Chapter 3

Common families of Distribution

3.1

$$\begin{aligned} & \text{EX} = \frac{1}{N_1 - N_0 + 1} (\sum_{x=0}^{N_1} i - \sum_{x=0}^{N_0 - 1} i) = \frac{N_1 + N_0}{2} \\ & \text{EX}^2 = \frac{1}{N_1 - N_0 + 1} (\frac{(N_1)(N_1 + 1)(2N_1 + 1) - (N_0 - 1)(N_0)(2N_0 - 1)}{6}) \\ & \text{Var} = \frac{(N_1 - N_0)(N_1 - N_0 + 2)}{12} \end{aligned}$$

3.2

(a)
$$P(X = 0 \mid M = 100, N = 6, K) = \frac{\binom{6}{0}\binom{94}{K}}{\binom{100}{K}}$$
 On solving K=32
(b) $P(X = 0 \mid M = 100, N = 6, K) = \frac{\binom{6}{0}\binom{94}{K}}{\binom{100}{K}} + \frac{\binom{6}{1}\binom{94}{K-1}}{\binom{100}{K}}$
On solving K = 50

3.3

(a) So pedestrian have to pass and that could have happen at any event of time lets say at 10 sec so past 3 secs need to be $(1-p)^3$. Now for the first 4 seconds car passes at 1^{st} second and rest none would be $p(1-p)^3$ We nee to do at any seconds after 4 would be $(1 - p(1-p)^3)(1-p)^3$

(a) So EX =
$$\sum_{i=0}^{\infty} \sum_{j=0}^{\infty} i \left(\frac{n-1}{n}\right)^j \left(\frac{1}{n}\right) = n$$

(a) So
$$EX = \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} i \left(\frac{n-1}{n}\right)^{j} \left(\frac{1}{n}\right) = n$$

(b) So $EX = \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} i \left(\frac{n-i}{n}\right)^{j} \left(\frac{1}{n}\right) = \frac{n+1}{2}$

3.5

(doubtful)

3.6

- (a) binomial distribution

(c)
$$\lambda = 2000 * \frac{1}{100} = 20$$

(a) Sinolinar distribution
(b)
$$\sum_{x=0}^{100} {}^{2000}C_x \left(\frac{1}{100}\right)^x \left(\frac{99}{100}\right)^{2000-x}$$
(c) $\lambda = 2000 * \frac{1}{100} = 20$

$$P(X=100) = \frac{1}{e^{20}} \left[1 + \sum_{i=1}^{i=100} \frac{20^i}{i!}\right] = .99 \Rightarrow 99percent$$

3.7

$$1 - \frac{1}{e^{\lambda}} - \frac{\lambda}{e^{\lambda}} = 0.99 \Rightarrow \lambda = 6.638$$

3.8

(doubtful)

3.9

$$P(X \ge 5) = 1 - \sum_{x=0}^{4} {60 \choose 2x} \left[\frac{1}{90}\right]^{2x} \left[\frac{89}{90}\right]^{60-2x}$$
 Let say answer is .0006

(a)
$$X \sim \text{Binomial}(60, \frac{1}{90})$$

 $P(X \ge 5) = 1 - \sum_{x=0}^{4} {60 \choose 2x} \left[\frac{1}{90}\right]^{2x} \left[\frac{89}{90}\right]^{60-2x}$ Let say answer is .0006
(b) $P \sim \text{Binomial}(310, .0006) \Rightarrow P(X \ge 0) = 1 - {310 \choose 0} .0006^{0} (1 - .0006)^{310} = .1698$

(c) P ~ Binomial(500, .1698)
$$\Rightarrow$$
 P(X \geq 0) = 1 - $\binom{310}{0}$.0006 0 (1 - .0006) 310 ~ 1

3.10

(a) Hyper-geometric distributions

$$P = \frac{\binom{N}{4}\binom{M}{2}}{\binom{N+M}{4}\binom{N+M-4}{2}}$$
(b) N + M = 496

 $\max (N)(N-1)(N-2)(N-3) * (M)(M-1) \text{ on solving } N = 331, M = 496 - 331 =$

