

# Conditional Copula

## Example of a Conditional Copula

Consider the two-dimensional random vector  $(X, Y)$  having joint conditional distribution

$$f(x, y|z) = f_X(x)f_Y(y)c(F_X(x), F_Y(y) | z)$$

where each marginal is a mixture of univariate normal random variables.

$$f_X(x) = f_Y(x) = \sum_{r=1}^R \pi_r \phi(x | \mu_r, \sigma_r)$$

We chose the following settings and parameter values:  $f_X = f_Y$ ,  $R = 6$ ,  $\mu_{1:6} = (-9, -5.4, -1.8, 1.8, 5.4, 9)$ , and  $\sigma_r = 1/\sqrt{10}$ ,  $\pi_r = 1/R$ .

and the copula is

$$C(u, v | x) = u^{1-\alpha(x)} v^{1-\beta(x)} [u^{-\theta\alpha(x)} + v^{-\theta\beta(x)} - 1]^{-1/\theta}$$

where

- $\theta = 20$
- 

$$\alpha(x) = \frac{2}{3} - \frac{1}{4} \times \frac{1}{\exp(x) + 1}$$

- 

$$\beta(x) = \frac{1}{2} + \frac{1}{4} \times \frac{\exp(x)}{\exp(x) + 1}$$

Draw a sample when  $x \in (-4, 4)$

```
set.seed(100)
```

```
R=6
```

```
mu=c(-9, -5.4, -1.8, 1.8, 5.4, 9)
```

```
sigmar=rep(1/sqrt(10), R)
```

```
pi=rep(1/R, R)
```

```
theta=40
```

```
# evaluate the function at the point x, where the components  
# of the mixture have weights w, means stored in u, and std deviations  
# stored in s - all must have the same length.
```

```
F = function(x,w,u,s) sum( w*pnorm(x,mean=u,sd=s) )
```

```
# provide an initial bracket for the quantile. default is c(-1000,1000).
```

```
F_inv = function(p,w,u,s,br=c(-1000,1000))
```

```
{
```

```
  G = function(x) F(x,w,u,s) - p
```

```
  return( uniroot(G,br)$root )
```

```

}

l=5
#function alpha(x)
a<-function(x){
  2/3-1/4*(exp(1*x)/(exp(1*x)+1))
}
#function beta(x)
b<-function(x){
  1/2+1/4*(exp(1*x)/(exp(1*x)+1))
}

n=1500
V=runif(n)
W=runif(n)

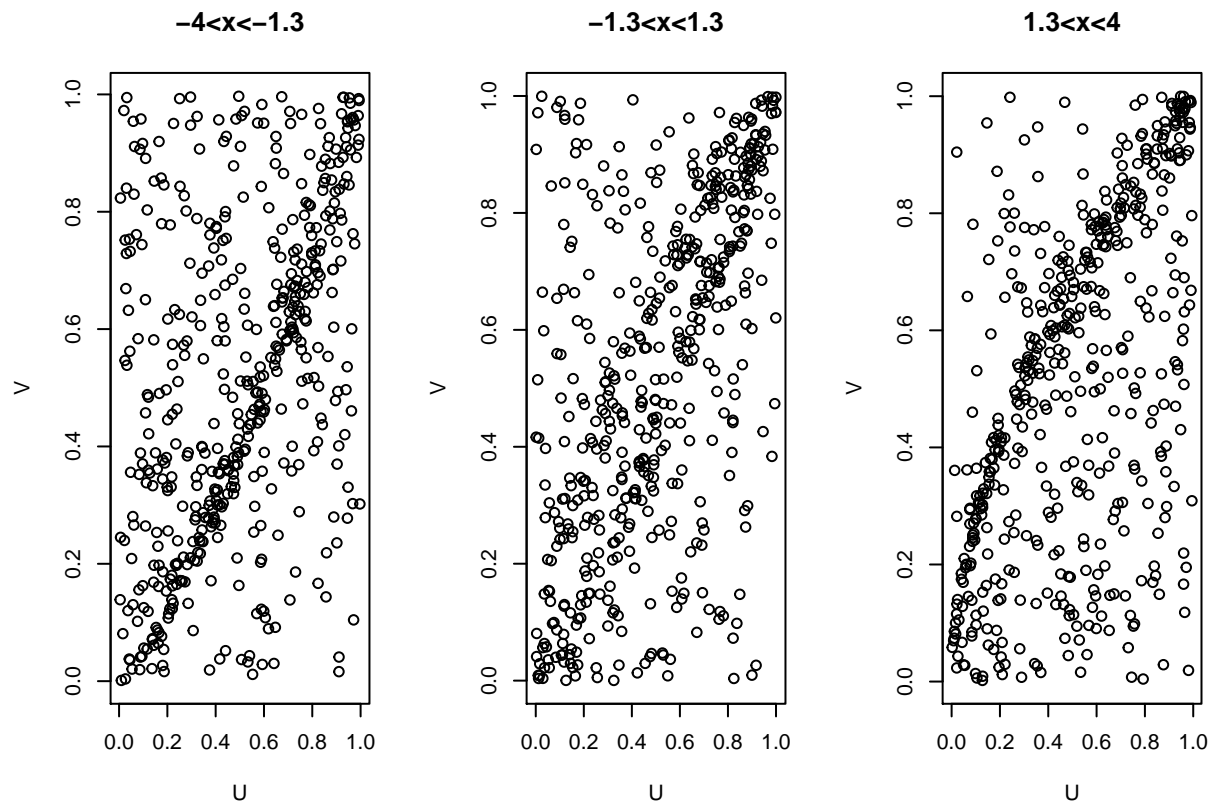
X=seq(-4,4, length.out = n)

C <- function(u) {
  (1-beta)*u^(1-alpha)*v^(-beta)*(u^(-theta*alpha)+v^(-theta*beta)-1)^(-1/theta)+
  beta*u^(1-alpha)*v^(-beta*(1+theta))*(u^(-theta*alpha)+v^(-theta*beta)-1)^(-1/theta-1)-w
}

U=rep(0,n)
for (i in 1:n) {
  v=V[i]
  w=W[i]
  alpha=a(X[i])
  beta=b(X[i])
  U[i]=uniroot(C, lower = 0, upper = 1)$root
}

par(mfrow=c(1,3))
plot(U[1:(1/3*n)], V[1:(1/3*n)], xlab = 'U', ylab='V', main = '-4<x<-1.3')
plot(U[(1/3*n):(2/3*n)], V[(1/3*n):(2/3*n)], xlab = 'U', ylab='V', main = '-1.3<x<1.3')
plot(U[(2/3*n):n], V[(2/3*n):n], xlab = 'U', ylab='V', main = '1.3<x<4')

