



This page contains handwritten notes and formulas from a statistics course, likely covering probability distributions and their properties. The content includes:

- Definitions and properties of various probability distributions (Binomial, Poisson, Normal, etc.)
- Formulas for moments (mean, variance) and moment-generating functions (MGFs)
- Graphs of probability density functions (PDFs) and cumulative distribution functions (CDFs) for different distributions
- Proofs of properties, such as the relationship between the MGF and the mean and variance of a distribution
- Formulas for the expected value and variance of a function of a random variable
- Derivations of formulas for the joint distribution of functions of random variables
- Notes on the relationship between the MGF and the characteristic function
- Formulas for the joint distribution of functions of independent random variables
- Notes on the central limit theorem and its applications

**PT 1**

$A_i = \{X \in S \mid X \in A_i \text{ for some } i\}$

$\bar{A}_i = \{X \in S \mid X \in A_i \text{ for all } i\}$

$\Rightarrow$  closed under complementation,  $\cap, \cup$

Show sets  $\mathcal{F}$  via obtaining from known elements of  $\mathcal{G}$  via a counting many set ops.

w/o replacement w/o replacement

odd:  $f(-x) = -f(x)$

even:  $\sup_{n \geq 1} |S_n(x) - S(x)| \rightarrow 0 \text{ as } n \rightarrow \infty$

ordered  $P_r^n = \frac{n!}{(n-r)!}$

unordered  $C_r^n = \frac{n!}{r!(n-r)!} = \frac{(n+r-1)!}{r!(n-1)!}$

$P(\text{at least one } A_i) = P\left(\bigcup_{i=1}^n A_i\right) = 1 - P\left(\bigcap_{i=1}^n A_i^c\right)$

E.g. generalized:  $P(A \cup B \cup C) = P(A) + P(B) + P(C) - [P(A \cap B) + P(A \cap C) + P(B \cap C)] + P(A \cap B \cap C)$

Bayes:  $P(A|B) = P(A \cap B)/P(B) \Leftrightarrow P(A|B)P(B) = P(A|B)P(B)$

chain:  $P(A_1 \cap A_2 \cap \dots \cap A_n) = P(A_1)P(A_2|A_1)P(A_3|A_1 \cap A_2) \dots P(A_n|A_1 \cap A_2 \cap \dots \cap A_{n-1})$

Bayes:  $P(B|S) = \sum_i P(B \cap A_i) / \sum_i P(B \cap A_i) = \sum_i P(B|A_i)P(A_i)$

law of total prob.:  $P(X) = \sum_i P(X|A_i)P(A_i)$

$P(A_i|B) = [P(B|A_i)P(A_i)] / [\sum_i P(B|A_i)P(A_i)]$

RV:  $P_A(X \in A) = P(X^{-1}(A)) = P(\{x \in S \mid X(x) \in A\})$

CDF:  $F_X(x) = P(X \leq x) \wedge x \in X$

PDF:  $f_X(x) = \int_{-\infty}^x f_X(t) dt \quad \forall x \in X$

PMF:  $f_X(x) = P(X=x) \quad \forall x$

PT 1-TEST 2:  $y(s) = g(X(s))$ ;  $y'(s) = x \cdot g'(X(s))$

Prop. Let  $X$  r.v.,  $Y = g(X)$ ; then  $F(y) = P(Y \leq y) = \int_{-\infty}^y f(x) dx$ .  $\approx X \sim \text{Bin}(n, p), np \rightarrow \infty$ , then  $X \xrightarrow{d} Y \sim \text{Pois}(np)$

$P(g(x) \leq y) = P(x \leq g^{-1}(y)) = \int_{-\infty}^{g^{-1}(y)} f(x) dx$

Thm:  $X \sim F_x(x), Y = g(X), \text{then } Y = g(X)$ , given  $y = g(x)$

i)  $g: Y \rightarrow Y$ , then  $F_y(y) = F_x(g^{-1}(y)) \wedge y \in Y$

ii)  $g: X \rightarrow Y$ , then  $F_y(y) = 1 - F_x(g^{-1}(y)) \wedge y \in Y$

cov:  $f_{Y|X}(y|x) = f_X(g^{-1}(y)) \mid \frac{dy}{dx} g'(x)$

Inf: Let  $A \subset \mathbb{R}$ .  $(\inf A) = \text{largest } a \in \mathbb{R} \cup \{-\infty\} \text{ s.t. } a \leq x \forall x \in A$ , e.g.  $\inf(\{a, b\}) = a \neq \min(a, b)$  DNE

$F^{-1}(p) = \inf \{x \in \mathbb{R} : F(x) \geq p\} = -\infty, p \leq 0$

$F^{-1}(1) = a, F^{-1}(0) = -\infty$

$F^{-1}(p) = a, p \in (0, 1)$

$E[g(x)] = \int_R g(x) f(x) dx$

$E[aX+bY+c] = aE(X)+bE(Y)+c, a, b, c \in \mathbb{R}; \text{const.}$

$F_X(x) = \begin{cases} 0, & x \leq 0, \\ \frac{x}{2}, & x \in (0, 1), \\ 1, & x \geq 1 \end{cases}$

$E[X] = \int_0^1 x f(x) dx + 1 \cdot \Delta$

$x_0 = 1$

assign  $\Delta$  mass @ discontinuity point  $x_0$ .

$M_n := E(X^n); M_n := E((X - E(X))^n); V(X) = E(X - E(X))^2$

$V(X) = E(X^2) - [E(X)]^2; V(aX+b) = a^2 \text{Var}(X)$

Thm. Let  $x_i \stackrel{iid}{\sim} X = X_1, \dots, X_n; \text{Var}(X) = n \cdot \text{Var}(X_i)$

inf:  $M_X(t) = E(e^{tX})$ ; provided  $E(e^{tX}) \exists$  in some neighborhood of  $t=0$ , i.e.  $t \in (-h, h)$  for  $h > 0$

justify  $\int_R e^{tx} f(x) dx \leq \int_R e^{t^2 x^2} f(x) dx$  via  $|e^{t^2 x^2}|$  dom. conv. thm.