3.11

(a)
$$P(X = x|N, M, K) = \frac{\binom{M}{x}\binom{N-M}{K-x}}{\binom{N}{K}}$$

$$P = \frac{M!}{x!M-x!} * \frac{N-M!}{K-x!(N-M-(K-x))} * \frac{K!}{N!N-K!} P = \binom{K}{x} \left(\frac{M!N-M!}{N!M-x!(N-M-(K-x))} \right)$$

$$P = \binom{K}{x} \left(\frac{(M*M-1*M-2...M-x+1)*(N-M*N-M-1...N-M-(K-x))}{N*N-1*N-2...N-k+1} \right)$$

$$Applying limits M \to \infty, M \to \infty N/M M \to p$$

$$Applying limits P = \binom{K}{x} \left(\frac{M^x N^{K-x}(1-p)^{K-x}}{N^K} \right)$$

$$P = \binom{K}{x} p^x (1-p)^{K-x}$$
(b) See text (c) Using some steps from above
$$P = \left(\frac{M!N-M!K!N-K!}{x!M-x!N-M-K+x!N!} \right)$$

$$P = \frac{1}{x!} \left[\frac{M^x K^x}{M^x} \right] \left[1 - \frac{K}{N} \right]^{M-x}$$

$$P = \frac{\lambda^x}{x!} \left[1 - \frac{\lambda}{M} \right]^M = \frac{e^{-\lambda} \lambda^x}{x!}$$

3.12

$$\begin{split} F_X(r-1) &= P(X \leq r-1) \\ &= P(\text{in n trial total of r}^{\text{th success}}) \\ &= 1 - P(\text{in n trail total for r}^{\text{th failure}}) \\ &= 1 - P(\text{in n trail total for (r+1)}^{\text{th success}}) \text{ (doubtful)} \end{split}$$

(a)
$$P(X_T = x) = \frac{P(X=x)}{P(X>0)}$$

 $P(X_T = x) = \frac{e^{-\lambda}\lambda^x}{x!(1-e^{-\lambda})}$
 $EX = \frac{\lambda}{1-e^{-\lambda}} EX^2 = \frac{\lambda^2 + \lambda}{1-e^{-\lambda}}$
 $VarX = \frac{\lambda^2 + \lambda}{1-e^{-\lambda}} - \left[\frac{\lambda}{1-e^{-\lambda}}\right]^2$

(b)
$$P(X_T = x) = \frac{P(X=x)}{P(X>0)}$$

= $\frac{\binom{r+y-1}{y}p^r(1-p)^y}{1-p^r}$
 $EX = \frac{r(1-p)}{p(1-p^r)}EX = \frac{r(1-p)-r^2(1-p)^2}{p^2(1-p^r)} - \left(\frac{r(1-p)}{p(1-p^r)}\right)^2$

(a)
$$\sum_{x=1}^{x=\infty} \frac{(1-p)^x}{x} = -\log(1-(1-p))$$
 So $P(X = x) = 1$
(b) $EX = -\frac{1}{\log p} \left[\frac{1-p}{p} \right]$
 $EX^2 = -\frac{1}{\log p} \left[\frac{1-p}{p^2} \right]$
 $VarX = \frac{-(1-p)}{p^2 \log p} \left[1 + \frac{1-p}{\log p} \right]$

3.15

$$M_X(t) = \left[\frac{p}{(1 - (1 - p)e^t)}\right]^r$$

$$M_X(t) = \left[1 + \frac{1r(1 - p)(e^t - 1)}{r(1 - (1 - p)e^t)}\right]^r$$

$$M_X(t) = \lambda(e^t - 1)$$

3.16

$$\begin{array}{l} \text{(a) } \Gamma(\alpha) = \int_{t=0}^{t=\infty} t^{\alpha} e^{-t} dt = \left[t^{\alpha} e^{-t}\right]_{0}^{\infty} + \alpha \int_{t=0}^{\infty} t^{\alpha-1} e^{-t} dt = \alpha \Gamma(\alpha) \\ \text{(b) } \left(\int_{0}^{\infty} e^{-\frac{z^{2}}{2}} dz\right)^{2} = \left(\int_{0}^{\infty} e^{-\frac{u^{2}}{2}} du\right) \left(\int_{0}^{\infty} e^{-\frac{v^{2}}{2}} dv\right) \\ \int_{0}^{\infty} \int_{0}^{\infty} e^{\frac{-(u^{2}+v^{2})}{2}} du dv = \frac{\sqrt{\pi}}{2} \text{ taking } \mathbf{u} = \text{rcos}(\theta), \, \mathbf{v} = \text{rsin}(\theta) \\ \Gamma(\frac{1}{2}) = \int_{0}^{\infty} w^{-1/2} e^{-w} dw = \sqrt{\pi} \\ \end{array}$$