```

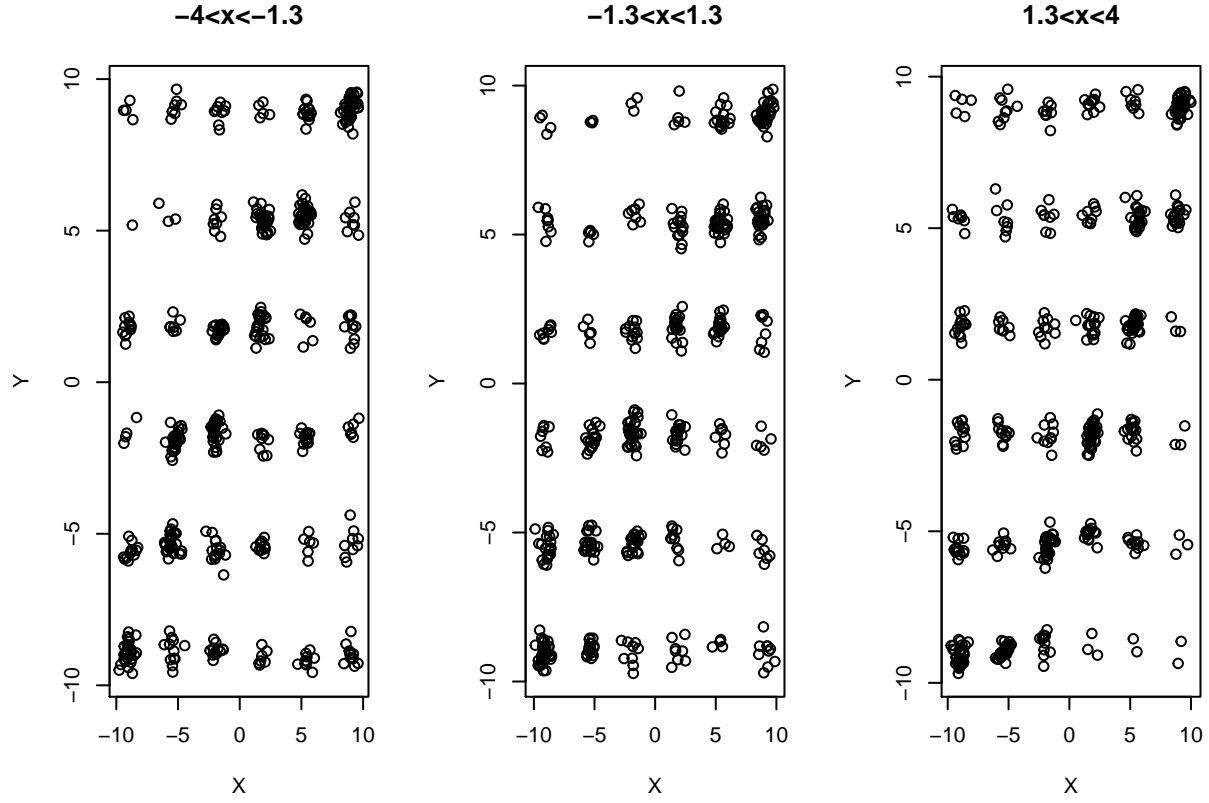


```

X1=sapply(V, F_inv, w=pi, u=mu, s=sigmar)
X2=sapply(U, F_inv, w=pi, u=mu, s=sigmar)

par(mfrow=c(1,3))
plot(X1[1:(1/3*n)], X2[1:(1/3*n)], xlab = 'X', ylab='Y', main = '-4<x<-1.3')
plot(X1[(1/3*n):(2/3*n)], X2[(1/3*n):(2/3*n)], xlab = 'X', ylab='Y', main = '-1.3<x<1.3')
plot(X1[(2/3*n):n], X2[(2/3*n):n], xlab = 'X', ylab='Y', main = '1.3<x<4')