Thm:  $\forall n \in \mathbb{N}, E[X] = \frac{d^n}{dt^n} M_X(t) \Big|_{t=0}$

justify  $M_X'(t) = \frac{1}{t} \int_R e^{tx} f(x) dx = \int_R x e^{tx} f(x) dx$

via  $(xe^{tx} f(x))$  dom. conv. thm.

Thm:  $F_X(x), F_Y(y)$  - moments  $\exists$ , then  $F_X(x) \rightarrow F_Y(y) \wedge$  cont. point of  $F_Y$ .

$F_X(u) = F_Y(u) \wedge u \in E(X) = E(Y) \wedge u_1, \dots$

$M_X(u) = M_Y(u) \wedge u \in E(X-h, h) \text{ for } h > 0 \Rightarrow F_X(u) = F_Y(u) \wedge u_1, \dots$

**PT 2** UNDER CONDITIONS

$\int_a^b F(x, \theta) dx = \int_a^b \frac{\partial F(x, \theta)}{\partial \theta} dx$

$\lim_{\theta \rightarrow 0} \int_R h(x, \theta) dx = \int_R h(x, 0) dx$

$\int_R \int_R f(x, \theta) dx \int_R \frac{\partial f(x, \theta)}{\partial \theta} d\theta$

$\int_R \int_R h(x, \theta) dx = \int_R \int_R \frac{\partial h(x, \theta)}{\partial \theta} dx d\theta$

$\Rightarrow$  closed under composition,  $\cap, \cup$

Show sets  $\mathcal{G}$  via obtaining from known elements of  $\mathcal{G}$  via a counting many set ops.

w/o replacement w/o replacement

odd:  $f(-x) = -f(x)$

even:  $\sup_{n \geq 1} |S_n(x) - S(x)| \rightarrow 0 \text{ as } n \rightarrow \infty$

ordered  $P_r^n = \frac{n!}{(n-r)!}$

unordered  $C_r^n = \frac{n!}{r!(n-r)!} = \frac{(n+r-1)!}{r!(n-1)!}$

$P(\text{at least one } A_i) = P\left(\bigcup_{i=1}^n A_i\right) = 1 - P\left(\bigcap_{i=1}^n A_i^c\right)$

E.g. generalized:  $P(A \cup B \cup C) = P(A) + P(B) + P(C) - [P(A \cap B) + P(A \cap C) + P(B \cap C)] + P(A \cap B \cap C)$

Bayes:  $P(A|B) = P(A \cap B)/P(B) \Leftrightarrow P(A|B)P(B) = P(A|B)P(B)$

chain:  $P(A_1 \cap A_2 \cap \dots \cap A_n) = P(A_1)P(A_2|A_1)P(A_3|A_1 \cap A_2) \dots P(A_n|A_1 \cap A_2 \cap \dots \cap A_{n-1})$

Bayes:  $P(B|S) = \sum_i P(B \cap A_i) / \sum_i P(B \cap A_i) = \sum_i P(B|A_i)P(A_i)$

law of total prob.:  $P(X) = \sum_i P(X|A_i)P(A_i)$

$P(A_i|B) = [P(B|A_i)P(A_i)] / [\sum_i P(B|A_i)P(A_i)]$

RV:  $P_A(X \in A) = P(X^{-1}(A)) = P(\{x \in S \mid X(x) \in A\})$

CDF:  $F_X(x) = P(X \leq x) \wedge x \in X$

PDF:  $f_X(x) = \int_{-\infty}^x f_X(t) dt \quad \forall x \in X$

PMF:  $f_X(x) = P(X=x) \quad \forall x$

PT 2-TEST 2:  $y(s) = g(X(s))$ ;  $y'(s) = x \cdot g'(X(s))$

Prop. Let  $X$  r.v.,  $Y = g(X)$ ; then  $F(y) = P(Y \leq y) = \int_{-\infty}^y f(x) dx$ .  $\approx X \sim \text{Bin}(n, p), np \rightarrow \infty$ , then  $X \xrightarrow{d} Y \sim \text{Pois}(np)$

$P(g(x) \leq y) = P(x \leq g^{-1}(y)) = \int_{-\infty}^{g^{-1}(y)} f(x) dx$

Thm:  $X \sim F_x(x), Y = g(X), \text{then } Y = g(X)$ , given  $y = g(x)$

i)  $g: Y \rightarrow Y$ , then  $F_y(y) = F_x(g^{-1}(y)) \wedge y \in Y$

ii)  $g: X \rightarrow Y$ , then  $F_y(y) = 1 - F_x(g^{-1}(y)) \wedge y \in Y$

cov:  $f_{Y|X}(y|x) = f_X(g^{-1}(y)) \mid \frac{dy}{dx} g'(x)$

Inf: Let  $A \subset \mathbb{R}$ .  $(\inf A) = \text{largest } a \in \mathbb{R} \cup \{-\infty\} \text{ s.t. } a \leq x \forall x \in A$ , e.g.  $\inf(\{a, b\}) = a \neq \min(a, b)$  DNE

$F^{-1}(p) = \inf \{x \in \mathbb{R} : F(x) \geq p\} = -\infty, p \leq 0$

$F^{-1}(1) = a, F^{-1}(0) = -\infty$

$F^{-1}(p) = a, p \in (0, 1)$

$E[g(x)] = \int_R g(x) f(x) dx$

$E[aX+bY+c] = aE(X)+bE(Y)+c, a, b, c \in \mathbb{R}; \text{const.}$

$F_X(x) = \begin{cases} 0, & x \leq 0, \\ \frac{x}{2}, & x \in (0, 1), \\ 1, & x \geq 1 \end{cases}$

$E[X] = \int_0^1 x f(x) dx + 1 \cdot \Delta$

$x_0 = 1$

assign  $\Delta$  mass @ discontinuity point  $x_0$ .