$$\begin{split} f(x|\alpha,\beta) &= \frac{1}{\Gamma(\alpha)\beta^{a}} x^{\alpha-1} e^{\frac{-x}{\beta}} \\ \mathrm{EX} &= \frac{1}{\Gamma(\alpha)\beta^{\alpha}} \int_{0}^{\infty} x^{v+\alpha-1} e^{\frac{-x}{\beta}} dx \text{ taking y} = \beta \mathbf{x} \text{ will simplify the expression.} \end{split}$$

$$\begin{aligned} M_x(t) &= \left[\frac{p}{(1-(1-p)e^{ty})}\right]^r \\ \text{Applying limit} \\ \lim_{p \to 0} \left[\frac{p}{(1-(1-p)e^{ty})}\right]^r \\ \text{Using L'Hospital Rule} \\ M_x(t) &= \left[\frac{1}{-[(1-p)te^{tp}-e^{tp}]}\right]^r \\ M_x(t) &= \left(\frac{1}{1-t}\right)^r \end{aligned}$$

3.19

On integration by parts
$$\int_{x}^{\infty} \frac{1}{\Gamma(\alpha)} z^{\alpha-1} e^{-z} = \sum_{\alpha=\alpha}^{0} \left[\frac{x^{\alpha-1}}{\alpha! e^{x}} \right]$$
 On rearranging the terms
$$\sum_{y=0}^{\alpha-1} \left[\frac{x^{y}}{y! e^{x}} \right]$$

3.20

(a)
$$EX = \sqrt{\frac{\pi}{2}}, EX^2 = 1$$

(b) $f_y(y) = \frac{1}{\Gamma(\alpha)\beta^{\alpha}} y^{\alpha-1} e^{\frac{-y}{\beta}}$
 $Y = g(X) \Rightarrow X = g^{-1}(Y)$
 $f_y(y) = f_x(g^{-1}(Y)) \left| \frac{dg^{-1}(Y)}{dx} \right|$
 $f_y(y) = \frac{2}{\sqrt{2\pi}} e^{\frac{-y}{g^{-1}(x)^2}} \left| \frac{dg^{-1}(Y)}{dx} \right| \text{ let } g^{-1}(x)^2 = y \text{ so } \beta = 2 \text{ on solving } \alpha = -\frac{1}{2}$

3.21

Integral is infinite $f(x) = \int_{-\infty}^{\infty} \frac{1}{\pi} * \frac{1}{1+x^2} * e^{tx} dx$

3.22

(a), (b), (c), (d), (e) Integration and parts, Do rough work

$$\begin{array}{l} \text{(a)} \ \int_{x=\alpha}^{\infty} \frac{\beta \alpha^{\beta}}{x^{\beta+1}} dx = - \left[\frac{\beta \alpha^{\beta}}{\beta x^{\beta}} \right]_{\alpha}^{\infty} = 1 \\ \text{(b)} \text{EX} = \int_{x=\alpha}^{\infty} x \frac{\beta \alpha^{\beta}}{x^{\beta+1}} dx = \frac{\alpha \beta}{1-\beta} \\ \text{EX}^2 = \int_{x=\alpha}^{\infty} x^2 \frac{\beta \alpha^{\beta}}{x^{\beta+1}} dx = \frac{\alpha \beta}{1-\beta} = \frac{\alpha \beta^2}{2-\beta} \\ \text{Var} = \frac{\alpha \beta^2}{2-\beta} - \left[\frac{\alpha \beta}{1-\beta} \right]^2 \\ \text{(c)} \ \text{If} \ \beta < 2 \ \text{the var is infinite} \\ \end{array}$$

3.24

$$\begin{aligned} h_T(t) &= \lim_{\delta \to 0} \frac{P(t \leq T < t + \delta)}{P(T \geq t)} \\ \text{As } \delta \to 0, \ t \to T \\ h_T(t) &= \frac{f_T(t)}{1 - F_T(t)} \end{aligned}$$

3.25

(a), (b), (c) simple calculation

3.26

differentiate the function and solve it for zero

3.27

for (a), (b), (c), (d) Equate with all the function and get the desired result. $f(x|\theta) = h(x)c(\theta)exp\left(\sum_{i=1}^k w_i(\theta)t_i(x)\right) \text{ Equate term by term}$

3.28

Equate terms and get the result!

