Random variables and probability distributions (1) MAE301 Applied Experimental Statistics

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discrete random variables

Discrete random variable: can take distinct discrete values

Probability mass function: $f(x_i) = P(X = x_i)$

What are the properties of f(x)?

Cumulative distribution function:

$$F(x) = P(X \le x_i) = \sum_{x_i \le x} f(x_i)$$

$$F(-\inf) = ?, F(\inf) = ?$$

mean and variance

For a given random variable X with probability mass function f(x) defined on the set $\{x_1, \dots, x_n\}$:

Mean (expected value, expectation):
$$\mu := E(X) := \sum_{i=1}^{n} x_i f(x_i)$$

Variance:
$$\sigma^2 := E((X - \mu)^2) = \sum_{i=1}^n (x_i - \mu)^2 f(x_i)$$

 σ is called the **standard deviation** of X.

sample mean and sample variance

Note that the mean and variance of a random variable is usually unknown. What we can observe is the sample mean and sample variance. Given samples x_1, \dots, x_m drawn from f(x), we have:

Sample mean (average):
$$\bar{x} = \frac{1}{m} \sum_{i=1}^{m} x_i$$

Sample variance :
$$s^2 := \frac{1}{m-1} \sum_{i=1}^{m} (x_i - \bar{x})^2$$

degree of freedom

Why m-1 in the denominator of sample variance? Because sample variance has a DOF of m-1. But what does that mean? Well it means that $x_i - \bar{x}$ are sampled from a m-1 dimensional space. What? Well you see $\sum_{i=1}^{m} (x_i - \bar{x}) = 0$.

More explicit explanation: $s^2 = \frac{1}{m-1} \sum_{i=1}^m (x_i - \bar{x})^2$ is an **unbiased** estimation of σ^2 , i.e., $E(s^2) = \sigma^2$. (Proof?)

exercise

For a class of n students, consider each student's final grade as a random variable X_i , with mean μ_i and variance σ_i^2 . What is the average grade of the class?

The average grade is defined as $\bar{X} = \frac{1}{n} \sum_{i=1}^{n} X_i$. Since X_i is a random variable, \bar{X} is a random variable as well. The mean of \bar{X} is:

$$\mu_X = E(\bar{X}) = E(\frac{1}{n} \sum_{i=1}^n X_i) = \frac{1}{n} \sum_{i=1}^n E(X_i) = \frac{1}{n} \sum_{i=1}^n \mu_i.$$
 (1)

exercise (cont.)

The variance of \bar{X} is:

$$\sigma_X^2 = E\left((X - \mu_X)^2\right)$$

$$= E\left(\left(\frac{1}{n}\sum_{i=1}^n X_i - \frac{\sum_{i=1}^n \mu_i}{n}\right)^2\right)$$

$$= E\left(\frac{\left(\sum_{i=1}^n (X_i - \mu_i)\right)^2}{n^2}\right)$$

$$= \frac{\sum_{i=1}^n \sigma_i^2}{n^2}$$
(2)

What do you learn from here?

exercise

Assume that the total power output of a power plant can be mathematically modeled as Z=3X-2Y, where X and Y are two independent random variables: X takes values 1, 2 and 3 with probabilities 0.2, 0.3 and 0.5 respectively. Y takes values 3 and 5 with probabilities 0.5 and 0.5.

What are the mean and variance of Z?

binomial variable

A random variable is binomial when it describes the number of successes in a sequence of n independent success/failure experiments, each of which yields success with probability p.

E.g., the number of heads in 100 coin flips is a binomial variable.

The success/failure experiment is called a **Bernoulli experiment** or Bernoulli trial.

Bernoulli process

A **Bernoulli process** consists of repeated Bernoulli experiments.

- ► Each trial results in an outcome that may be classified as a success or a failure
- ► The probability of success, denoted by *p*, remains constant from trial to trial
- The repeated trials are independent

binomial distribution

Consider a Bernoulli process with n experiments, each has probability p to be successful. Let X be the number of successes in total. What values can X take and what are the probabilities?

Assume out of the n experiments, there are m < n successes. There are in total $\binom{n}{m}$ combinations. The chance for each combination to happen is $p^m(1-p)^{n-m}$ (why?). So in total, the chance of having m successes is $\binom{n}{m}p^m(1-p)^{n-m}$.

The binomial distribution:

$$f(x) = \binom{n}{x} p^{x} (1-p)^{n-x} \quad x \le n, x \in \mathbb{Z}$$
 (3)

A binomial variable X has $\mu = np$ and $\sigma^2 = np(1-p)$ (why?).



exercise

Traffic engineers install 10 street lights with new bulbs. The probability that a bulb fails within 50,000 hours of operation is 0.25. Assume that each of the bulbs fails independently.

- ▶ Determine the probability that fewer than two of the bulbs will fail within 50,000 hours of operation. (0.2440)
- ▶ Determine the probability that no bulbs will have to be replaced within 50,000 hours. (0.0563)
- ▶ Determine the probability that more than four of the bulbs will need replacing within 50,000 hours. (0.078127)

Summary of the class

- ► Discrete random variable: probability mass function, cumulative distribution function
- (population) mean and variance, sample mean and variance (are random variables!)
- binomial variable

Python code for the birthday problem

```
## mean, variance, sample mean, and sample variance
# define a distribution
from scipy import stats
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
xbar = \prod
ss = []
ssn = []
xk = np.arange(4) # variable takes 0, 1, 2, 3
pk = (0.1, 0.2, 0.3, 0.4) # probability masses are 0.1, 0.2, 0.3, 0.4
custm = stats.rv_discrete(name='custm', values=(xk, pk))
# calculate mean and variance
mu = np.sum(pk*xk)
variance = np.sum((xk-mu)**2*pk)
for i in np.arange(10000):
   R = custm.rvs(size=10)
   # calculate sample mean and sample variance
   xbar += [np.sum(R)/float(R.size)]
   ss += [np.sum((R-xbar[i])**2)/float(R.size-1)]
   ssn += [np.sum((R-xbar[i])**2)/float(R.size)]
hist, bins = np.histogram(xbar, bins=10)
width = 0.7 * (bins[1] - bins[0])
center = (bins[:-1] + bins[1:]) / 2
plt.bar(center, hist, align='center', width=width)
plt.show()
```

Python code for demos in the class

```
## histogram
discrete uniform = np.random.randint(0.10.100000)
hist, bins = np.histogram(discrete_uniform, bins=10)
width = 0.7 * (bins[1] - bins[0])
center = (bins[:-1] + bins[1:]) / 2
plt.bar(center, hist, align='center', width=width)
plt.show()
## hinomial distribution
from scipy.stats import binom
n, p = 20, 0.4
mean, var = binom.stats(n, p, moments='mv')
x = np.arange(binom.ppf(0.0001, n, p), binom.ppf(0.9999, n, p))
fig, ax = plt.subplots(1, 1)
ax.plot(x, binom.pmf(x, n, p), 'bo', ms=8, label='binom.pmf')
ax.vlines(x, 0, binom.pmf(x, n, p), colors='b', lw=5, alpha=0.5)
```