$M_n := E(X^n); M_n := E((X - E(X))^n); V(X) = E(X - E(X))^2$

$V(X) = E(X^2) - [E(X)]^2; V(aX+b) = a^2 \text{Var}(X)$

Thm. Let  $x_i \stackrel{iid}{\sim} X = X_1, \dots, X_n; \text{Var}(X) = n \cdot \text{Var}(X_i)$

inf:  $M_X(t) = E(e^{tX})$ ; provided  $E(e^{tX}) \exists$  in some neighborhood of  $t=0$ , i.e.  $t \in (-h, h)$  for  $h > 0$

justify  $\int_R e^{tx} f(x) dx \leq \int_R e^{t^2 x^2} f(x) dx$  via  $|e^{t^2 x^2}|$  dom. conv. thm.

Thm:  $\forall n \in \mathbb{N}, E[X] = \frac{d^n}{dt^n} M_X(t) \Big|_{t=0}$

justify  $M_X'(t) = \frac{1}{t} \int_R e^{tx} f(x) dx = \int_R x e^{tx} f(x) dx$

via  $(xe^{tx} f(x))$  dom. conv. thm.

Thm:  $F_X(x), F_Y(y)$  - moments  $\exists$ , then  $F_X(x) \rightarrow F_Y(y) \wedge$  cont. point of  $F_Y$ .

$F_X(u) = F_Y(u) \wedge u \in E(X) = E(Y) \wedge u_1, \dots$

$M_X(u) = M_Y(u) \wedge u \in E(X-h, h) \text{ for } h > 0 \Rightarrow F_X(u) = F_Y(u) \wedge u_1, \dots$

**PT 2** UNDER CONDITIONS

$\int_a^b F(x, \theta) dx = \int_a^b \frac{\partial F(x, \theta)}{\partial \theta} dx$

$\lim_{\theta \rightarrow 0} \int_R h(x, \theta) dx = \int_R h(x, 0) dx$

$\int_R \int_R f(x, \theta) dx \int_R \frac{\partial f(x, \theta)}{\partial \theta} d\theta$

$\int_R \int_R h(x, \theta) dx = \int_R \int_R \frac{\partial h(x, \theta)}{\partial \theta} dx d\theta$

$\Rightarrow$  closed under composition,  $\cap, \cup$

show sets  $\mathcal{G}$  via obtaining from known elements of  $\mathcal{G}$  via a counting many set ops.

w/o replacement w/o replacement

odd:  $f(-x) = -f(x)$

even:  $\sup_{n \geq 1} |S_n(x) - S(x)| \rightarrow 0 \text{ as } n \rightarrow \infty$

ordered  $P_r^n = \frac{n!}{(n-r)!}$

unordered  $C_r^n = \frac{n!}{r!(n-r)!} = \frac{(n+r-1)!}{r!(n-1)!}$

$P(\text{at least one } A_i) = P\left(\bigcup_{i=1}^n A_i\right) = 1 - P\left(\bigcap_{i=1}^n A_i^c\right)$

E.g. generalized:  $P(A \cup B \cup C) = P(A) + P(B) + P(C) - [P(A \cap B) + P(A \cap C) + P(B \cap C)] + P(A \cap B \cap C)$

Bayes:  $P(A|B) = P(A \cap B)/P(B) \Leftrightarrow P(A|B)P(B) = P(A|B)P(B)$

chain:  $P(A_1 \cap A_2 \cap \dots \cap A_n) = P(A_1)P(A_2|A_1)P(A_3|A_1 \cap A_2) \dots P(A_n|A_1 \cap A_2 \cap \dots \cap A_{n-1})$

Bayes:  $P(B|S) = \sum_i P(B \cap A_i) / \sum_i P(B \cap A_i) = \sum_i P(B|A_i)P(A_i)$

law of total prob.:  $P(X) = \sum_i P(X|A_i)P(A_i)$

$P(A_i|B) = [P(B|A_i)P(A_i)] / [\sum_i P(B|A_i)P(A_i)]$

RV:  $P_A(X \in A) = P(X^{-1}(A)) = P(\{x \in S \mid X(x) \in A\})$

CDF:  $F_X(x) = P(X \leq x) \wedge x \in X$

PDF:  $f_X(x) = \int_{-\infty}^x f_X(t) dt \quad \forall x \in X$

PMF:  $f_X(x) = P(X=x) \quad \forall x$

PT 2-TEST 2:  $y(s) = g(X(s))$ ;  $y'(s) = x \cdot g'(X(s))$

Prop. Let  $X$  r.v.,  $Y = g(X)$ ; then  $F(y) = P(Y \leq y) = \int_{-\infty}^y f(x) dx$ .  $\approx X \sim \text{Bin}(n, p), np \rightarrow \infty$ , then  $X \xrightarrow{d} Y \sim \text{Pois}(np)$

$P(g(x) \leq y) = P(x \leq g^{-1}(y)) = \int_{-\infty}^{g^{-1}(y)} f(x) dx$

Thm:  $X \sim F_x(x), Y = g(X), \text{then } Y = g(X)$ , given  $y = g(x)$

i)  $g: Y \rightarrow Y$ , then  $F_y(y) = F_x(g^{-1}(y)) \wedge y \in Y$

ii)  $g: X \rightarrow Y$ , then  $F_y(y) = 1 - F_x(g^{-1}(y)) \wedge y \in Y$

cov:  $f_{Y|X}(y|x) = f_X(g^{-1}(y)) \mid \frac{dy}{dx} g'(x)$

Inf: Let  $A \subset \mathbb{R}$ .  $(\inf A) = \text{largest } a \in \mathbb{R} \cup \{-\infty\} \text{ s.t. } a \leq x \forall x \in A$ , e.g.  $\inf(\{a, b\}) = a \neq \min(a, b)$  DNE