(a)
$$f(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} e^{\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)}$$

h(x) = 1 for all x;

$$c(\theta)=c(\mu,\sigma)=\frac{1}{\sqrt{2\pi}\sigma}e^{\left(\frac{-\mu^2}{2\sigma^2}\right)},\,-\infty<\mu<\infty,\,\sigma>0$$

$$w_1(\mu,\sigma)=\frac{1}{\sigma^2},\sigma>0; w_2(\mu,\sigma)=\frac{\mu}{\sigma^2}\sigma>0;$$

$$t_1(x)=-\frac{x^2}{2}; andt_2(x)=x$$
 Natural Parameter
$$=(\eta_1,\,\eta_2)=(-\frac{1}{2\sigma^2},\frac{\mu}{\sigma}),\,\eta_1<0\,\,\&\,\,\infty<\eta_2<\infty$$
 (b) For the gamma($\alpha,\,\beta$),
$$f(x)=\left(\frac{1}{\Gamma\beta^\alpha}\right)\left(e^{\alpha-1}log\,\,x-\frac{x}{\beta}\right)$$
 natural parameter is $(\eta_1,\,\eta_2)=(\alpha-1,\,\frac{1}{\beta})$ Varying the $\alpha,\,\beta\,\,\{(\eta_1,\eta_2):\eta_1>-1,\eta_2<0\}$ (c)
$$f(x)=\left(\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\right)e^{(\alpha-1)log\,\,x+(\beta-1)log\,\,(1-x)}$$
 Natural Parameter: $(\eta_1,\,\eta_2)=(\alpha-1),\,(\beta-1),\,$ Natural Parameter Space:
$$\{(\eta_1,\,\eta_2):\,\eta_1>-1,\,\eta_2>-1\}$$
 (d)
$$h(x)=\frac{1}{x!}I_{\{0,1,2,\ldots\}}(x),\,c(\theta)=e^{-\theta},\,w_1(\theta)=\log\theta,\,t_1(x)=x$$
 So Natural Parameter is $\eta=\log\theta$ Natural Parameter Space is
$$\{\eta:\,-\infty<\eta<\infty\}$$
 (e)
$$h(x)=\left(\frac{x-1}{r-1}\right)I_{\{r,r+1,r+2,\ldots\}}\,c(p)=\frac{p}{1-p}{}^r\,w_1(p)=\log(1-p)$$

$$t_1(x)=x$$
 Natural Space is $\eta=\log(1-p)$ Natural Parameter Space
$$=\{\eta:\,\eta<0\}$$

(a), (b) put values and get it

$$\begin{aligned} & \text{Differentiating both side with } \frac{d}{d\theta_i} \\ & c'(\theta) \left(\int h(x) exp(\sum_{i=0}^{i=k} w_i(\theta) t_i(x)) \right) + c(\theta) \left(\int h(x) exp(\sum_{i=0}^{i=k} w_i(\theta) t_i(x)(\sum_{i=0}^{i=k} \frac{dw_i}{d\theta_j}(\theta) t_i(x)) \right) \\ & \text{Rearranging terms} \\ & E \left[\left(\sum_{i=0}^{i=k} \frac{dw_i}{d\theta_j}(\theta) t_i(x) \right) \right] = -\frac{d}{d\theta_j} logc(\theta) \\ & \text{(b) } c''(\theta) \left(\int h(x) exp(\sum_{i=0}^{i=k} w_i(\theta) t_i(x)) \right) + 2c'(\theta) \left(\int h(x) exp(\sum_{i=0}^{i=k} w_i(\theta) t_i(x)(\sum_{i=0}^{i=k} \frac{dw_i}{d\theta_j}(\theta) t_i(x))) \right) + \\ & c(\theta) \left(\int h(x) exp(\sum_{i=0}^{i=k} w_i(\theta) t_i(x)(\sum_{i=0}^{i=k} \frac{d^2w_i}{d\theta_j^2}(\theta) t_i(x))) + \int h(x) exp(\sum_{i=0}^{i=k} w_i(\theta) t_i(x)(\sum_{i=0}^{i=k} \frac{dw_i}{d\theta_j}(\theta) t_i(x))^2) \right) \\ & \Rightarrow \frac{c''(\theta)}{c(\theta)} + 2\frac{c'(\theta)}{c(\theta)} E \left[\sum_{i=0}^{i=k} \frac{dw_i}{d\theta_j}(\theta) t_i(x) \right] + E \left[\sum_{i=0}^{i=k} \frac{d^2w_i}{d\theta_j^2}(\theta) t_i(x) \right] + E \left[\left(\sum_{i=0}^{i=k} \frac{dw_i}{d\theta_j}(\theta) t_i(x) \right)^2 \right] \\ & \Rightarrow \frac{d^2}{dx^2} log(x) + \left(\frac{d}{dx} log(x)^2 - 2 \left(\frac{d}{dx} log(x)^2 + E \left[\sum_{i=0}^{i=k} \frac{d^2w_i}{d\theta_j^2}(\theta) t_i(x) \right] + E \left[\left(\sum_{i=0}^{i=k} \frac{dw_i}{d\theta_j}(\theta) t_i(x) \right)^2 \right] \end{aligned}$$

