

# Review for Midterm Test

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## 1 Probability

i. Distributions

Table 1.

ii. Conditional Expectation

$$E(X) = E\{E(X|Y)\}$$

$$\text{Var}(X) = E(\text{Var}(X|Y)) + \text{Var}(E(X|Y))$$

iii. From conditional densities to marginal densities

Based on

$$f_X(x)f_{Y|X}(y|x) = f_Y(y)f_{X|Y}(x|y)$$

we have

$$f_X(x) \propto \frac{f_Y(y_0)f_{X|Y}(x|y_0)}{f_{Y|X}(y_0|x)}$$

$$f_X(x) = \left\{ \int \frac{f_{Y|X}(y|x)}{f_{X|Y}(x|y)} dy \right\}^{-1}$$

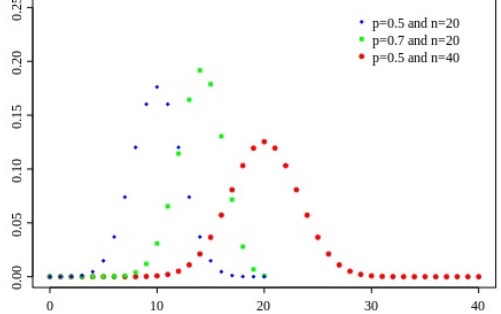
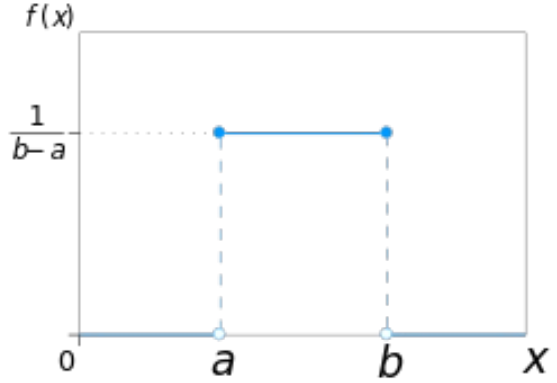
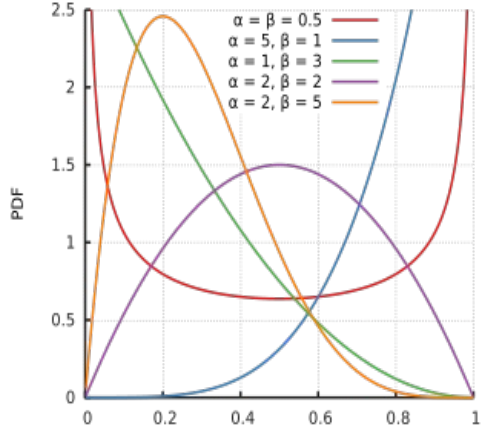
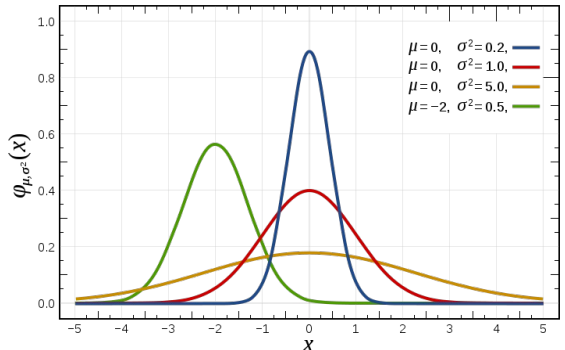
Similar,

$$p_i = \Pr(X = x_i) \propto \frac{\Pr(X = x_i | Y = y_j)}{\Pr(Y = y_j | X = x_i)} \triangleq q_i,$$

$$p_i = \frac{q_i}{\sum_i q_i},$$

$$\Pr(X = x_i) = \left( \sum_j \frac{\Pr(Y = y_j | X = x_i)}{\Pr(X = x_i | Y = y_j)} \right)^{-1}.$$

(Why the kernel is known?)

pmf/pdf	
Bernoulli(p)	$f_X(x) = \begin{cases} p & , x = 1 \\ 1 - p & , x \neq 1 \end{cases}$
Binomial(n,p)	$f_X(x) = \binom{n}{x} p^x (1-p)^{n-x}$
	
Uniform(a,b)	$f_X(x) = \begin{cases} \frac{1}{b-a} & , a \leq x \leq b \\ 0 & , \text{elsewhere} \end{cases}$ $E(X) = \frac{a+b}{2}$ $\text{Var}(X) = \frac{(b-a)^2}{12}$ $\text{mgf: } \frac{e^{tb} - e^{ta}}{t(b-a)}$
	
