

# R Notebook

Code ▾

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```
#Loading the data

library(quantmod)
getSymbols("EA",src="yahoo",from=as.Date("2018-02-06"),to=as.Date("2023-02-06"))
```

```
[1] "EA"
```

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```
head(EA)
```

	EA.Open	EA.High	EA.Low	EA.Close	EA.Volume	EA.Adjusted
2018-02-06	118.86	123.35	117.76	123.13	4652300	121.4598
2018-02-07	122.86	125.00	122.18	123.05	4066900	121.3809
2018-02-08	123.00	123.00	116.52	116.54	5478900	114.9592
2018-02-09	117.96	122.14	114.67	120.64	5945100	119.0036
2018-02-12	121.78	124.16	121.53	122.22	3695100	120.5622
2018-02-13	120.85	123.13	120.58	122.28	2388700	120.6214

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```
tail(EA)
```

	EA.Open	EA.High	EA.Low	EA.Close	EA.Volume	EA.Adjusted
2023-01-27	129.14	130.57	128.79	128.87	1786200	128.6496
2023-01-30	128.92	129.47	128.11	128.99	2446900	128.7694
2023-01-31	129.19	129.99	128.38	128.68	3067700	128.4599
2023-02-01	116.78	117.22	112.58	116.76	14492300	116.5603
2023-02-02	117.50	117.52	114.10	115.99	6355600	115.7916
2023-02-03	115.15	115.54	113.78	113.92	4393500	113.7252

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```
getSymbols("ATVI",src="yahoo",from=as.Date("2018-02-06"),to=as.Date("2023-02-06"))
```

```
[1] "ATVI"
```

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```
head(ATVI)
```

	ATVI.Open	ATVI.High	ATVI.Low	ATVI.Close	ATVI.Volume	ATVI.Adjusted
2018-02-06	66.00	69.84	65.72	69.70	10524300	67.60927
2018-02-07	69.62	70.86	69.43	69.46	6255200	67.37649
2018-02-08	69.63	69.79	65.76	65.83	11179300	63.85536
2018-02-09	66.99	67.78	63.32	67.08	18582300	65.06787
2018-02-12	67.16	69.20	67.16	68.32	8315700	66.27067
2018-02-13	67.96	68.21	67.18	68.03	5373600	65.98937

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```
tail(ATVI)
```

	ATVI.Open	ATVI.High	ATVI.Low	ATVI.Close	ATVI.Volume	ATVI.Adjusted
2023-01-27	75.50	76.76	75.22	76.61	4382700	76.61
2023-01-30	76.63	77.08	75.84	75.96	4247400	75.96
2023-01-31	76.13	77.00	75.85	76.57	4118000	76.57
2023-02-01	76.00	76.82	75.58	76.70	4575400	76.70
2023-02-02	76.50	77.39	76.07	77.11	4696100	77.11
2023-02-03	76.64	76.78	75.03	75.24	5781000	75.24

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```
#EA - Electronic Arts
#ATVI - Activision Blizzard

#EA Log Return Calculation
EA_log_return_1<-diff(log(EA[,6]))
EA_log_return<-as.numeric(EA_log_return_1[-1])
head(EA_log_return)
```

```
[1] -0.0006498333 -0.0543563003  0.0345762205  0.0130120086  0.0004906305
[6]  0.0121114982
```

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```
#Mean and sd EA Log Return Calculation
mean_EA<-mean(EA_log_return)
mean_EA
```

```
[1] -5.234602e-05
```

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```
sd_EA<- sd(EA_log_return)
sd_EA
```

```
[1] 0.01994566
```

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```
#EA Log Return Calculation
ATVI_log_return_1<-diff(log(ATVI[,6]))
ATVI_log_return<-as.numeric(ATVI_log_return_1[-1])
head(ATVI_log_return)
```

```
[1] -0.003448960 -0.053675557 0.018810337 0.018316492 -0.004253687
[6] 0.023533879
```