$F^{-1}(p) = \inf \{x \in \mathbb{R} : F(x) \geq p\} = -\infty, p \leq 0$

$F^{-1}(1) = a, F^{-1}(0) = -\infty$

$F^{-1}(p) = a, p \in (0, 1)$

$E[g(x)] = \int_R g(x) f(x) dx$

$E[aX+bY+c] = aE(X)+bE(Y)+c, a, b, c \in \mathbb{R}; \text{const.}$

$F_X(x) = \begin{cases} 0, & x \leq 0, \\ \frac{x}{2}, & x \in (0, 1), \\ 1, & x \geq 1 \end{cases}$

$E[X] = \int_0^1 x f(x) dx + 1 \cdot \Delta$

$x_0 = 1$

assign  $\Delta$  mass @ discontinuity point  $x_0$ .

$M_n := E(X^n); M_n := E((X - E(X))^n); V(X) = E(X - E(X))^2$

$V(X) = E(X^2) - [E(X)]^2; V(aX+b) = a^2 \text{Var}(X)$

Thm. Let  $x_i \stackrel{iid}{\sim} X = X_1, \dots, X_n; \text{Var}(X) = n \cdot \text{Var}(X_i)$

inf:  $M_X(t) = E(e^{tX})$ ; provided  $E(e^{tX}) \exists$  in some neighborhood of  $t=0$ , i.e.  $t \in (-h, h)$  for  $h > 0$

justify  $\int_R e^{tx} f(x) dx \leq \int_R e^{t^2 x^2} f(x) dx$  via  $|e^{t^2 x^2}|$  dom. conv. thm.

Thm:  $\forall n \in \mathbb{N}, E[X] = \frac{d^n}{dt^n} M_X(t) \Big|_{t=0}$

justify  $M_X'(t) = \frac{1}{t} \int_R e^{tx} f(x) dx = \int_R x e^{tx} f(x) dx$

via  $(xe^{tx} f(x))$  dom. conv. thm.

Thm:  $F_X(x), F_Y(y)$  - moments  $\exists$ , then  $F_X(x) \rightarrow F_Y(y) \wedge$  cont. point of  $F_Y$ .

$F_X(u) = F_Y(u) \wedge u \in E(X) = E(Y) \wedge u_1, \dots$

$M_X(u) = M_Y(u) \wedge u \in E(X-h, h) \text{ for } h > 0 \Rightarrow F_X(u) = F_Y(u) \wedge u_1, \dots$

**PT 2** UNDER CONDITIONS

$\int_a^b F(x, \theta) dx = \int_a^b \frac{\partial F(x, \theta)}{\partial \theta} dx$

$\lim_{\theta \rightarrow 0} \int_R h(x, \theta) dx = \int_R h(x, 0) dx$

$\int_R \int_R f(x, \theta) dx \int_R \frac{\partial f(x, \theta)}{\partial \theta} d\theta$

$\int_R \int_R h(x, \theta) dx = \int_R \int_R \frac{\partial h(x, \theta)}{\partial \theta} dx d\theta$

$\Rightarrow$  closed under composition,  $\cap, \cup$

show sets  $\mathcal{G}$  via obtaining from known elements of  $\mathcal{G}$  via a counting many set ops.

w/o replacement w/o replacement

odd:  $f(-x) = -f(x)$

even:  $\sup_{n \geq 1} |S_n(x) - S(x)| \rightarrow 0 \text{ as } n \rightarrow \infty$

ordered  $P_r^n = \frac{n!}{(n-r)!}$

unordered  $C_r^n = \frac{n!}{r!(n-r)!} = \frac{(n+r-1)!}{r!(n-1)!}$

$P(\text{at least one } A_i) = P\left(\bigcup_{i=1}^n A_i\right) = 1 - P\left(\bigcap_{i=1}^n A_i^c\right)$

E.g. generalized:  $P(A \cup B \cup C) = P(A) + P(B) + P(C) - [P(A \cap B) + P(A \cap C) + P(B \cap C)] + P(A \cap B \cap C)$

Bayes:  $P(A|B) = P(A \cap B)/P(B) \Leftrightarrow P(A|B)P(B) = P(A|B)P(B)$

chain:  $P(A_1 \cap A_2 \cap \dots \cap A_n) = P(A_1)P(A_2|A_1)P(A_3|A_1 \cap A_2) \dots P(A_n|A_1 \cap A_2 \cap \dots \cap A_{n-1})$

Bayes:  $P(B|S) = \sum_i P(B \cap A_i) / \sum_i P(B \cap A_i) = \sum_i P(B|A_i)P(A_i)$

law of total prob.:  $P(X) = \sum_i P(X|A_i)P(A_i)$

$P(A_i|B) = [P(B|A_i)P(A_i)] / [\sum_i P(B|A_i)P(A_i)]$

RV:  $P_A(X \in A) = P(X^{-1}(A)) = P(\{x \in S \mid X(x) \in A\})$

CDF:  $F_X(x) = P(X \leq x) \wedge x \in X$

PDF:  $f_X(x) = \int_{-\infty}^x f_X(t) dt \quad \forall x \in X$

PMF:  $f_X(x) = P(X=x) \quad \forall x$

PT 2-TEST 2:  $y(s) = g(X(s))$ ;  $y'(s) = x \cdot g'(X(s))$

Prop. Let  $X$  r.v.,  $Y = g(X)$ ; then  $F(y) = P(Y \leq y) = \int_{-\infty}^y f(x) dx$ .  $\approx X \sim \text{Bin}(n, p), np \rightarrow \infty$ , then  $X \xrightarrow{d} Y \sim \text{Pois}(np)$

