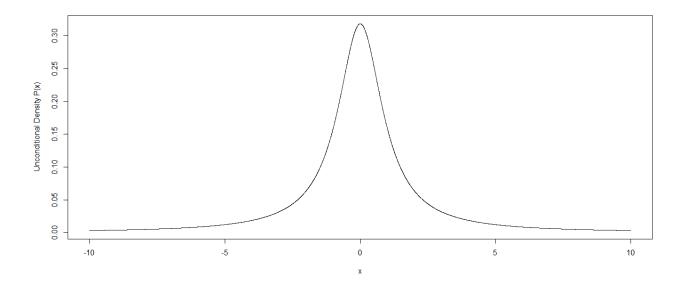
1. Find the Marginal Distribution p(x)

Lab Assignment 3 Dai Li
-Normal distribution X~N(4,02)
-Normal distribution $\chi \sim N(\mu, \sigma^2)$ $f(\chi \mu,\sigma) = \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{1}{2\sigma^2}(\chi-\mu)^2}, -\infty < \chi < \infty$
Cramma distribution x ~ Crammal 2. B)
$f(x \alpha,\beta) = \beta^{\alpha} \overline{\Gamma(\alpha)} \chi^{\alpha-1} e^{\beta \chi}, \chi \geqslant 0, \alpha, \beta > 0$
TNow, $\chi \mid \vec{z} \sim N(0, \frac{1}{z^2})$, $\vec{z} \sim Gamma(\frac{\gamma}{2}, \frac{\gamma}{2})$
So, $\pi(\vec{z}) = (\frac{1}{2})^{\frac{1}{2}} \frac{1}{\Gamma(\frac{1}{2})} (\vec{z})^{(\frac{1}{2}-1)} e^{-\frac{1}{2}\vec{z}^2}$
and, $f(x o,t) = \sqrt{\frac{1}{2\pi(t)}} e^{-\frac{1}{2(t)}(x-o)^{2}}$
$=\frac{\sqrt{z}}{\sqrt{z}}e(-\frac{z}{z}\chi^2)$
The marginal distribution of x, pox)
$p(x) = \left(\frac{f(x \vec{c})}{\lambda(\vec{c})} \frac{\lambda(\vec{c})}{\lambda(\vec{c})} \frac{\lambda(\vec{c})}{\lambda(\vec{c})} \right)$
- consequently, The marginal distribution of x, Pex)
FCA, C V
can be derived from
$p(x) = \int P(x z) \pi(x) dz^{2}$ $(J\overline{z}^{2} (-\overline{z}^{2}x^{2})) = \int P(x z) \pi(x) dz^{2}$
$=\int_{\overline{z}}^{\overline{z}} e^{\left(-\frac{z^{2}}{2}\chi^{2}\right)} \cdot \left(\frac{v}{z}\right)^{\frac{v}{2}} \frac{1}{\Gamma(\frac{v}{2})} (\overline{c})^{\left(\frac{v}{2}+1\right)} e^{-\frac{v}{2}} \overline{c}^{2} d\overline{c}$
$= \frac{(\nu/z)^{\frac{1}{2}}}{\Gamma'(\frac{\nu}{z})_{12\pi}} \int_{0}^{\infty} (-z^{2})^{(\frac{\nu}{z} - \frac{1}{z})} e^{-z^{2}} (\frac{1}{z}x^{2} + \frac{1}{z}\nu) dz^{2}$ $= \frac{(\sqrt{z})^{\frac{\nu}{z}}}{\Gamma(\frac{\nu}{z})_{12\pi}} \cdot \frac{\Gamma(\frac{\nu+1}{z})}{(\frac{1}{z}(x^{2} + \nu))^{\frac{\nu+1}{z}}}$
$-\frac{(\sqrt{2})^{\frac{1}{2}}}{(\sqrt{2})^{\frac{1}{2}}}\cdot \Gamma(\frac{\sqrt{1}}{2})$
「(生)Jzス (主(x²+v)) ***********************************
$=\frac{P(\frac{\sqrt{\pm}}{2})}{\sqrt{\sqrt{2}}(\frac{\sqrt{2}}{2})}\left(1+\frac{\chi^2-\frac{1}{2}}{\sqrt{2}}\right)^{\frac{1}{2}} \text{ which is}$
TVZ P(Z) (II V) 2, WENCENS
The pdf of students t distribution.