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```
#Mean and sd EA Log Return Calculation
mean_ATVI<-mean(ATVI_log_return)
mean_ATVI
```

```
[1] 8.507391e-05
```

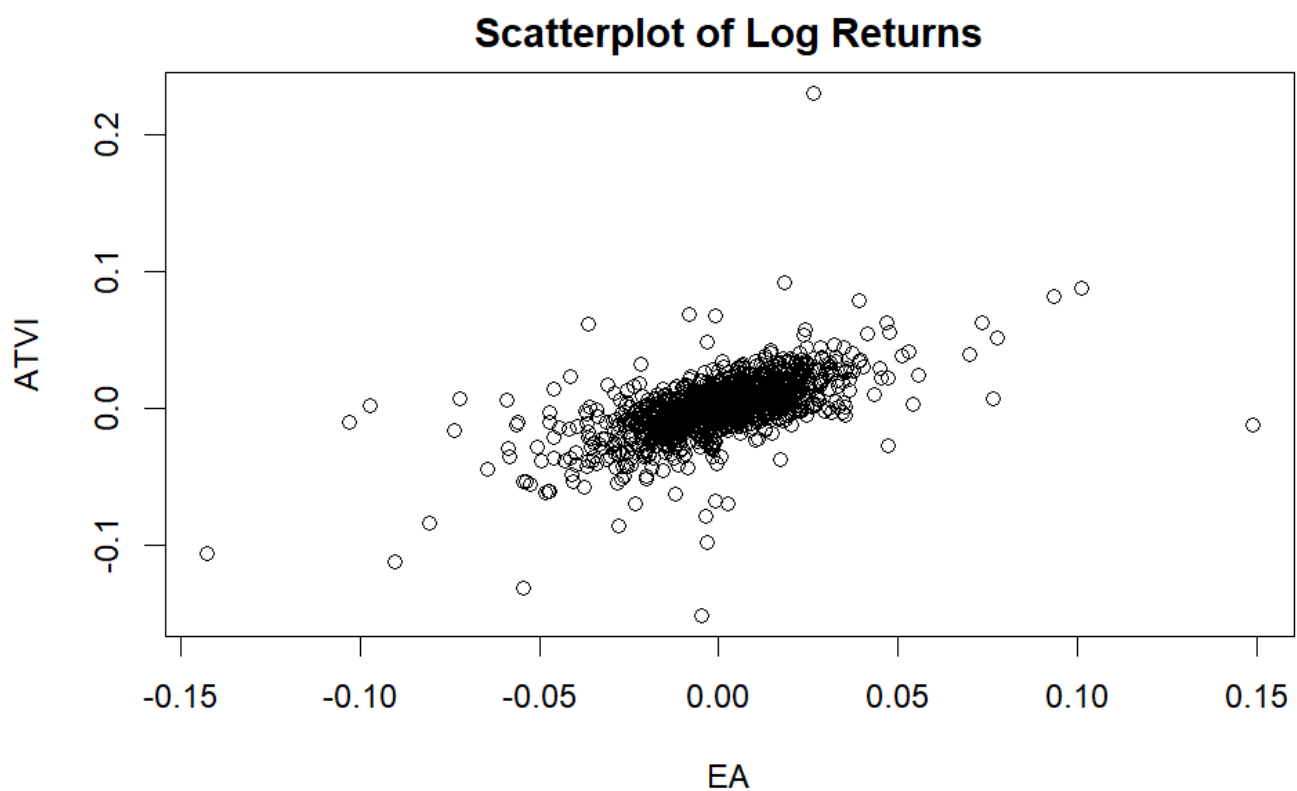
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```
sd_ATVI<- sd(ATVI_log_return)
sd_ATVI
```

```
[1] 0.02164873
```