Rearranging terms
$$E\left[\left(\left(\sum_{i=0}^{i=k}\frac{dw_i}{d\theta_j}(\theta)t_i(x)\right)\right)^2\right]-\left(\frac{d}{dx}\log x\right)^2=-\frac{d^2}{d\theta_j^2}\log c(\theta)-E\left[\sum_{i=0}^{i=k}\frac{d^2w_i}{d\theta_j^2}(\theta)t_i(x)\right]$$

Right Hand Site is Var function

(a)
$$\mathrm{E}\left[\sum_{i=0}^{i=k} \frac{\partial \eta_i}{\partial \eta_j}\right] = t_j(x)$$
 double differentiation leads to 0 $\mathrm{E}\left[\sum_{i=0}^{i=k} \frac{\partial^2 \eta_i}{\partial \eta_j^2}\right] = 0$ Substitute it we will get the terms (b) Substitute an solve

3.33

(a), (b), (c), (d) solve yourself

3.34

(a)
$$\bar{X} \sim n(\lambda, \lambda/n)$$
 You split the term according to exponential family $\mu = \lambda, \sigma^2 = \lambda/n$ $n\sigma^2 = \mu$

The parameters of theta lies on parabola

(b) $\bar{X} \sim n(p,(1-p)/n)$ You split the term according to exponential family n'=p,p'=p(1-p)/n

On rearranging the equation becomes parabola p' = n'(1 - n')/n

(c)
$$\bar{X} \sim n(r(1-p)/p, r(1-p)/np^2)$$

$$p' = r'/(np)$$

The parameter lies in 1st quadrant

3.35

as previous questions

3.36

(a), (b), (c)



Figure 3.1:

$$\begin{pmatrix} \int_{-\infty}^m (\frac{1}{\sigma}) f(\frac{x-\mu}{\sigma}) dx \end{pmatrix} = \left(\int_m^\infty (\frac{1}{\sigma}) f(\frac{x-\mu}{\sigma}) dx \right)$$
 t = $\frac{x-\mu}{\sigma}$ substituting and differentiating σ dt = dx
$$\left(\int_{-\infty}^{\frac{m-\mu}{\sigma}} f(t) dt \right) = \frac{1}{2}$$
 $\frac{m-\mu}{\sigma} = 0 \Rightarrow m = \mu$

3.38

$$\begin{array}{l} (\frac{1}{\sigma})f(\frac{x-\mu}{\sigma}) \\ x_{\alpha} = \sigma z_{\alpha} + \mu \\ \alpha = P(Z > z_{\alpha}) = \int_{z_{\alpha}}^{\infty} f(z)dz \\ z_{\alpha} = \frac{x_{\alpha}-\mu}{\sigma} \ \alpha = \int_{z_{\alpha}}^{\infty} f(z)dz \\ \text{Generalizing it } z = \frac{x-\mu}{\sigma} \int_{\frac{x-\mu}{\sigma}}^{\infty} (\frac{1}{\sigma})f(\frac{x-\mu}{\sigma})dx = P(\frac{X-\mu}{\sigma} > \frac{x_{\alpha}-\mu}{\sigma}) = P(X > x_{\alpha}) = \alpha \end{array}$$