```



## Another Example of Conditional Copula

Notation:

- $\Phi$  is the cdf of the standard normal distribution.
- $\phi$  is the pdf of standard normal distribution.
- $\phi_2$  is the pdf of bivariate normal.

Then they have

$$p(u_1, u_2 \mid \mu, \sigma) = \frac{\phi_2(\Phi^{-1}(u_1), \Phi^{-1}(u_2) \mid \mu, \sigma I_2)}{\phi(\Phi^{-1}(u_1))\phi(\Phi^{-1}(u_2))}$$

A mixture of  $p(u)$  can be used to estimate any arbitrarily continuous density on  $(0, 1)^2$ .

$$\tilde{c}(u_1, u_2 \mid \pi, \mu, \sigma) = \sum_{j=1}^J \pi_j \frac{\phi_2(\Phi^{-1}(u_1), \Phi^{-1}(u_2) \mid \mu_j, \sigma_j I_2)}{\phi(\Phi^{-1}(u_1))\phi(\Phi^{-1}(u_2))}$$

where  $\pi_j$ s are mixing proportions.

When  $\pi_j$  and  $\mu_j$  are conditioned on covariates:

•

$$\pi_j(x_i) = \frac{\exp(\beta_j^T x_i)}{\sum_{j=1}^J \exp(\beta_j^T x_i)}$$

•

$$\mu_j = \begin{bmatrix} \lambda_{j1}^T x_i \\ \lambda_{j2}^T x_i \end{bmatrix}$$

We give an example of a mixture with two components

- $\beta = \begin{bmatrix} 0.1 \\ 0.3 \end{bmatrix}$
- $\lambda_{11} = \begin{bmatrix} 0.1 \\ 0.3 \end{bmatrix}$   
 $\lambda_{12} = \begin{bmatrix} 0.1 \\ 0.4 \end{bmatrix}$   
 $\lambda_{21} = \begin{bmatrix} 0.3 \\ 0.1 \end{bmatrix}$   
 $\lambda_{22} = \begin{bmatrix} 0.4 \\ 0.1 \end{bmatrix}$
- $\sigma_1 = 0.5$  and  $\sigma_2 = 1$ .

Draw a random sample from above model when  $X \in (0, 5)$ .

```
n=1500
X=seq(0,5, length.out = n)
X=cbind(rep(1, n), X)
beta1=c(0.1, 0.3)

pi=cbind(exp(X%%beta1)/(exp(X%%beta1)+1), 1/(exp(X%%beta1)+1))

h=t(apply(pi, 1, rmultinom, n=1, size=1))

Z1=matrix(rep(0, 2*n), nrow = n)

lambda11=c(0.1,0.3)
lambda12=c(0.1,0.4)
sigma=0.5
I=matrix(c(1,0,0,1), nrow = 2)
mu1=cbind((X%%lambda11)[,1], (X%%lambda12)[,1])

for (i in 1:n) {
  Z1[i, ]=rmvnorm(1,mu1[i,], sigma*I)
}

Z2=matrix(rep(0, 2*n), nrow = n)

lambda21=c(0.3, 0.1)
lambda22=c(0.4, 0.1)
sigma2=1
I=matrix(c(1,0,0,1), nrow = 2)
mu2=cbind((X%%lambda21)[,1], (X%%lambda22)[,1])

for (i in 1:n) {
  Z2[i, ]=rmvnorm(1,mu2[i,], sigma2*I)
}
```