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```
#1-Scatterplot of the two log returns
plot(EA_log_return, ATVI_log_return, main="Scatterplot of Log Returns", xlab="EA", ylab="ATV
I")
```



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```
# After generating the scatterplot between the two sets of log returns, due to their positive correlation, it can indicate that they have a linear relationship (many points clustered in the middle in an upward form). Other techniques could also be applied to better determine their relationship.
```

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```
#2-Maximum likelihood method to fit a bivariate t distribution. v- tail index parameter, for v estimate vector mean and correlation matrix
```

```
library(mnormt)
library(MASS)

df <- seq(2.25, 6, 0.01)
n <- length(df)
loglik <- rep(0, n)

dat <- cbind(ATVI_log_return, EA_log_return)

for(i in 1:n) {
  fit <- cov.trob(dat, nu = df[i])
  loglik[i] <- sum(log(dmt(dat, mean = fit$center, S = fit$cov, df = df[i])))
}

aic_t <- -max(2 * loglik) + 2 * (8 + 10 + 1) + 64000
z1 <- (2 * loglik > 2 * max(loglik) - qchisq(0.95, 1))
z1
```

```

[1] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[13] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[25] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[37] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[49] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[61] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[73] FALSE FALSE FALSE FALSE FALSE FALSE TRUE TRUE TRUE TRUE TRUE TRUE
[85] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
[97] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
[109] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
[121] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
[133] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
[145] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
[157] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
[169] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
[181] TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[193] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[205] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[217] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[229] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[241] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[253] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[265] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[277] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[289] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[301] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[313] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[325] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[337] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[349] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[361] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[373] FALSE FALSE FALSE FALSE

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```

plot(df, 2 * loglik - 64000, type = "l", cex.axis = 1.5, cex.lab = 1.5, ylab = "2 * loglikeli
hood - 64,000", lwd = 2)
abline(h = 2 * max(loglik) - qchisq(0.95, 1) - 64000)

```

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```

abline(h = 2 * max(loglik) - 64000)
abline(v=(df[78]+df[79])/2)

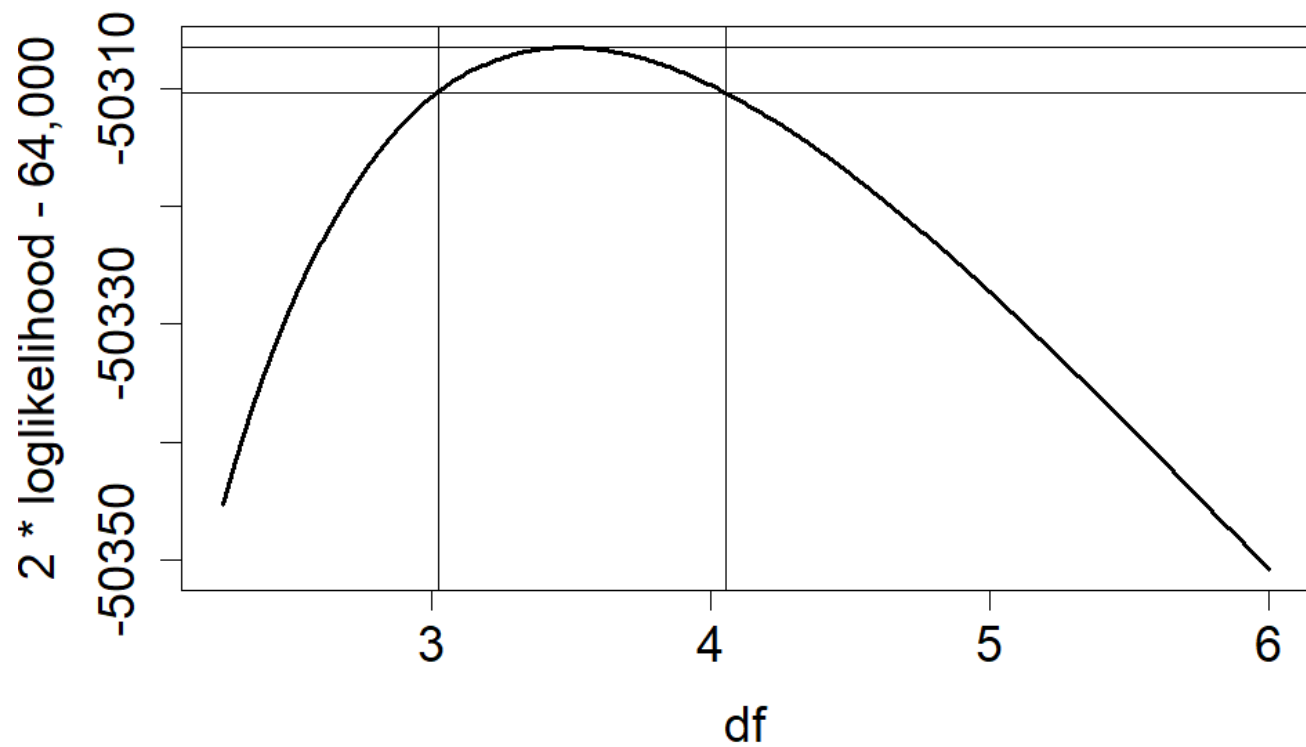
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abline(v=(df[181]+df[182])/2)