(a)
$$\int_{-\infty}^{\mu} \frac{1}{\sigma\pi(1+(\frac{x-\mu}{\sigma}))} dx = \int_{\mu}^{\infty} \frac{1}{\sigma\pi(1+(\frac{x-\mu}{\sigma}))} dx$$
 substituting $z = \frac{x-\mu}{\sigma}$ we will get standard Cauchy with median 0. So $x = \mu$ (b)
$$\int_{-1}^{1} \frac{dx}{\sigma\pi\left(1+\left(\frac{x-\mu}{\sigma}\right)^{2}\right)},$$
 putting $\mu = 0, \ \sigma = 1.$ We get $\frac{1}{2}$ With symmetry we get $\frac{1}{4}$ adding a general location (μ) and scale family (σ)

$$f^*(x) = \frac{1}{\sigma} f(\frac{x-\mu}{\sigma})$$

3.41

Scholastically greater $F_X(t) \leq F_Y(t)$ for all t

Say let X, Y = X + μ' are two random variables for same family distribution where μ' is fixed differences between the their mean. $P(t \ge x) > P(t \ge y)$ as for same σ the area as the distribution is same P(X) will be more than P(Y) $F_X(x) > F_Y(y)$

Y is scholastically greater than X also Y is greater than X hence Provved

(b) Refer next section

3.42

- (a) For location family μ changes keeping the scale parameter constant, Refer to above section a logic you will get for the same.
- (b) Let $\sigma_1 > \sigma_2$

$$F(x|\sigma_1) = P(X_1 \le x) = P(\sigma_1 Z \le x) = P(Z \le x\sigma_1) = F(x/\sigma_1) \le F(x/\sigma_2) = P(Z \le x/\sigma_2) = P(\sigma_2 Z \le x) = P(X_2 \le x) = F(x|\sigma_2).$$

3.43

$$\begin{array}{l} \text{(a)}\ P(X \leq x | \theta_1) \leq P(X \leq x | \theta_2) \\ \Rightarrow P(\frac{1}{Y} \leq \frac{1}{y} | \theta_1) \leq P(\frac{1}{Y} \leq \frac{1}{y} | \theta_2) \\ \Rightarrow P(y \leq Y | \theta_1) \leq P(y \leq Y | \theta_2) \\ \Rightarrow P(Y \leq y | \theta_1) \geq P(Y \leq y | \theta_2) \\ \text{(b)}\ P(X \leq x \mid \theta) \leq P(X \leq x \mid \theta + d\theta) \\ P(X \ le \ x \mid \frac{1}{\theta}), \ P(X \leq x \mid \frac{1}{\theta} - \frac{d\theta}{\theta^2}) \\ \text{Clearly}\ P(X \ le \ x \mid \frac{1}{\theta}) \geq P(X \leq x \mid \frac{1}{\theta} - \frac{d\theta}{\theta^2}) \end{array}$$

Using Chebychev Inequality's
$$\begin{split} & \text{P}(|\mathbf{X}| \geq \mathbf{b}) \leq \frac{E|X|}{b} \\ & \text{P}(|\mathbf{X}| \geq \mathbf{b}) = \text{P}(X^2 \geq \mathbf{b}) \leq \frac{EX^2}{b^2} \\ & \text{E}|\mathbf{X}|/\mathbf{b} = 1/3 > 2/9 = EX^2/b^2 \end{split}$$

 $E|X|/b = 1/\sqrt{2} < 1 = EX^2/b^2.$

3.45

- (a) $M_X(t) = \int_{-\infty}^{\infty} e^{tx} f_X(x) dx \ge$ $\int_a^{\infty} e^{tx} f_X(x) dx \ge e^{ta} \int_a^{\infty} f_X(x) dx = e^{ta} P(X \ge a)$ (b) same as above
- (c) It must be a non negative

3.46

Draw graph

3.47

(a) $P(Z \ge t) \le \int_t^\infty \frac{x^2+1}{x^2+1} e^{-\frac{x^2}{2}} dx = \int_t^\infty \frac{x^2}{x^2+1} e^{-\frac{x^2}{2}} dx + \int_t^\infty \frac{1}{x^2+1} e^{-\frac{x^2}{2}} dx$ On solving first you will get the equality. Second term must be discarded

3.48

(a),(b),(c) Divide P(X = x+1)/P(X = x) to derive it for all

3.49

(a)(b) solve mathematically

3.50

(a) (b) solve mathematically