$P(g(x) \leq y) = P(x \leq g^{-1}(y)) = \int_{-\infty}^{g^{-1}(y)} f(x) dx$

Thm:  $X \sim F_x(x), Y = g(X), \text{then } Y =$

**Ch.4 (cont.)**

Prop & ACR<sup>2</sup>:  $P(X_1 \cup X_2 \cup \dots \cup X_n) = P(\{X_i\} \cup \{X_j\})$

$\text{discrete: } f_{XY}(x,y) = \sum f_{XY}(x,y)$

$\text{cont. } g: \mathbb{R}^2 \rightarrow \mathbb{R}^2: 1-1 \text{ mapping}$

$g^{-1}\{y\} = \{(x_1, y_1), (x_2, y_2), \dots\}$  has at most one element

$g^{-1}\{y\} = h(x, y) = (h_1(x, y), h_2(x, y))$

$f_{XY}(x,y) = f_{XY}(h_1(x, y), h_2(x, y))$

$J = \frac{\partial(h_1, h_2)}{\partial(x_1, x_2)} = \begin{vmatrix} \frac{\partial h_1}{\partial x_1} & \frac{\partial h_1}{\partial x_2} \\ \frac{\partial h_2}{\partial x_1} & \frac{\partial h_2}{\partial x_2} \end{vmatrix}$

$(x, y) \rightarrow g(x, y) \in \mathbb{R}^2, \text{ many-to-one; partition}$

$A = \{x \in \Omega | f_{XY}(x, y) > 0\} = A_1 \cup \dots \cup A_k \text{ s.t.}$

$A_i \rightarrow g(A_i) \text{ 1-1, } i=1, \dots, k \text{ - then } f_{XY}(x, y) = \sum f_{A_i}(h_1(x, y), h_2(x, y))$

$f_{XY}(x, y) = \sum f_{A_i}(h_1(x, y), h_2(x, y))$

$\text{further: } f_{XY}(x, y) = f_{XY}(h_1(x, y), h_2(x, y))$

$E[g(X)] = \int g(x) f_{XY}(x, y) dx dy$

$\text{marginal: } f_{X_1, \dots, X_n}(x_1, \dots, x_n) = \sum_{y_1, \dots, y_n} f_{XY}(x_1, \dots, x_n, y_1, \dots, y_n)$

$\text{conditional: } f_{Y|X_1, \dots, X_n}(y_1 | x_1, \dots, x_n) = \frac{f(y_1, \dots, x_n, y_2, \dots, y_n)}{f(x_1, \dots, x_n)}$

$\text{admits factorization; joint = marginal cond.}$

$\text{char: } f(x_1, \dots, x_n) = f_1(x_1) \dots f_n(x_n) = f(x_1) f(x_2) \dots f(x_n)$

$\text{mutual ind.: } f(x_1, \dots, x_n) = \prod_{i=1}^n f(x_i)$

**MIXTURE DIST: of  $X$  depends on RV  $Y$ , e.g.**

$X | Y \sim \text{Binomial}(Y, p)$  mixture of bin dist's;  $P(X=x) = \sum_y P(X=x | Y=y) = \sum_y P(Y=y)P(X=x | Y=y) = \sum_y e^{-\lambda} \frac{\lambda^y}{y!} p^y (1-p)^{y-\lambda}$

$Y \sim \text{Pois}(n)$  Pois mixing mechanism

**Prop.**  $\forall t \in \mathbb{R}, P(Y=t) = P_{t+1, \dots, t+k, X | Y=t} N(\mu_t, \sigma_t^2)$

$F_X(t) = \sum P_{t+1, \dots, t+k} \exp\left(-\frac{1}{2\sigma_t^2}(t-\mu_t)^2\right)$

(mixture of  $k$  normal components)

Hierarchical:  $X$  dist. obtained w/ many stages of cond. dist's

$\text{e.g. } X | Y \sim \text{Bin}(Y, p), Y \sim \text{Pois}(n), n = \text{Exp}(t)$

$\Leftrightarrow Y \sim \text{Pois}(n)$

$P(Y=y) = \int f_{Y, n}(y, \lambda) d\lambda = \int P(Y=y | n) \lambda^n e^{-\lambda} / n! d\lambda$

$\Leftrightarrow X | Y \sim \text{Bin}(Y, p) = \int_0^\infty e^{-\lambda} \frac{1}{Y!} \frac{\lambda^Y}{Y!} p^Y (1-p)^{Y-\lambda} d\lambda$

$\sim \text{NBin}\left(\frac{1}{p}, \frac{1}{p}\right)$

$X | \theta \sim \text{Bin}(n, \theta), \theta \sim U(0, 1)$

$\theta \sim \text{Beta}(\alpha, \beta)$  marginalize

$P(X=x) = \int P(X=x | \theta) f_\theta(\theta) d\theta = \int \binom{n}{x} \theta^x (1-\theta)^{n-x} \frac{\alpha+\theta-1}{\alpha+n-1} \theta^{\alpha-1} (1-\theta)^{\beta-1} d\theta$

$\text{var} X = E[\text{var}[X | Y]] + \text{var}[E[X | Y]]$

$P(A) = E(T_A) \vee \text{event } A \text{ where } T_A \stackrel{1}{\sim} \text{Unif}(0, 1)$

$\phi(t) = \frac{1}{\sqrt{\pi}} \exp\left(-\frac{t^2}{2}\right); X \sim N(0, 1) \Rightarrow f(x) = \phi\left(\frac{x-0}{\sqrt{2}}\right)$

$\text{cov}(X, Y) = E[(X-E[X])(Y-E[Y])]$

$\text{cov}(X, Y) = \frac{\text{cov}(X, Y)}{\text{var} X \text{ var} Y} \text{ standardized covariance}$

$\text{corr}(X, Y) = \text{cov}(X, Y) / \text{std}(X) \text{ std}(Y)$

$\text{CSI: } E[XY] \leq \sqrt{E[X^2] E[Y^2]} \Leftrightarrow [E(XY)]^2 \leq E(X^2) E(Y^2)$