```



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```
best_index <- which.max(loglik)

# best degree of freedom
best_df <- df[best_index]
best_df
```

```
[1] 3.49
```

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```
# best fit using the best df
bestfit <- cov.trob(dat,nu=best_df,cor=TRUE)
bestfit
```



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```
cat("ATVI log-return:\n")
```

ATVI log-return:

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```
cat("Mean:", fit_ATVI$estimate[1], "\n")
```

Mean: 0.0007543853

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```
cat("Scale parameter:", fit_ATVI$estimate[2], "\n")
```

Scale parameter: 0.01324006

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```
cat("Degrees of freedom:", fit_ATVI$estimate[3], "\n\n")
```

Degrees of freedom: 3.053332

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```
# Fit t-distribution to EA log-returns
fit_EA <- fitdistr(EA_log_return, "t")
```

Warning: NaNs producedWarning: NaNs producedWarning: NaNs producedWarning: NaNs producedWarni  
ng: NaNs producedWarning: NaNs producedWarning: NaNs producedWarning: NaNs producedWarning: N  
aNs producedWarning: NaNs producedWarning: NaNs produced

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```
cat("EA log-return:\n")
```

EA log-return:

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```
cat("Mean:", fit_EA$estimate[1], "\n")
```

Mean: 0.0004849973

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```
cat("Scale parameter:", fit_EA$estimate[2], "\n")
```



```
Scale parameter: 0.01406657
```

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```
cat("Degrees of freedom:", fit_EA$estimate[3], "\n")
```

```
Degrees of freedom: 4.018489
```

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```
# Now convert estimated scale parameters to estimated standard deviations
```

```
cat("Standard deviation:", fit_ATVI$estimate[2] * sqrt((fit_ATVI$estimate[3] )/(fit_ATVI$estimate[3]-2)), "\n")
```

```
Standard deviation: 0.0225421
```

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```
cat("Standard deviation:", fit_EA$estimate[2] * sqrt((fit_EA$estimate[3])/(fit_EA$estimate[3]-2)), "\n")
```

```
Standard deviation: 0.01984752
```

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#4- calculate the sample Kendall's Tau rank correlation  $\hat{\rho}_\tau$  and the sample Pearson correlation  $\hat{\rho}$  for the pair of log-return series. Then compare  $\hat{\rho}$  with the estimate  $\sin(\pi/2 \times \hat{\rho}_\tau)$  and discuss briefly

```
#Kendall
```

```
 $\rho_\tau$ <-cor(ATVI_log_return, EA_log_return, method = "kendall") # kendall  
 $\rho_\tau$ 
```

