z_{21} - Z_{22}$$

#### 3. Copula for Correlation:

To impose correlation between  $X_1$  and  $X_2$ , use a copula approach:

- **Step 3a:** Generate standard normal correlated variables  $N_1$  and  $N_2$  with the desired correlation  $\rho$ .
- **Step 3b:** Transform these normals to uniform variables using the cumulative distribution function (CDF) of the normal distribution:

$$U_1 = \Phi(N_1), \quad U_2 = \Phi(N_2)$$

#### 4. Rank Transformation:

Sort  $X_1$  and  $X_2$  based on the ranks of  $U_1$  and  $U_2$  to introduce the desired correlation structure directly on  $X_1$  and  $X_2$  without any additional rescaling.

## Visualization

The final correlated variables  $X_1$  and  $X_2$  can be visualized using both a 2D heatmap and a 3D histogram to represent the joint distribution and observe the effect of the copula on the correlation.

