

## Problem Background

### Fitting Copula Models

In this lab we are going to fit copula models to a bivariate data set of daily returns on IBM and S&P500 Index.

First, we need to fit a model with the univariate marginal  $t$ -distributions and a  $t$ -copula.

This model will have three degrees of freedom parameters:

- IBM tail index
- S&P 500 Index tail index
- Joint tail index (the copula)

```
net.returns <- read.csv(paste0(data.dir, "IBM_SP500_04_14_daily_netRtns.csv"),
                        header = T)

ibm <- net.returns[, "IBM"]
sp500 <- net.returns[, "SP500"]

suppressWarnings({
  est.ibm = as.numeric( fitdistr( ibm, "t" )$estimate )
  est.sp500 = as.numeric( fitdistr( sp500, "t" )$estimate )
})

est.ibm[2] = est.ibm[2] * sqrt( est.ibm[3] / (est.ibm[3]-2) )
est.sp500[2] = est.sp500[2] * sqrt( est.sp500[3] / (est.sp500[3]-2) )
```

The univariate estimates will be used as starting values when we estimate the *meta-t* distribution is fit by maximum likelihood. Before we do that, we need to compute an estimate of the correlation coefficient in the  $t$ -copula.

## Problem 1

**Using Kendall's tau, compute omega, which is the estimate of the Pearson correlation from Kendall's tau.**

From 8.27 we have Kendall's tau,  $\rho_\tau$ , =

$$\rho_\tau(Y_i, Y_j) = \frac{2}{\pi} \arcsin(\Omega_{i,j}).$$

Inverting, we derive that:

$$\Omega_{i,j} = \sin\left[\frac{\pi}{2} \rho_\tau(Y_i, Y_j)\right]$$

```
cor_tau = cor(ibm, sp500, method = "kendall")
omega = sin((pi/2) * cor_tau)
```

$$\Omega = 0.701835$$

The  $t$ -copula using omega as the correlation parameter and 4 as the degrees of freedom:

```
cop_t_dim2 <- tCopula(omega, dim = 2, dispstr = "un", df = 4)
```

```
t-copula, dim. d = 2
Dimension: 2
Parameters:
  rho.1    = 0.7018346
  df       = 4.0000000
```

Now fit copulas to the uniformed-transformed data:

```
n = nrow(net.returns)

data1 = cbind( pstd( ibm, mean=est.ibm[1], sd=est.ibm[2], nu=est.ibm[3] ),
               pstd( sp500, mean=est.sp500[1], sd=est.sp500[2], nu=est.sp500[3] ) )

data2 = cbind( rank(ibm)/(n+1), rank(sp500)/(n+1) )

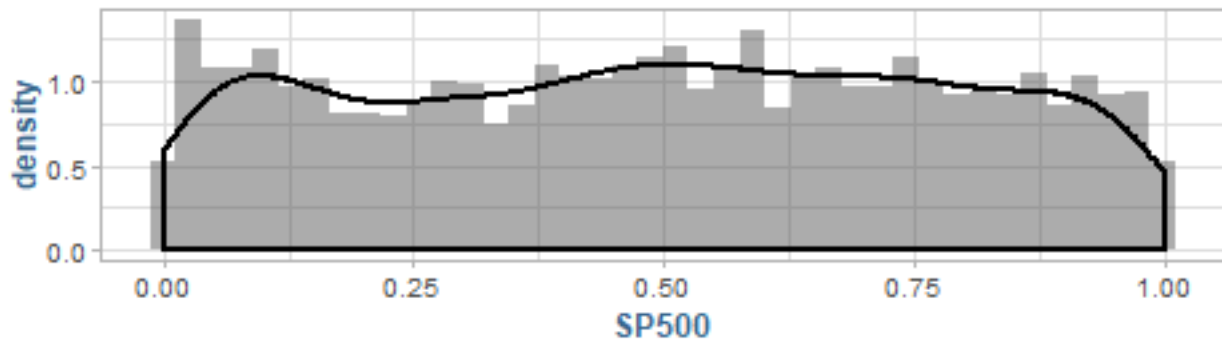
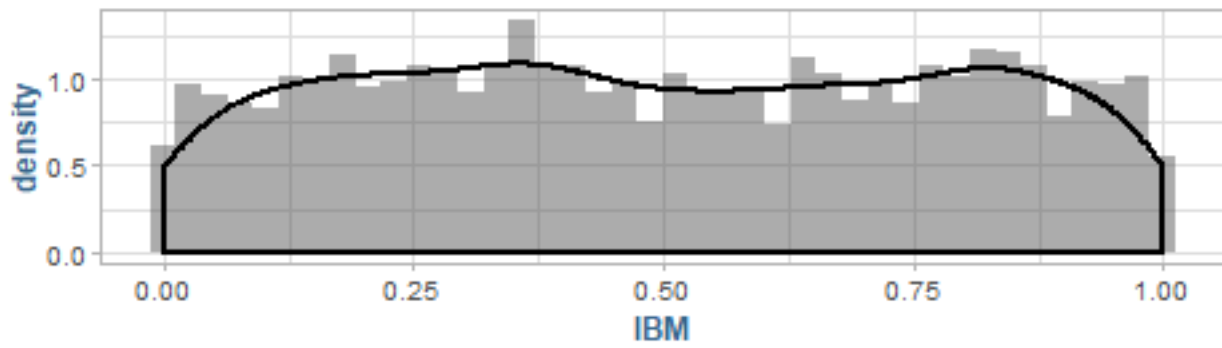
ft1 = fitCopula(cop_t_dim2, data=data1, method="ml", start=c(omega,4))
ft2 = fitCopula(cop_t_dim2, data=data2, method="ml", start=c(omega,4))
```