```
[1] 0.4676636
```

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```
#Pearson
```

```
 $\rho$ <-cor(ATVI_log_return, EA_log_return, method = "pearson") #pearson  
 $\rho$ 
```

```
[1] 0.5981101
```

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```
# Pearson estimation based on Kendall
```

```
omega<-sin( $\rho_\tau$ *pi/2)  
omega
```

```
[1] 0.6702935
```

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# The estimate  $\sin(\pi/2 \times \hat{\rho}^\tau)$  is greater than the sample Pearson correlation  $\hat{\rho}$ , suggesting that the relationship between ATVI and EA log returns may not be linear. This is consistent with our earlier observations that the log returns do not follow a normal distribution and may have a non-linear relationship even though they have a strong and positive correlation, but they may have some normality between them

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```
#5-t-Copula (connection between two series) generation
library(copula)
library(fGarch)

# t-copula values
cop_t_dim2<-tCopula(omega, dim = 2, dispstr = "un", df=best_df)
cop_t_dim2
```

```
t-copula, dim. d = 2
Dimension: 2
Parameters:
  rho.1    = 0.6702935
  df       = 3.4900000
```

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```
# ATVI data percentiles
ATVI_data<-pstd(ATVI_log_return,fit_ATVI$estimate[1], fit_ATVI$estimate[2] * sqrt((fit_ATVI$estimate[3] )/(fit_ATVI$estimate[3]-2)), fit_ATVI$estimate[3])

# EA data percentiles
EA_data<-pstd(EA_log_return,fit_EA$estimate[1], fit_EA$estimate[2] * sqrt((fit_EA$estimate[3] )/(fit_EA$estimate[3]-2)), fit_EA$estimate[3])

#fit the copulas to the uniform -transformed data

data1<- cbind(ATVI_data, EA_data)

#n=nrow(dat);n
#data2<- cbind(rank(ATVI_log_return)/(n+1),rank(EA_log_return)/(n+1))

# fit the t-copula on data1
fit1<- fitCopula(cop_t_dim2, data1, method="ml", start=c(omega, best_df) )

# Estimated values for the correlation and for the tail-index parameter, along with the standard errors of these estimates
summary(fit1)
```

```
Call: fitCopula(cop_t_dim2, data = data1, ... = pairlist(method = "ml", start = c(omega,
  best_df)))
```

Fit based on "maximum likelihood" and 1257 2-dimensional observations.

t-copula, dim. d = 2

Estimate Std. Error

rho.1 0.6687 0.016

df 4.5858 0.703

The maximized loglikelihood is 384

Optimization converged

Number of loglikelihood evaluations:

function gradient

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# from the summary we can conclude that the bivariate t-copula has successfully been fit to the data, capturing a positive dependence between the two assets and accounting for tail dependence. To check how good this estimation it is important to also look at other copulas summaries.

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#6- fit a normal (Gaussian) copula, a Clayton copula, and a Joe Copula to your data using maximum likelihood

#Gaussian copula

```
fnorm<- fitCopula(copula = normalCopula(dim=2), data=data1, method="ml")
```

```
summary(fnorm)
```

```
Call: fitCopula(normalCopula(dim = 2), data = data1, ... = pairlist(method = "ml"))
```

Fit based on "maximum likelihood" and 1257 2-dimensional observations.

Normal copula, dim. d = 2

Estimate Std. Error

rho.1 0.6497 0.014

The maximized loglikelihood is 344

Optimization converged

Number of loglikelihood evaluations:

function gradient

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#Clayton copula

```
fclayton<- fitCopula(copula = claytonCopula(1,dim=2), data=data1, method="ml")
```

```
summary(fclayton)
```

```
Call: fitCopula(claytonCopula(1, dim = 2), data = data1, ... = pairlist(method = "ml"))
Fit based on "maximum likelihood" and 1257 2-dimensional observations.
Clayton copula, dim. d = 2
      Estimate Std. Error
alpha    1.757      0.072
The maximized loglikelihood is 233.4
Optimization converged
Number of loglikelihood evaluations:
function gradient
      3          3
```

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```
#Joe copula
fjoe<- fitCopula(copula = joeCopula(2,dim=2), data=data1, method="ml")
summary(fjoe)
```