**Equality i.e. F.F.  $Y \stackrel{d}{=} X \Leftrightarrow P(Y=x) = 1$ , const & TR**

$\text{Prop. Let } U = X - E[X], V = Y - E[Y]$

$E(UV) = E(U^2) E(V^2) \Leftrightarrow \text{corr}(U, V) = 1$

$\text{Equality i.e. F.F. } U \stackrel{d}{=} V \Leftrightarrow P(U=V) = 1 \Rightarrow \text{corr}(U, V) = 1$

**Thm.**  $\text{cov}(X, Y) = E(XY) - E(X)E(Y)$ ;  $C(XY) = E(XY) - E(X)E(Y)$

$X \perp Y \Rightarrow \text{cov}(X, Y) = \text{cov}(X, A) + \text{cov}(X, B)$

$\text{var}(x+bY) = a^2 \text{var}(x) + b^2 \text{var}(Y) + 2ab \text{cov}(X, Y)$

**Thm.**  $\text{corr}(X, Y) = 1 \Leftrightarrow Y = bX + c, b > 0, c \in \mathbb{R}$

$\text{corr}(X, Y) = -1 \Leftrightarrow Y = bX + c, b < 0, c \in \mathbb{R}$

Bivariate Normal:  $Z = (X, Y) \sim N(\mu, \Sigma) \mid Z \in \mathbb{R}^{2 \times 2}$

$f_{Z|X}(z|x) = \frac{1}{\sqrt{2\pi} \sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)}(z-x)^2 - \frac{2\rho(z-x)(y-x)}{\sqrt{1-\rho^2}}}$

$E(Z) = E\left[\begin{pmatrix} X \\ Y \end{pmatrix}\right] = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}; \text{cov} Z = \begin{pmatrix} \text{var} X & \text{cov}(X, Y) \\ \text{cov}(Y, X) & \text{var} Y \end{pmatrix} = \begin{pmatrix} \mu_1 & \mu_2 \\ \mu_2 & \mu_1 \end{pmatrix}$

$\text{Identities: } \text{corr}(X, Y) = \rho$

$\iint f(x, y) dx dy = 1$

**Ch.5: Random Sample Properties**

$X_1, \dots, X_n \stackrel{iid}{\sim} f$ . If  $f$ :  $(n-1)d$  Sample

statistic:  $Y = T(X_1, \dots, X_n)$

e.g.  $\bar{X} = \frac{1}{n} (X_1 + \dots + X_n), S^2 = \frac{1}{n-1} \sum (X_i - \bar{X})^2$

$X_{(1)} = \min\{X_1, \dots, X_n\} \quad X_{(n)} = \max\{X_1, \dots, X_n\}$

k-th smallest number; order stat:  $(X_{(1)}, \dots, X_{(n)})$

Thm. Let  $(X_1, \dots, X_n) \stackrel{iid}{\sim} f$  with  $\mu, \sigma^2 < \infty$ :

Then  $E\bar{X} = \mu, \text{var} \bar{X} = \sigma^2/n, E S^2 = \sigma^2$

$\Rightarrow$  and  $S^2$  unbiased estimates

DIST. OF  $\bar{X}$ : 1) moments, 2) convolution

1)  $M_{\bar{X}}(t) = E e^{t\bar{X}} = (M_X(t/n))^n$ ; easy

if we can recognize  $f$  from known family or dist

2)  $X \sim f_x, Y \sim f_y, Z = X+Y, X \sim f_Z$

$f_Z(z) = \int f_X(x) f_Y(z-x) dx$ ; useful

when  $f(x_1, \dots, x_n)$  does not belong to known/unrecognized family

$f(Z) = \sum_{x_1, \dots, x_n} f(x_1, \dots, x_n) f_Z(z)$

$\Leftrightarrow Z = x_1 + \dots + x_n \Rightarrow f_Z(z) = \frac{1}{n!} f(x_1, \dots, x_n)$

**Final 3) EXP family:**  $f(x | \theta) = c(\theta) h(x) \exp(\sum w_i(\theta)x_i + b(\theta)) = c(\theta) h(x) \exp(\sum w_i(\theta)x_i + b(\theta))$

$N(\mu, \sigma^2); P(X | \mu) = f(x | \mu)$  whereas  $P(X | \mu) \neq f(\mu | x)$ ; cannot factorize ( $x - \mu$ )! (separable)

$f(x | \mu, \sigma^2, \beta) = \sum_{i=1}^n \text{Norm}(x_i | \mu, \beta) + f(\mu | \beta); \text{cannot rewrite } E_p[e^{\lambda x_i}] \text{ as mixture involves addition}$

$P(X=x) = p_x \mid_{\theta \in \Theta} \text{only many } f_{\theta}(x) \text{ requires finite dim } \theta$

5)  $X | P_1, P_2, \dots, P_m \sim N(\mu_1, \sigma_1^2), X | P_1, P_2, \dots, P_m \sim \text{Beta}(\alpha, \beta)$

$P(A) = P(A \cap P_1, P_2, \dots, P_m) = E[P(A | P_1, P_2, \dots, P_m)] = 2 \sim \text{Beta}(\alpha + 1, \beta + 1)$

$E[X] = E[E[X | P_1, P_2, \dots, P_m]] = M_0 P_1 + \dots + M_m P_m = M_0 + (M_1 - M_0) P_1 + \dots + (M_m - M_{m-1}) P_m$

$P(2|M) = [f(X | P_1) f(P_1)] / f(X) \mid_{P_1=1} = [\alpha \phi(x - \mu_1) / \beta^2 \phi(x - \mu_1)^2 + \delta \phi(x - \mu_1)] \mid_{P_1=1}$

any linear transformation of  $\theta$  is jointly normal

vector is jointly normal

**Final 3) EXP family:**  $f(x | \theta) = c(\theta) h(x) \exp(\sum w_i(\theta)x_i + b(\theta)) = c(\theta) h(x) \exp(\sum w_i(\theta)x_i + b(\theta))$