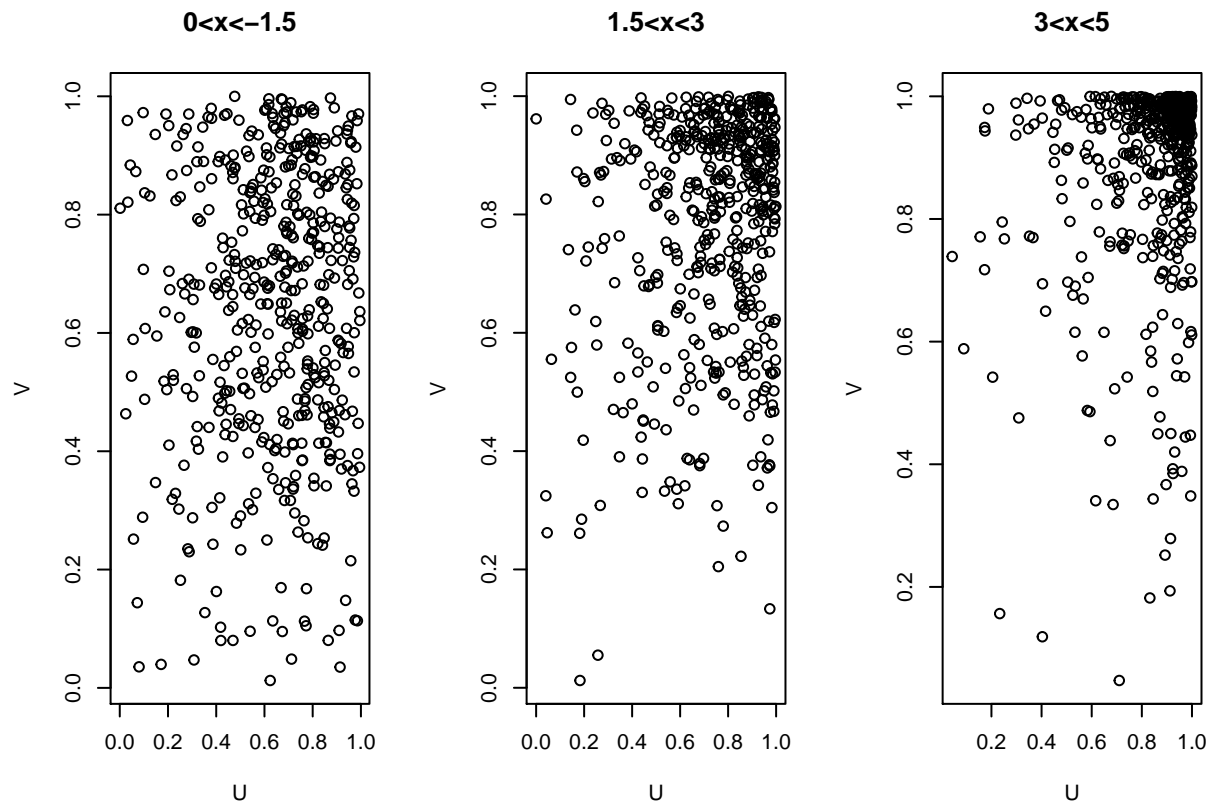
```

Z=matrix(rep(0, 2*n), nrow = n)
for (i in 1:n) {
  Z[i,]=Z1[i,]*h[i,1]+Z2[i,]*h[i,2]
}

u=t(apply(Z, 1, pnorm))
U=u[,1]
V=u[,2]

par(mfrow=c(1,3))
plot(U[1:(1/3*n)], V[1:(1/3*n)], xlab = 'U', ylab='V', main = '0<x<-1.5')
plot(U[(1/3*n):(2/3*n)], V[(1/3*n):(2/3*n)], xlab = 'U', ylab='V', main = '1.5<x<3')
plot(U[(2/3*n):n], V[(2/3*n):n], xlab = 'U', ylab='V', main = '3<x<5')

```



```

set.seed(100)
R=6
mu=c(-9, -5.4, -1.8, 1.8, 5.4, 9)
sigmar=rep(1/sqrt(10), R)
pi=rep(1/R, R)
X1=sapply(V, F_inv, w=pi, u=mu, s=sigmar)
X2=sapply(U, F_inv, w=pi, u=mu, s=sigmar)

par(mfrow=c(1,3))
plot(X1[1:(1/3*n)], X2[1:(1/3*n)], xlab = 'X', ylab='Y', main = '0<x<-1.5')
plot(X1[(1/3*n):(2/3*n)], X2[(1/3*n):(2/3*n)], xlab = 'X', ylab='Y', main = '1.5<x<3')
plot(X1[(2/3*n):n], X2[(2/3*n):n], xlab = 'X', ylab='Y', main = '3<x<5')

```