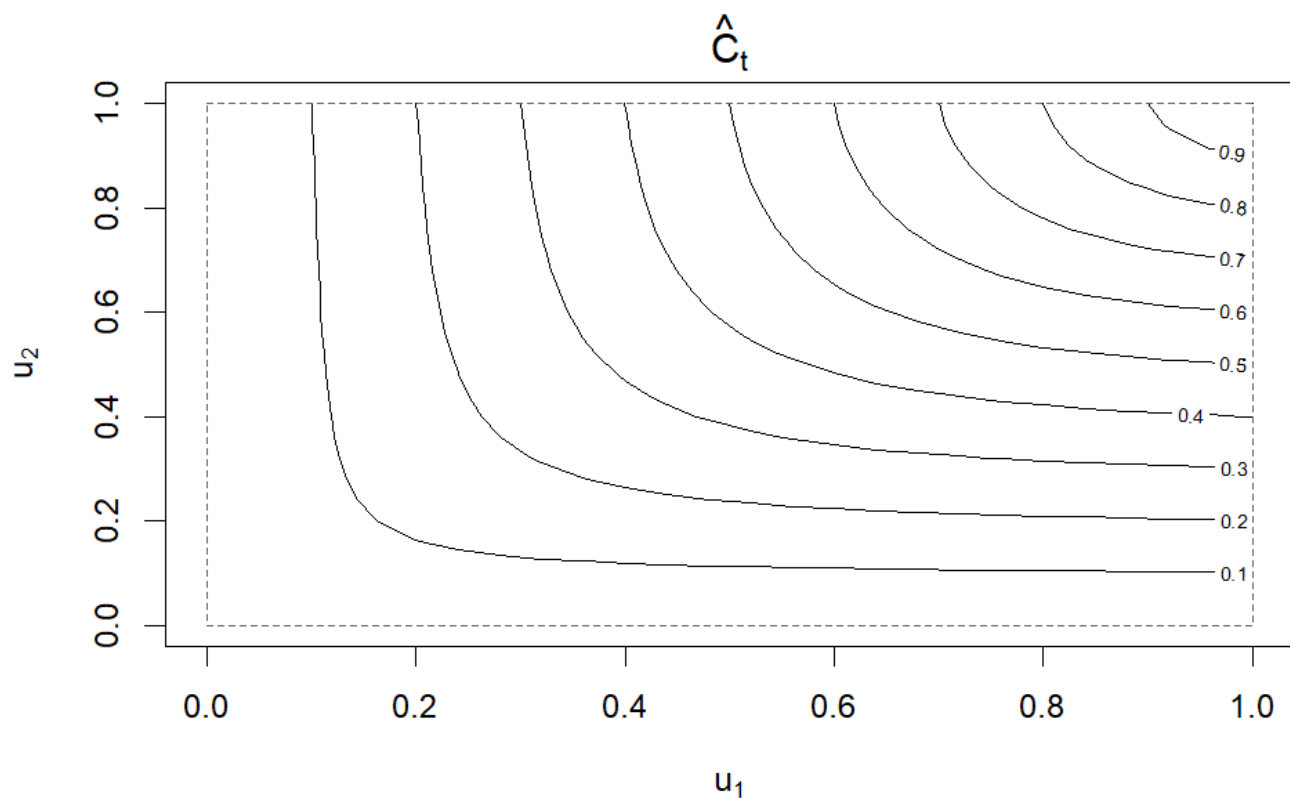
```
Call: fitCopula(joeCopula(2, dim = 2), data = data1, ... = pairlist(method = "ml"))
Fit based on "maximum likelihood" and 1257 2-dimensional observations.
Joe copula, dim. d = 2
      Estimate Std. Error
alpha     2.09      0.06
The maximized loglikelihood is 276.8
Optimization converged
Number of loglikelihood evaluations:
function gradient
      7          7
```

