

## Lecture Notes 11

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## 0.1 Discrete Distributions

**Definition 1 (Discrete Uniform Distribution)** Suppose  $X$  follows discrete uniform distribution then it has density

$$f_X(|N) = \frac{1}{N} \mathbb{1}_{\{1,2,3,\dots,N\}}(x)$$

where  $N$  is an integer, with notation  $X \sim \text{Discrete Uniform}(N)$ .

**Property 1** Given  $N$ ,  $X$  follows discrete uniform distribution then,

1.  $E[X|N] = \sum_{i=1}^N P(X=i) i = \frac{N+1}{2}$
2.  $\text{Var}(X|N) = E[X^2|N] - E[X|N]^2 = \frac{N^2-1}{12}$

**Intuition (Usage in statistics)**

How can we test the two given data group  $X, Y$  follows the same distribution?

$X_1, X_2, \dots, X_n \stackrel{iid}{\sim} F_1(x)$  and  $Y_1, Y_2, \dots, Y_m \stackrel{iid}{\sim} F_2(x)$  want to test  $H_0 : F_1(x) = F_2(x) \forall x$

**Kolmogorov statistics:** Using empirical distribution of  $F_1(x), F_2(x)$

$$\hat{F}_1(x) = \frac{1}{n} \sum_{i=1}^n \mathbb{1}(X_i \leq x)$$

$$\hat{F}_2(x) = \frac{1}{m} \sum_{i=1}^m \mathbb{1}(Y_i \leq x)$$

We have Kolmogorov statistics:

$$\sup_x |\hat{F}_1(x) - \hat{F}_2(x)|$$

which can not be too big if  $X$  and  $Y$  following same distributions.

**Rank statistics (Wilcoxon test):** Instead of using true value as the predictor. We use the order i.e. rank of the data in the group. We combine  $X$  and  $Y$  and sort them to give rank

$$W = \frac{1}{n} \sum_{i=1}^n \text{Rank}(X_i)$$

To prevent the issue that extreme values dominated the statistics. And  $X \sim Y$  if  $W$  is not too big or too small.

**Definition 2 (Bernoulli Distribution)**  $X$  follows Bernoulli distribution then it has density

$$f_X(x|p) = p^x(1-p)^{1-x} \mathbb{1}_{\{0,1\}}(x)$$

where  $0 \leq p \leq 1$  denoting as  $X \sim \text{Bernoulli}(p)$ .

**Property 2** Given  $p$ ,  $X$  follows binomial distribution then,

1.  $E[X^m|p] = E[X|p] = p$
2.  $\text{Var}(X|p) = p - p^2 = p(1-p)$
3.  $F_X(x) = P(X \leq x) = E[I(X \leq x)] = E[N(x)]$

**Definition 3 (Binomial Distribution)**  $X_1, X_2, \dots, X_n$  i.i.d follows Bernoulli( $p$ ), let  $X = \sum_{i=1}^n X_i$ ,  $X$  follows binomial distribution having density

$$f_X(x) = \binom{n}{x} p^x (1-p)^{n-x} \mathbb{1}_{\{0,1,2,3,\dots,n\}}(x)$$

#### Intuition (Independent)

$X_1, X_2, \dots, X_n$  are independent iff

$$P(X_1 = x_1, X_2 = x_2, \dots, X_n = x_n) = \prod_{i=1}^n f(x_i|p)$$

The mutually independent property automatically satisfied since we can think of  $\Omega = \Omega_1 \times \Omega_2 \times \dots \times \Omega_n$  where  $\Omega_i = \{0,1\}$  for the  $i$ th Bernoulli trial. And  $\bigcup (A_i \in \Omega_1)(\Omega_2 \times \dots \times \Omega_n)$  augmented  $\Omega$ .

**Remark 1** In reality,  $X_1, X_2, \dots, X_n$  are not i.i.d.. Since we sometimes sample population with common factors. They may affect each other, within positive or negative relation.

1. Over-dispersion binomial distribution: There are positive correlation among populations. That is, if the event happens on one member, then other members will have higher tendency to success.
2. Under-dispersion binomial distribution: There are negative correlation among populations.

Formally, if the variance of a random variable look like:  $\text{var}[X] = \phi p(1-p)$ . If  $\phi > 1$ , we say  $X$  is a over-dispersion binomial and on the contrary if  $\phi < 1$ , then we say  $X$  is an under-dispersion binomial. Note that, although we call them "binomial", they are definitely not a binomial random variable!