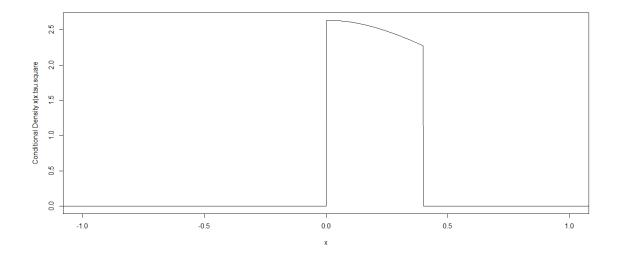
2. Let nu=1. Get a sample of 10,000 from marginal distr. of x by drawing 10,000 tau^2's and then 10,000 x's given the tau^2's. Plot sample (either histogram or density is fine). Give two names for the actual marginal distribution p(x) when nu=1. Also, compute 2.5% & 97.5% percentile points of the distribution using the random samples and compare them to the theoretical values.

The actual marginal distribution p(x) when nu=1 is plotted below:

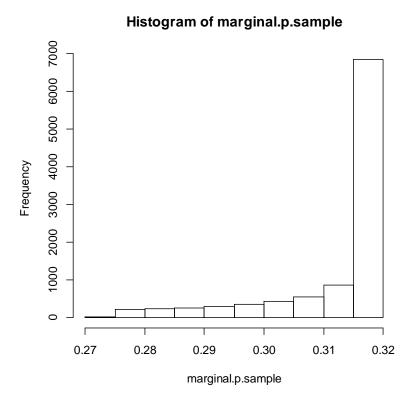


Which is a <u>Students' T Distribution with parameter Nu=1</u>. As, Nu=1, it is also a Cauchy Distribution with location parameter=0 and a scale parameter.

While using the 10000 sample points, we can draw out the theoretical conditional density of p(x|tau.square), which is plotted below:



Which is a Student's T distribution truncated to [min(x.tau.square.sample), max(x.tau.square.sample)], whose p(x)sample value histogram is also plotted below:



The 2.5% & 97.5% percentile points of theoretical p(x) are (-12.7062, 12.7062). While, the 2.5% & 97.5% percentile points of sampled p(x) are (0.009560445, 0.3877215).

3. Use Kolmogorov-Smirnov test (ks.test in R) to test whether your observed distribution is equal to a t(df=1). Report p-value. What is the conclusion of the test?

Under null-hypothesis, p-value < 2.2e-16,

Using the sample points, D= 0.5853.

Conclusion of the test: R eject the hypothesis-the observed distribution is not equal to a t(df=1).

4. Does the Central Limit Theorem hold for the mean of a sample from p(x) when nu=1? What about nu=2? nu=3? Why or why not? A quick explanation will do; an involved proof is NOT required.

Given nu=1,2,or 3, there are finite value of X, so that there are finite value of mean E(x) and variance Var(x), and thus, the Central Limit Theorem hold for the sampled p(x).

Code:

```
theta=seq(0,100,length=10001);nu=1
tau.square <- dgamma(theta,(nu/2),(nu/2))
x=seq(-10,10,length=10001)
x.tau.square <- dnorm(0,1/tau.square)</pre>
marginal.p.unconditional <- dt(x,nu)
marginal.p.conditional <- dt(x,nu)*as.numeric(x > min(x.tau.square) & x <
max(x.tau.square))/(pt(max(x.tau.square),nu)-pt(min(x.tau.square),nu))
#draw 10000 samples
theta.sample <- runif(10000,0,1)
tau.square.sample <- dgamma(theta.sample,(nu/2),(nu/2))
x.tau.square.sample <- dnorm(0,1/tau.square.sample)</pre>
marginal.p.sample <- dt(x.tau.square.sample,nu)
#Plotting
par(mfrow = c(2,2))
plot(x,marginal.p.unconditional,xlim=c(-10,10),type="l",xlab="x",ylab="Unconditional Density P(x)")
plot(x,marginal.p.conditional,xlim=c(-1.0,1),type="l",xlab="x",ylab="Conditional Density x | x.tau.square")
hist(marginal.p.unconditional,breaks=10,plot=TRUE)
hist(marginal.p.sample,breaks=10,plot=TRUE)
#Calculating Credible Interval
truncated.inverse.cdf <- function(x,x.tau.square,nu){
F.a=pt(min(x.tau.square),nu)
F.b=pt(max(x.tau.square),nu)
z=qt((F.b-F.a)*x+F.a,nu)
return(z)
}
lower.theoretical <- qt(0.025,nu)
upper.theoretical <- qt(0.975,nu)
lower.actual <- truncated.inverse.cdf(.025,x.tau.square.sample,nu)
upper.actual <- truncated.inverse.cdf(.975,x.tau.square.sample,nu)
ks.test(marginal.p.sample,"pt",1)
```