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```
#7- Use contour to create diagrams of the four fitted copulas (t, Normal, Clayton, and Joe)
```

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```
#tCopula
contour(tCopula(param=0.6702994, dim=2, df=round(3.49)), pCopula,main=expression(hat(C)[t]))
```


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```
#NormalCopula
contour(normalCopula(param=0.6497, dim=2), pCopula, main=expression(hat(C)[Gauss]))
```

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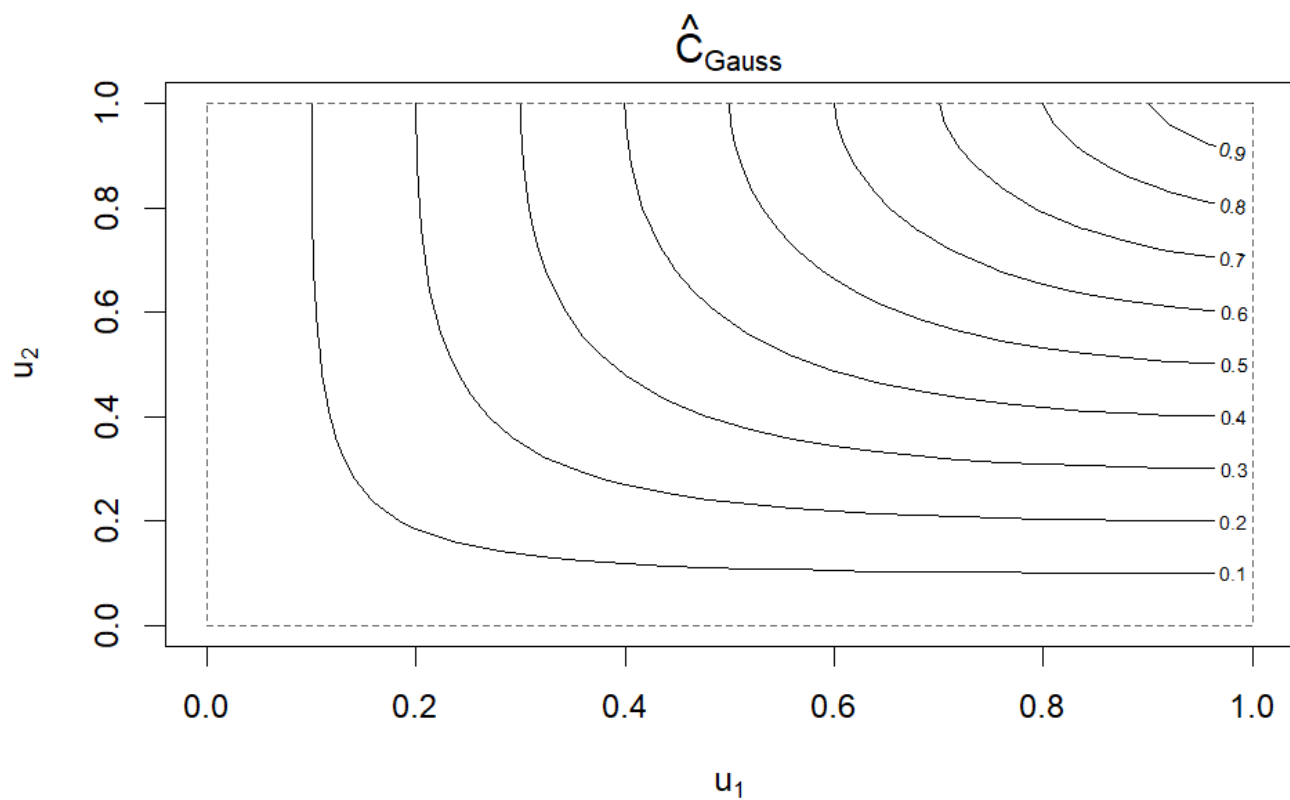
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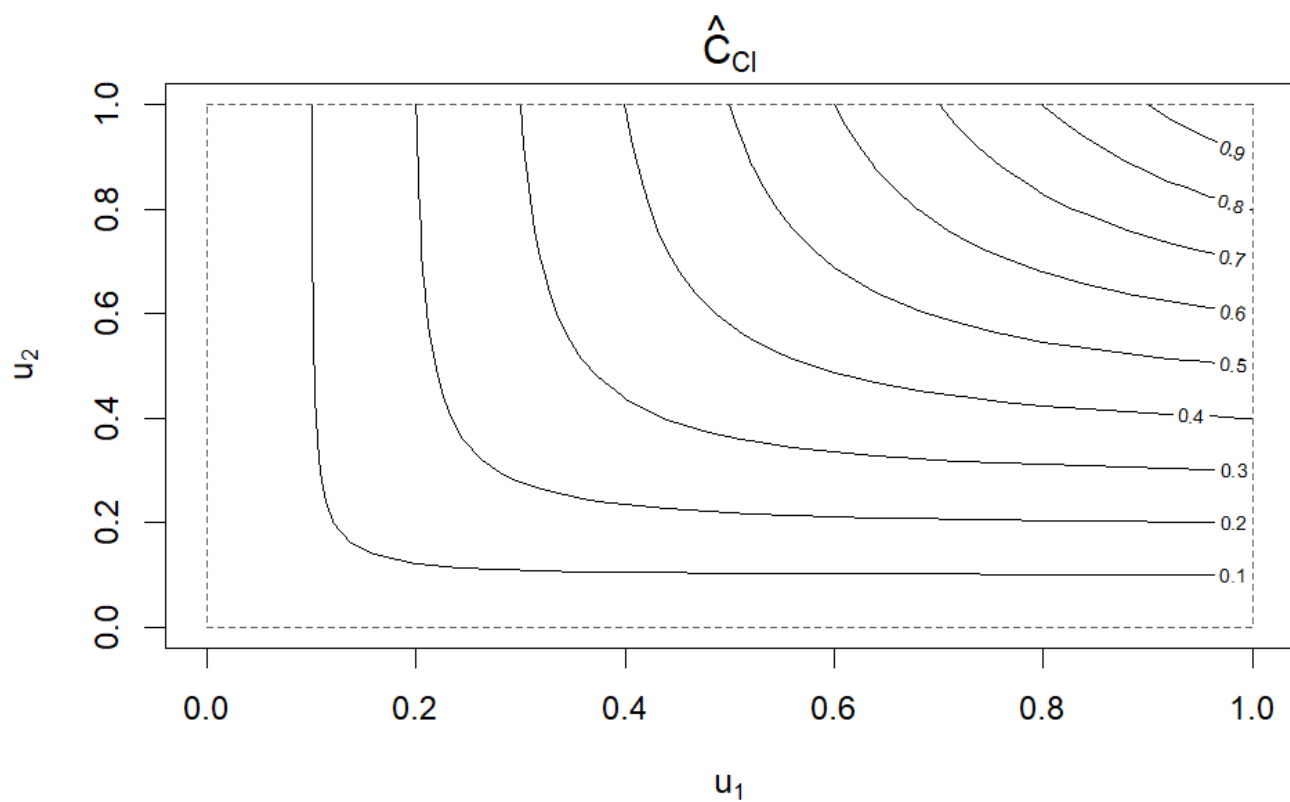
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```
#claytonCopula  
contour(claytonCopula(param=1.757, dim=2), pCopula, main=expression(hat(C)[Cl]))
```

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```
#joeCopula  
contour(joeCopula(param=2.09, dim=2), pCopula,main=expression(hat(C)[Joe]))
```