## Problem 2

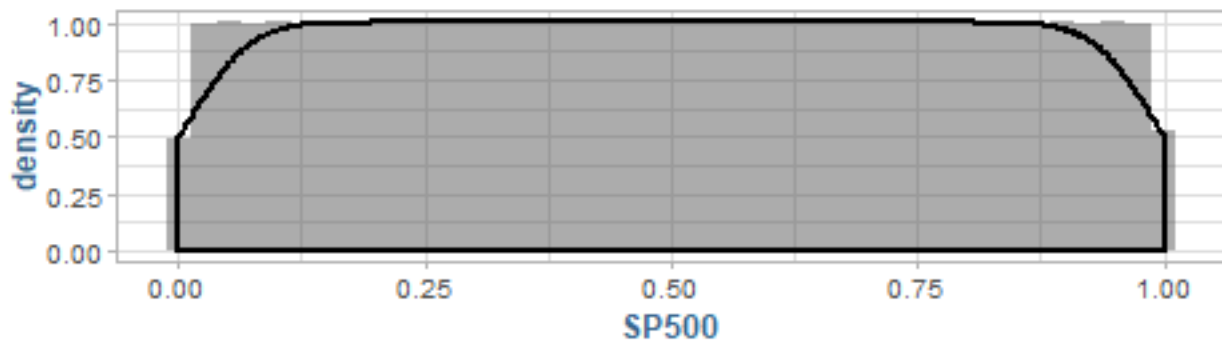
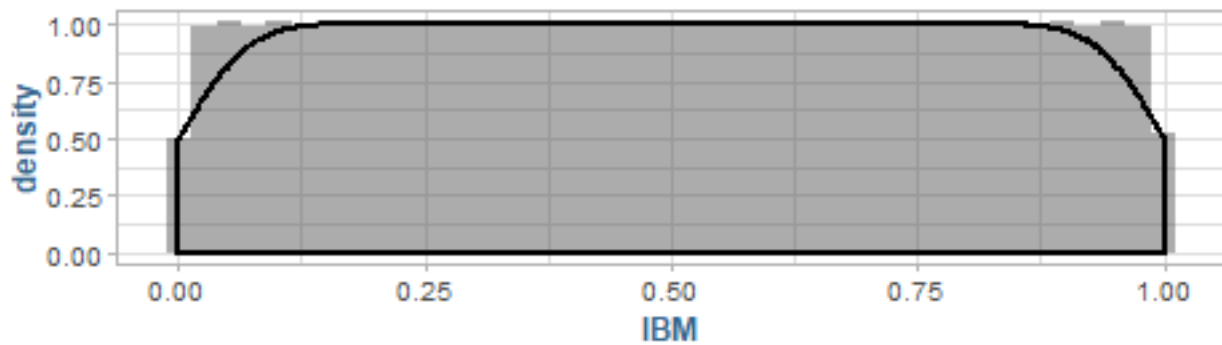
Explain the difference between methods used to obtain the two estimates *ft1* and *ft2*.

For *ft1* we pass in the probability

data1: Marginal Densities



data2: Marginal Densities



Do the two estimates seem significantly different (*in a practical sense*)?

```
summary(ft1)
```

```
Call: fitCopula(copula, data = data, method = "ml", start = .2)
Fit based on "maximum likelihood" and 2516 2-dimensional observations.
t-copula, dim. d = 2
      Estimate Std. Error
rho.1  0.7022      0.012
df      2.9834      0.269
The maximized loglikelihood is 967.2
Optimization converged
Number of loglikelihood evaluations:
function gradient
      40          9
```

```
summary(ft2)
```

```
Call: fitCopula(copula, data = data, method = "ml", start = .2)
Fit based on "maximum likelihood" and 2516 2-dimensional observations.
t-copula, dim. d = 2
      Estimate Std. Error
rho.1  0.7031      0.012
df      3.0222      0.278
The maximized loglikelihood is 964.6
Optimization converged
Number of loglikelihood evaluations:
function gradient
      38          9
```

### Problem 3

Next, we will define a meta-*t*-distribution by specifying its *t*-copula and its univariate marginal distributions.

```
mvdc_t_t = mvdc( cop_t_dim2, c("std","std"), list(
  list(mean=est.ibm[1],sd=est.ibm[2],nu=est.ibm[3]),
  list(mean=est.sp500[1],sd=est.sp500[2],nu=est.sp500[3])))
```

```
mvdc_t_t
```

```
Multivariate Distribution Copula based ("mvdc")
@ copula:
t-copula, dim. d = 2
Dimension: 2
Parameters:
  rho.1    = 0.7018346
  df       = 4.0000000
@ margins:
[1] "std" "std"
      with 2 (not identical) margins; with parameters (@ paramMargins)
List of 2
 $ :List of 3
  ..$ mean: num 0.05015879
  ..$ sd   : num 1.42823
  ..$ nu   : num 3.254383
 $ :List of 3
  ..$ mean: num 0.07918415
  ..$ sd   : num 1.968172
  ..$ nu   : num 2.249776
```

## Problem 4