Beta(a,b)	$f_X(x) = \frac{x^{a-1}(1-x)^{b-1}}{B(a,b)}, \quad (0 \leq x \leq 1)$ $a, b > 0$ $E(X) = \frac{a}{a+b}$ $\text{Var}(X) = \frac{ab}{c^2(c+1)}$
	
$N(\mu, \sigma^2)$	$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$ $\text{mgf: } e^{\mu t + 0.5\sigma^2 t^2}$
	

**Table 1.** The pmf/pdf of some distribution

## 2 Sample Distribution

Three methods to find the distribution of the Function of Random Variables.

### 2.1 cdf

### 2.2 Transformation

Monotone transformation

$$g(y) = f(x) \times |dx/dy|.$$

Piecewise monotone transformation(分段)

$$g(y) = \sum_{i=1}^n f(h_i^{-1}(y)) \times \left| \frac{dh_i^{-1}(y)}{dy} \right| \text{ (???)}$$

Bivariate transformation

$$g(y_1, y_2) = f(x_1, x_2) \times \left| \frac{\partial(x_1, x_2)}{\partial(y_1, y_2)} \right| \text{ (need to understand)}$$

Multivariate transformation

$$g(y_1, \dots, y_n) = f(x_1, \dots, x_n) \times \left| \frac{\partial(x_1, \dots, x_n)}{\partial(y_1, \dots, y_n)} \right|.$$

Moment generating function

### 2.3 Order Statistics

The cdf and pdf of  $X_{(1)} = \min \{X_1, \dots, X_n\}$

$$\begin{aligned} G_1(x) &= 1 - [1 - F(x)]^n, \\ g_1(x) &= n[1 - F(x)]^{n-1} f(x) \end{aligned}$$

The cdf and pdf of  $X_{(n)} = \max \{X_1, \dots, X_n\}$

$$\begin{aligned} G_n(x) &= [F(x)]^n \\ g_n(x) &= n[F(x)]^{n-1} f(x) \end{aligned}$$

The cdf and pdf of  $X_{(r)}$

$$\begin{aligned} G_r(x) &= \sum_{i=r}^n \binom{n}{i} F^i(x) [1 - F(x)]^{n-i} \\ g_r(x) &= \frac{n!}{(r-1)!(n-r)!} f(x) F^{r-1}(x) [1 - F(x)]^{n-r} \end{aligned}$$

The joint pdf of  $X_{(1)}, \dots, X_{(n)}$  is

$$g_{X_{(1)}, \dots, X_{(n)}}(x_{(1)}, \dots, x_{(n)}) = n! f_X(x_{(1)}) \cdots f_X(x_{(n)})$$

## 2.4 Central Limit Theorem

Theorem 2.9 Let  $\{X_n\}_{n=1}^{\infty}$  be a sequence of i.i.d. r.v.'s with common mean  $\mu$  and common variance  $\sigma^2 > 0$ . Let

$$\bar{X}_n = \sum_{i=1}^n X_i / n \quad \text{and} \quad Y_n = \sqrt{n} \left( \bar{X}_n - \mu \right) / \sigma$$

then  $Y_n \xrightarrow{L} Z$ , where  $Z \sim N(0, 1)$

## 3 Point Estimation

Joint density and likelihood function

(b) We can write

$$\begin{aligned} \sum_{i=1}^n a_i Y_i &= \sum_{i=1}^n a_i \left( \sum_{k=0}^{i-1} \frac{Z_{k+1}}{n-k} \right) \\ &= \sum_{k=0}^{n-1} \left( \sum_{i=k+1}^n a_i \right) \frac{Z_{k+1}}{n-k} \\ &= \sum_{j=1}^n \left( \sum_{i=j}^n a_i \right) \frac{Z_j}{n-j+1}, \end{aligned}$$

which is a linear function of independent random variables  $Z_1, \dots, Z_n$ .

$$\text{Exponential}(1) = \text{Gamma}(1, 1) = \frac{1}{2} \text{Gamma} \left( \frac{2}{2}, \frac{1}{2} \right) = \frac{1}{2} \chi^2(2),$$

then, we obtain

$$\frac{X}{Y} \sim \frac{\chi^2(2)/2}{\chi^2(2)/2} = F(2, 2).$$

## 4 Confidence Intervals

## 5 Reference

- [https://en.wikipedia.org/wiki/Beta\\_distribution](https://en.wikipedia.org/wiki/Beta_distribution)