$N(\mu, \sigma^2); P(X | \mu) = f(x | \mu)$  whereas  $P(X | \mu) \neq f(\mu | x)$ ; cannot factorize ( $x - \mu$ )! (separable)

$f(x | \mu, \sigma^2, \beta) = \sum_{i=1}^n \text{Norm}(x_i | \mu, \beta) + f(\mu | \beta); \text{cannot rewrite } E_p[e^{\lambda x_i}] \text{ as mixture involves addition}$

$P(X=x) = p_x \mid_{\theta \in \Theta} \text{only many } f_{\theta}(x) \text{ requires finite dim } \theta$

5)  $X | P_1, P_2, \dots, P_m \sim N(\mu_1, \sigma_1^2), X | P_1, P_2, \dots, P_m \sim \text{Beta}(\alpha, \beta)$

$P(A) = P(A \cap P_1, P_2, \dots, P_m) = E[P(A | P_1, P_2, \dots, P_m)] = 2 \sim \text{Beta}(\alpha + 1, \beta + 1)$

$E[X] = E[E[X | P_1, P_2, \dots, P_m]] = M_0 P_1 + \dots + M_m P_m = M_0 + (M_1 - M_0) P_1 + \dots + (M_m - M_{m-1}) P_m$

$P(2|M) = [f(X | P_1) f(P_1)] / f(X) \mid_{P_1=1} = [\alpha \phi(x - \mu_1) / \beta^2 \phi(x - \mu_1)^2 + \delta \phi(x - \mu_1)] \mid_{P_1=1}$

any linear transformation of  $\theta$  is jointly normal

vector is jointly normal

**Final 3) EXP family:**  $f(x | \theta) = c(\theta) h(x) \exp(\sum w_i(\theta)x_i + b(\theta)) = c(\theta) h(x) \exp(\sum w_i(\theta)x_i + b(\theta))$

$N(\mu, \sigma^2); P(X | \mu) = f(x | \mu)$  whereas  $P(X | \mu) \neq f(\mu | x)$ ; cannot factorize ( $x - \mu$ )! (separable)

$f(x | \mu, \sigma^2, \beta) = \sum_{i=1}^n \text{Norm}(x_i | \mu, \beta) + f(\mu | \beta); \text{cannot rewrite } E_p[e^{\lambda x_i}] \text{ as mixture involves addition}$

$P(X=x) = p_x \mid_{\theta \in \Theta} \text{only many } f_{\theta}(x) \text{ requires finite dim } \theta$

5)  $X | P_1, P_2, \dots, P_m \sim N(\mu_1, \sigma_1^2), X | P_1, P_2, \dots, P_m \sim \text{Beta}(\alpha, \beta)$

$P(A) = P(A \cap P_1, P_2, \dots, P_m) = E[P(A | P_1, P_2, \dots, P_m)] = 2 \sim \text{Beta}(\alpha + 1, \beta + 1)$

$E[X] = E[E[X | P_1, P_2, \dots, P_m]] = M_0 P_1 + \dots + M_m P_m = M_0 + (M_1 - M_0) P_1 + \dots + (M_m - M_{m-1}) P_m$

$P(2|M) = [f(X | P_1) f(P_1)] / f(X) \mid_{P_1=1} = [\alpha \phi(x - \mu_1) / \beta^2 \phi(x - \mu_1)^2 + \delta \phi(x - \mu_1)] \mid_{P_1=1}$

any linear transformation of  $\theta$  is jointly normal

vector is jointly normal

**Final 3) EXP family:**  $f(x | \theta) = c(\theta) h(x) \exp(\sum w_i(\theta)x_i + b(\theta)) = c(\theta) h(x) \exp(\sum w_i(\theta)x_i + b(\theta))$

$N(\mu, \sigma^2); P(X | \mu) = f(x | \mu)$  whereas  $P(X | \mu) \neq f(\mu | x)$ ; cannot factorize ( $x - \mu$ )! (separable)

$f(x | \mu, \sigma^2, \beta) = \sum_{i=1}^n \text{Norm}(x_i | \mu, \beta) + f(\mu | \beta); \text{cannot rewrite } E_p[e^{\lambda x_i}] \text{ as mixture involves addition}$

$P(X=x) = p_x \mid_{\theta \in \Theta} \text{only many } f_{\theta}(x) \text{ requires finite dim } \theta$

5)  $X | P_1, P_2, \dots, P_m \sim N(\mu_1, \sigma_1^2), X | P_1, P_2, \dots, P_m \sim \text{Beta}(\alpha, \beta)$

$P(A) = P(A \cap P_1, P_2, \dots, P_m) = E[P(A | P_1, P_2, \dots, P_m)] = 2 \sim \text{Beta}(\alpha + 1, \beta + 1)$

$E[X] = E[E[X | P_1, P_2, \dots, P_m]] = M_0 P_1 + \dots + M_m P_m = M_0 + (M_1 - M_0) P_1 + \dots + (M_m - M_{m-1}) P_m$

$P(2|M) = [f(X | P_1) f(P_1)] / f(X) \mid_{P_1=1} = [\alpha \phi(x - \mu_1) / \beta^2 \phi(x - \mu_1)^2 + \delta \phi(x - \mu_1)] \mid_{P_1=1}$

any linear transformation of  $\theta$  is jointly normal

vector is jointly normal

**Final 3) EXP family:**  $f(x | \theta) = c(\theta) h(x) \exp(\sum w_i(\theta)x_i + b(\theta)) = c(\theta) h(x) \exp(\sum w_i(\theta)x_i + b(\theta))$

$N(\mu, \sigma^2); P(X | \mu) = f(x | \mu)$  whereas  $P(X | \mu) \neq f(\mu | x)$ ; cannot factorize ( $x - \mu$ )! (separable)

$f(x | \mu, \sigma^2, \beta) = \sum_{i=1}^n \text{Norm}(x_i | \mu, \beta) + f(\mu | \beta); \text{cannot rewrite } E_p[e^{\lambda x_i}] \text{ as mixture involves addition}$

$P(X=x) = p_x \mid_{\theta \in \Theta} \text{only many } f_{\theta}(x) \text{ requires finite dim } \theta$

5)  $X | P_1, P_2, \dots, P_m \sim N(\mu_1, \sigma_1^2), X | P_1, P_2, \dots, P_m \sim \text{Beta}(\alpha, \beta)$

$P(A) = P(A \cap P_1, P_2, \dots, P_m) = E[P(A | P_1, P_2, \dots, P_m)] = 2 \sim \text{Beta}(\alpha + 1, \beta + 1)$

$E[X] = E[E[X | P_1, P_2, \dots, P_m]] = M_0 P_1 + \dots + M_m P_m = M_0 + (M_1 - M_0) P_1 + \dots + (M_m - M_{m-1}) P_m$

$P(2|M) = [f(X | P_1) f(P_1)] / f(X) \mid_{P_1=1} = [\alpha \phi(x - \mu_1) / \beta^2 \phi(x - \mu_1)^2 + \delta \phi(x - \mu_1)] \mid_{P_1=1}$

any linear transformation of  $\theta$  is jointly normal

vector is jointly normal

**Final 3) EXP family:**  $f(x | \theta) = c(\theta) h(x) \exp(\sum w_i(\theta)x_i + b(\theta)) = c(\theta) h(x) \exp(\sum w_i(\theta)x_i + b(\theta))$

$N(\mu, \sigma^2); P(X | \mu) = f(x | \mu)$  whereas  $P(X | \mu) \neq f(\mu | x)$ ; cannot factorize ( $x - \mu$ )! (separable)

$f(x | \mu, \sigma^2, \beta) = \sum_{i=1}^n \text{Norm}(x_i | \mu, \beta) + f(\mu | \beta); \text{cannot rewrite } E_p[e^{\lambda x_i}] \text{ as mixture involves addition}$

$P(X=x) = p_x \mid_{\theta \in \Theta} \text{only many } f_{\theta}(x) \text{ requires finite dim } \theta$

5)  $X | P_1, P_2, \dots, P_m \sim N(\mu_1, \sigma_1^2), X | P_1, P_2, \dots, P_m \sim \text{Beta}(\alpha, \beta)$

$P(A) = P(A \cap P_1, P_2, \dots, P_m) = E[P(A | P_1, P_2, \dots, P_m)] = 2 \sim \text{Beta}(\alpha + 1, \beta + 1)$

$E[X] = E[E[X | P_1, P_2, \dots, P_m]] = M_0 P_1 + \dots + M_m P_m = M_0 + (M_1 - M_0) P_1 + \dots + (M_m - M_{m-1}) P_m$

$P(2|M) = [f(X | P_1) f(P_1)] / f(X) \mid_{P_1=1} = [\alpha \phi(x - \mu_1) / \beta^2 \phi(x - \mu_1)^2 + \delta \phi(x - \mu_1)] \mid_{P_1=1}$

any linear transformation of  $\theta$  is jointly normal

vector is jointly normal

**Final 3) EXP family:**  $f(x | \theta) = c(\theta) h(x) \exp(\sum w_i(\theta)x_i + b(\theta)) = c(\theta) h(x) \exp(\sum w_i(\theta)x_i + b(\theta))$

$N(\mu, \sigma^2); P(X | \mu) = f(x | \mu)$  whereas  $P(X | \mu) \neq f(\mu | x)$ ; cannot factorize ( $x - \mu$ )! (separable)

$f(x | \mu, \sigma^2, \beta) = \sum_{i=1}^n \text{Norm}(x_i | \mu, \beta) + f(\mu | \beta); \text{cannot rewrite } E_p[e^{\lambda x_i}] \text{ as mixture involves addition}$

$P(X=x) = p_x \mid_{\theta \in \Theta} \text{only many } f_{\theta}(x) \text{ requires finite dim } \theta$

5)  $X | P_1, P_2, \dots, P_m \sim N(\mu_1, \sigma_1^2), X | P_1, P_2, \dots, P_m \sim \text{Beta}(\alpha, \beta)$

$P(A) = P(A \cap P_1, P_2, \dots, P_m) = E[P(A | P_1, P_2, \dots, P_m)] = 2 \sim \text{Beta}(\alpha + 1, \beta + 1)$

$E[X] = E[E[X | P_1, P_2, \dots, P_m]] = M_0 P_1 + \dots + M_m P_m = M_0 + (M_1 - M_0) P_1 + \dots + (M_m - M_{m-1}) P_m$

$P(2|M) = [f(X | P_1) f(P_1)] / f(X) \mid_{P_1=1} = [\alpha \phi(x - \mu_1) / \beta^2 \phi(x - \mu_1)^2 + \delta \phi(x - \mu_1)] \mid_{P_1=1}$

any linear transformation of  $\theta$  is jointly normal

vector is jointly normal

**Final 3) EXP family:**  $f(x | \theta) = c(\theta) h(x) \exp(\sum w_i(\theta)x_i + b(\theta)) = c(\theta) h(x) \exp(\sum w_i(\theta)x_i + b(\theta))$

$N(\mu, \sigma^2); P(X | \mu) = f(x | \mu)$  whereas  $P(X | \mu) \neq f(\mu | x)$ ; cannot factorize ( $x - \mu$ )! (separable)

$f(x | \mu, \sigma^2, \beta) = \sum_{i=1}^n \text{Norm}(x_i | \mu, \beta) + f(\mu | \beta); \text{cannot rewrite } E_p[e^{\lambda x_i}] \text{ as mixture involves addition}$

$P(X=x) = p$